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Full Length Research Paper

Impacts of common processes in multistage production system under machine breakdown and quality uncertainties

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The work desires to determine the optimum level of batch size in bottleneck facility and to analyze the effect of common processes on throughput and cycle time in a production system under uncertain situations 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. The experimental settings are executed in WITNESS, a simulation package. It is observed that the variation in level of common process in the system has significant impact on the production quantity and cycle time. The main contribution of this research is determination of the optimal level of batch size in a bottleneck resource under imperfect quality of product and resources breakdown uncertainties. This approach can be generalized to any multistage production system, regardless of the precedence relationships among the various production stages in the system.

Key words: Process commonality, uncertainty, quality.

INTRODUCTION

Commonality is the use of same version of components/processes in multiple/group of products in a product family. In literatures, two sources of commonality are identified - the component part commonality and the process commonality. The process commonality index incorporates such concerns as process flexibility, lot sizing, sequencing and scheduling common alarms into one analytical measurement (Jiao and Tseng, 2000). In manufacturing, components commonality refers to the use the same components for two or more products in their final assemblies. Commonality substantially lowers the costs of proliferated product lines, mitigate the effects of product proliferation on product and process complexity (Heese and Swaminathan, 2006). It reduces the cost of safety stock, decreases the set-up time, increases productivity and improves flexibility (Zhou and Grubbstrom, 2004); reduces the required number of order (or setups) (Mirchandani and Mishra, 2002; Hillier, 2002); reduces risk-pooling and lead time uncertainty, improve the economy of scale, simplify planning, schedule and control process, streamlines and speeds up product development process (Ma et al., 2002). The authors would like to refer the readers to Wazed et al. (2010) for details about the commonality, its measurements and models. The commonality occurs in its own way in the system or can be planned for its preferred happening as well. The number and diversity of component parts and the corresponding processes mirror the complexity of product design and that of production planning and control.

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,

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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 (Du and Chen, 2000). 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. 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 (Koh and Saad, 2003). It wields a reduction of capacity level and delays the release of products or subassemblies (Wazed et al., 2008). 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.

In the operations management literature, two concepts of quality stand out. One defines it as the degree of conformance to design specification. This corresponds to the view of the quality control technicians. The second view considers quality of the design itself. Quality defines as the degree to which a system, component, or process meets specified requirements or meets customers' expectations (Aas et al., 1992). 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. (2008).

In the quality literature, the quality of a product may fail due to variations called chance (or common or random) cause variations and assignable cause variations. Assignable cause variation can occur at any stage of production process and once a defective part is produced, all subsequent parts will be bad (Kim and Gershwin, 2005). Some of the assignable cause variations are defective raw material, improper machine setup, worn equipment, man power expertise and skill, the product design and specification and poor quality of machine. In this article, the inspection is performed at the final stages only and the defective product(s) is simply rejected.

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.

The effects of the reworking of defective items on the economic production quantity (EPQ) model with backlogging as studied by Peter (2003). In his study, a random defective rate is considered and when regular production ends, the reworking of defective items starts immediately. Ouyang et al. (2007) 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 (2004) 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 process.

Porteus (1986) 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 modeling the quality improvement problems. Zhang and Gerchak (1990) 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 (1998) 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. (2002) 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. (2003) 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 (2003) 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 process commonality.

Hong (1995) 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 (1999) have presented a batch sizing model that minimizes the

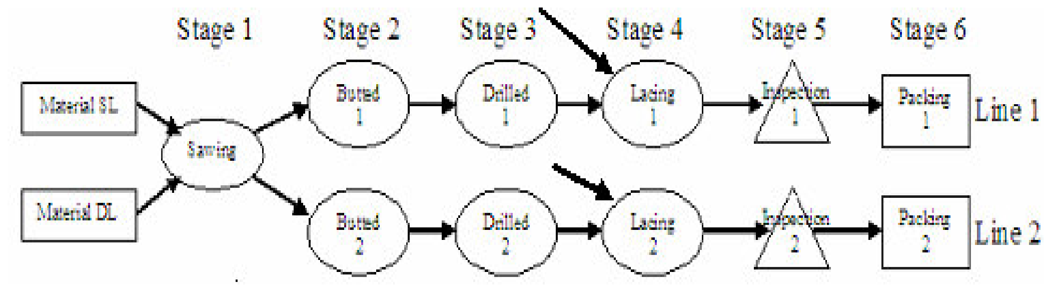

Figure 1. Existing production layout of XDE.

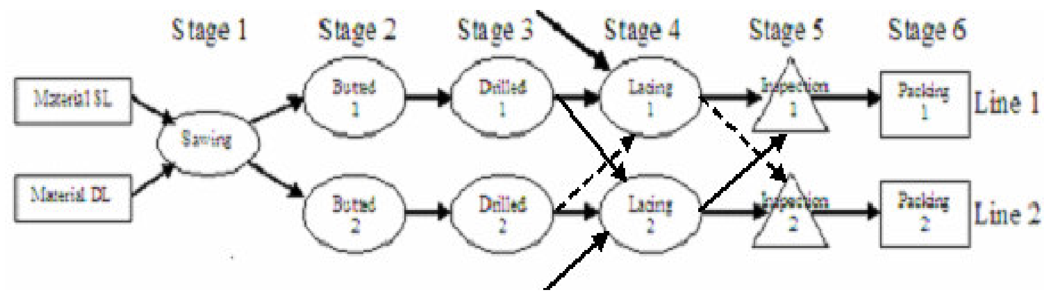

Figure 2. Proposed/modified production layout of XDE.

average queuing delay for a multi-item, single-machine work-centre. Later, they investigated the relationship between batch size and lead time variability. Machine breakdown and common processes 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 process and brought out live case. Under such circumstances, the authors studied the effects of process 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 process commonality in a disturbed environment.

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. Parts are initially processed 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.

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 processes 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) 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 processes for analysis.

In this study, two factors are considered and the effects of these factors on the system performance are tested. The level of common process 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 process on production cycle time and throughput quantity. Before confirmed the results, interaction effect are observed to make sure that the characteristic of the control factors is additive.

The ranges of factor levels are selected based on capacity limitation and in consultation with the engineers in the company (Table 1). Based on the historical data, three defective rates are

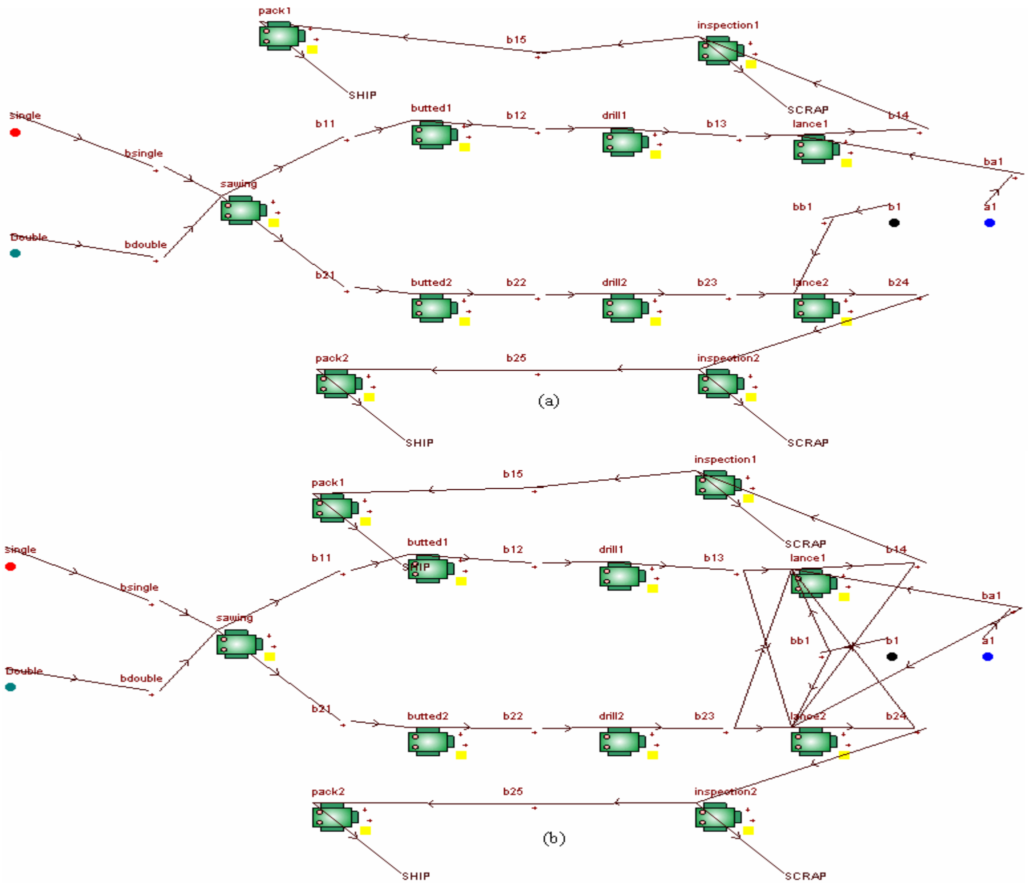

Figure 3. (a) Base and (b) Proposed commonality models in WITNESS.

considered: 3, 5 and 7% and the machine breakdown are taken as 40, 20 and 10 operations.

Since this study contains two control factors (one is four levels and other one is two levels) and two noise factors of three levels for each, thus $\left(4^1 \times 2^1 \times 3^2\right) = 72$ 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.

COLLECTION AND VALIDATION OF DATA/MODEL

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 historical data shows that 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.

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 260 days after a warm-up period of 2 × 260 days and then the simulated results are generated. The run time for a 9 h shift for 260 days is 9 × 60 × 260 min, 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 2. 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.

DATA ANALYSIS AND DISCUSSION

The authors have conducted a total of 72 experiments. The summary of experimental results for the production cycle time and production quantities with corresponding S/N ratio for each exercise of line 1 and Line 2 are observed. The smaller the better characteristic is used for cycle time and in calculating the corresponding S/N ratio.

Table 1. Control factors and their levels for Taguchi method.

Control factors	Level 1	Level 2	Level 3	Level 4
Batch size at the bottleneck station (that is Lancing), A	2	6	12	20
Common process, B	0	2	-	-

Table 2. Comparison between the existing system and simulation model for 260 days.

Response	Existing system	Simulation model
Mean yearly throughput for SL	2030	2067
Mean yearly throughput for DL	2050	2077
Mean cycle time for SL (min)	300	279.73
Mean cycle time for DL (min)	290	272.32

Table 3. Response table for production quantity for Lines 1 and 2 (the larger the better).

Level	Mean (line 1)		S/N ratio (line 1)		Mean (line 2)		S/N ratio (line 2)	
	Batch size	Common process	Batch size	Common process	Batch size	Common process	Batch size	Common process
Level 1	1930	3872	65.70	71.16	1933	3859	65.72	71.13
Level 2	4446	6308	72.78	74.58	4426	6312	72.73	74.59
Level 3	7233	-	76.69	-	7233	-	76.69	-
Level 4	6750	-	76.30	-	6750	-	76.30	-
Diff	7233	6308	76.69	74.58	7233	6312	76.69	74.59
Rank	1930	3872	65.70	71.16	1933	3859	65.72	71.13
Opt	5303	2436	10.99	3.41	5300	2453	10.97	3.46

The larger the better principle is adopted for production quantity and for corresponding S/N ratio.

Since the experiment design is orthogonal, the effect of batch size and common process for different levels are separated out. Table 3 shows the response for mean and S/N ratio for production quantity and the same for production cycle time is shown in Table 4 for both of the production lines. Since the characteristic of these factors for production quantities are the larger the better, the batch sizes are chosen based on larger mean and S/N ratio for production level and for production cycle time, the smaller the better policy is used. The selection in later case is based on the 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 yield an increase in production level in the system, but the capacity restrains the further increase in the batch size. Thus, based on response table (Tables 3 and 4), the batch size and common process are chosen as 12 and 2 respectively.

Figures 4 and 5 shows the interaction effects of variation in levels of control factors for (a) mean value and (b) S/N ratio of production quantity and cycle time respectively for Line 1. The same for Line 2 are shown in Figures 6 and 7. The figures show that the effect of batch size on production level and cycle time at two different levels of common process is not the same. This implies that there is an interaction between these two factors. The production quantity is peak and cycle time is least when the batch size is 12 and common process is at the highest levels.

Table 5 shows the ANOVA for production quantity in mean and S/N ratio for Line 1 and Line 2. The same for production cycle time for both of the lines are shown in Table 6. These tables show the relative importance of the control factors affecting the throughput and cycle time. Both mean and signal to noise ANOVA indicates that batch sizes in lancing station (factor A) and use of common process (factor B) is statistically significant. The factors have impacts on production quantity and cycle time.

Based on ANOVA (Tables 5 and 6) and response table (Tables 3 and 4), it is obvious that batch size of 12 in the lancing station and 2 common processes yield the lowest cycle time and maximum throughput in the system.

Conclusions

The authors have developed the simulation models of the

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

Level	Mean (line 1)		S/N ratio (line 1)		Mean (line 2)		S/N ratio (line 2)	
	Batch size	Common process	Batch size	Common process	Batch size	Common process	Batch size	Common process
Level 1	277.80	283.70	-48.88	-49.06	282.40	287.80	-49.02	-49.18
Level 2	194.30	123.10	-44.78	-39.56	196.20	123.70	-44.85	-39.58
Level 3	165.90	-	-41.14	-	167.40	-	-41.18	-
Level 4	175.60	-	-42.42	-	176.90	-	-42.47	-
Diff	277.80	203.66	-41.14	-39.56	282.40	210.59	-41.18	-39.58
Rank	165.90	123.13	-48.88	-49.06	167.40	123.69	-49.02	-49.18
Opt	111.90	160.50	7.73	9.50	115.00	164.10	7.84	9.61

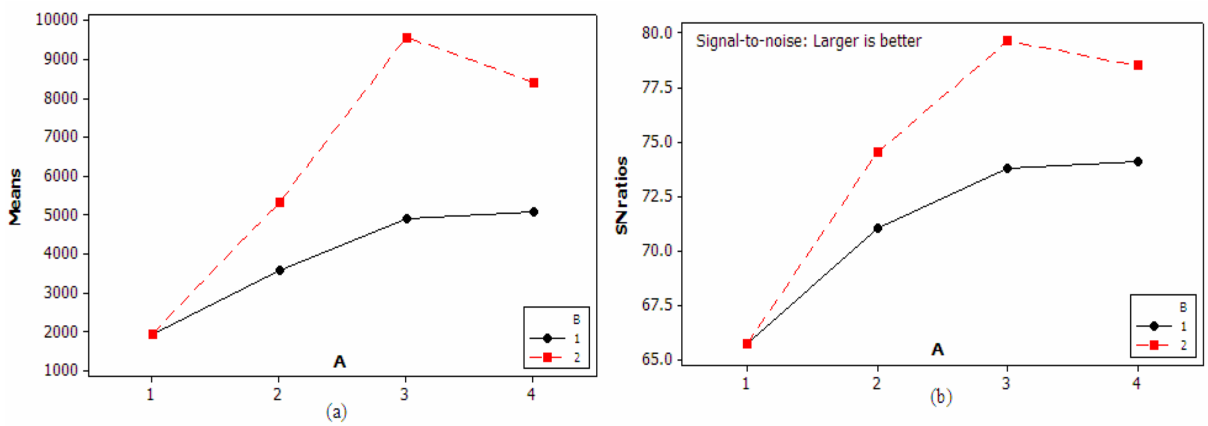

Figure 4. Interaction plot for (a) mean value and (b) S/N ratio of production level for Line 1.

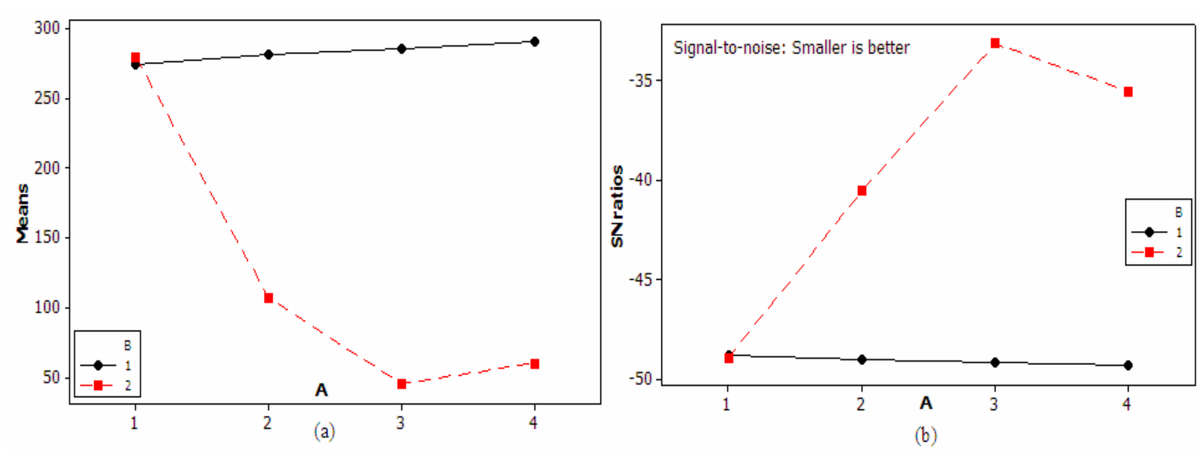

Figure 5. Interaction plot for (a) mean value and (b) S/N ratio of production cycle time for Line 1.

production line of a Malaysian company producing various bicycle wheels under the machine breakdown and quality uncertainties. The models have been run for a reasonable warm-up period. The necessary data and information has been collected from the floor and face-to-face conversations. The data and models have been verified and validated. Intensive investigations have been carried out. From the experiences of the analysis and from the outcomes of the models, the authors would like to conclude that:

The developed simulation models for the production

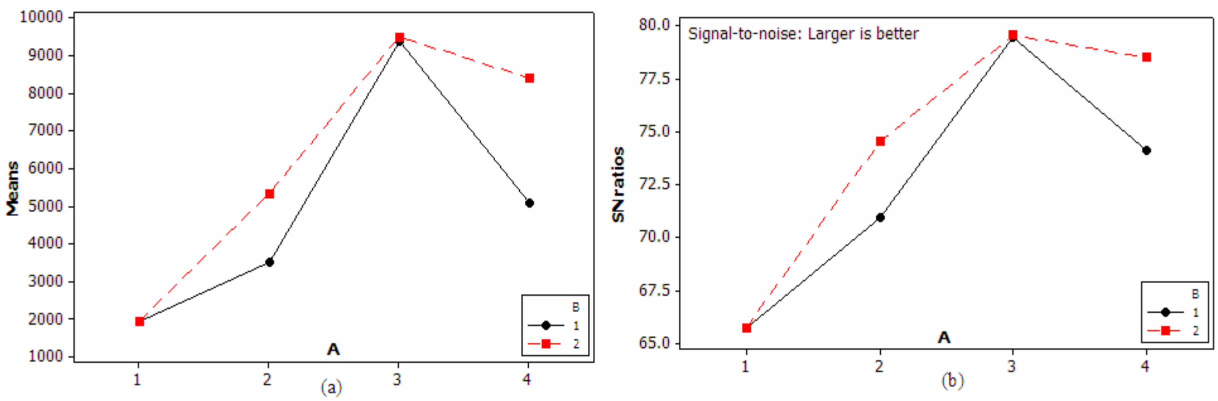

Figure 6. Interaction plot for (a) mean value and (b) S/N ratio of production level for Line 2.

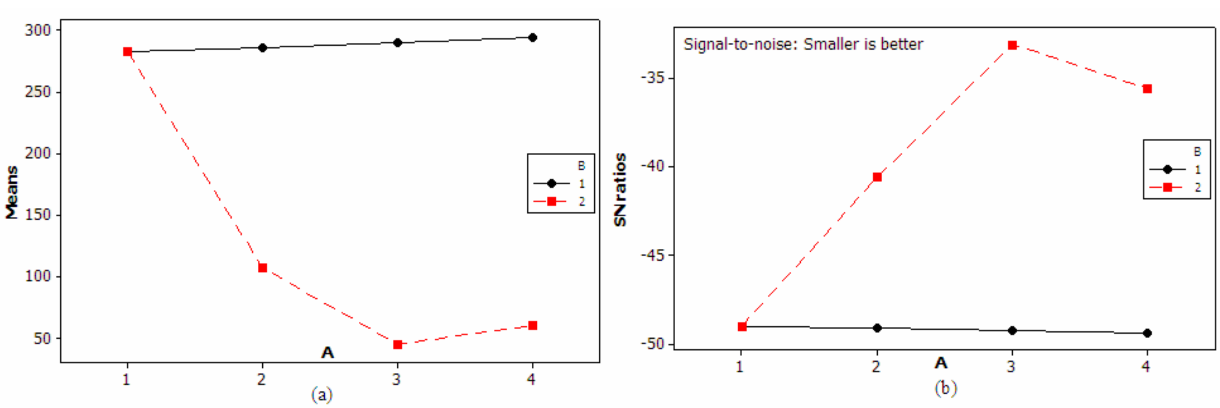

Figure 7. Interaction plot for (a) mean value and (b) S/N ratio of production cycle time for Line 2.

Table 5. ANOVA for Mean value and S/N ratio of production quantity of Lines 1 and 2.

Source	Mean value (line 1)					S/N ratio (line 1)			
	DF	SS	MS	F	P	SS	MS	F	P
A	3	12341766	4113922	108.518	0.001	306.887	102.296	68.32	0.003
B	1	389207	389207	10.2666	0.048	8.967	8.967	5.99	0.039
Error	3	113730	37910			4.492	1.497		
Total	7	128444703				320.346			
	S = 615.7; R-Sq = 99.09%; R-Sq(adj) = 97.88%					S = 1.224; R-Sq = 98.56%; R-Sq(adj) = 96.65%			
	Mean value (line 2)					**S/N ratio (line 2)**			
A	3	12423798	4141266	103.142	0.002	307.354	102.451	64.23	0.003
B	1	434519	434519	10.8221	0.037	6.45975	6.45975	4.05	0.038
Error	3	120453	40151			4.786	1.595		
Total	7	12978770				318.6			
	S = 633.7; R-Sq = 99.04%; R-Sq(adj) = 97.77%					S = 1.263; R-Sq = 98.48%; R-Sq(adj) = 96.44%			

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.

Since the lancing stations process a batch of parts at a time and they are bottleneck of the system, the authors have analyzed (varying the batch size and making the processes common) for detail investigations. Based on

Table 6. ANOVA for Mean value and S/N ratio of production cycle time of Lines 1 and 2.

Source	Mean value (line 1)					S/N ratio (line 1)			
	DF	SS	MS	F	P	SS	MS	F	P
A	3	105029	35009.7	12.29	0.025	405.176	135.059	5.83	0.049
B	1	104766.6	104767	6.85	0.042	104.497	104.497	4.51	0.05
Error	3	45883	15294.4			69.51	23.17		
Total	7	255678.6				579.183			
	S = 123.7; R-Sq = 72.00%; R-Sq(adj) = 34.67%					S = 4.814; R-Sq = 85.71%; R-Sq(adj) = 66.66%			
	Mean value (line 2)					S/N ratio (line 2)			
A	3	109612	36537.3	22.5539	0.026	420.891	140.297	6.01	0.047
B	1	15100	15100.3	9.32117	0.04	107.08	107.08	4.59	0.049
Error	3	4860	1620			69.988	23.329		
Total	7	129572				597.959			
	S = 127.3; R-Sq = 71.96%; R-Sq(adj) = 34.56%					S = 4.830; R-Sq = 86.13%; R-Sq(adj) = 67.64%			

the least manufacturing cycle time and maximum throughput the optimum batch sizes 12 when the two processes are common for both production lines.

Batch sizes in lancing stations and making the processes common for both lines, the system outcomes improved. ANOVA for mean and S/N ratio for cycle time and throughput indicate that no important factor is omitted from experiments.

There is strong interaction among the common process and the batch sizes in lancing stations. The production quantity is peak and cycle time is least when the batch size is 12 and common process is at the highest level.

The authors have considered only two noise factors (uncertainties) in this article (viz. machine breakdown and quality variation) and have analyzed the impacts of common process and batch size on production quantities and cycle time. In real production systems, there are so many uncertainties (Wazed et al., 2009) those need to deal with.

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