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Full Length Research Paper

Impacts of quality and processing time uncertainties in multistage production system

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The primary objectives of this research are to develop simulation models for multistage production system under processing time and quality variation, to identify areas of potential bottleneck in production system and to determine the optimum production lot size for each station in a multistage production system under the uncertainties to minimize the WIP level and lead time and thereby the total system cost. A simulation model is developed based on a live case from a Malaysian company. Taguchi approach for orthogonal array is used in designing experiments and these are executed in WITNESS. The models are verified and validated by face validity, the historical data from the company and analytical model. The delivery performances, average lead time and work-in-progress (WIP) in the system, are examined for different experimental scenarios. Interaction effects and confirmation tests are also performed. The optimal batch sizes respectively for polishing unit (PU), quality control (QC) and packing stations are 8, 16 and 3 at minimum WIP and lead time. If the company uses these optimal batch sizes, a total of 24% improvement can be obtained. The simulation models show that Gasketing station is the bottleneck and batch size selection in PU station is the most critical decision in the system. The interaction effects are insignificant. The main contribution of this research is determination of the optimal lot sizes under imperfect quality of product and stochastic processing time. 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: Simulation, batch size, lead time, work-in-progress.

INTRODUCTION

The classical lot sizing model which assumes the output of the production process is of perfect quality. However, in more realistic manufacturing system, non-conforming items may produce as time goes. These non-conforming 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.

Multistage production is common in manufacturing industry. Serial production system such as assembly system, semiconductor fabrication facilities and packing system are special type of multistage production system (Hadjinicola and Soteriou, 2003). The fundamental challenge of multi-stage production is the propagation and accumulation of uncertainties, which influences the conformity of the outputs (Du and Chen, 2000).

A simulation model is a surrogate for actually experimenting with a manufacturing system, which is often infeasible or not cost-effective. This approach is more realistic to model a real manufacturing system

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Abbreviation: WIP, Work-in-progress; **PU,** polishing unit; **QC,** quality control; **CV,** coefficient of variation.

(Oraifige, 2006). Therefore, in this article, simulation model is chosen for study the multistage production system under quality and processing time variations.

Uncertainty always present in manufacturing environment. These uncertainties affect the performance of a system, including its service level in terms of fill rate or delivery lead time, which in turn affects the bottom line of an enterprise in today's competitive environment (Liu et al., 2004). For details on the factors and sources of various uncertainties, the authors humbly like to refer the readers to Wazed et al. (2009b).

Lead time refers to the time span from material availability at the first processing operation to completion at the last operation. This time is composed of processing, waiting and transportation times. However, lead time may differ from early planned due to uncertainty. Lead time uncertainty may increase the total cost of the product because it provokes either some shortages or surplus in inventories which in turn increase either backlogging or holding cost respectively. The manufacturing lead time increased with an increase in batch size. This added complexity in the production environment. Long manufacturing lead time permits a buildup of buffer inventory and reduces customer satisfaction. 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 processing time and quality are stochastic.

Quality is defined as the degree to which a system, component, or process meets specified requirements or meets customers' expectations (Aas et al., 1992). Quality, in this article, means a measure of perfection of a product. In the operations management literature, two concepts of quality stand out. One defines it as the degree of conformance to design specification. The second view considers quality of the design itself. 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. (2009a). EOQ model generally considers inventory holding costs for finished goods not for WIP inventories (Koo et al., 2007). In an unbalanced manufacturing, WIP inventories are more important than the parts completed through the bottleneck machine. 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 modelling 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) provided 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 inspecting errors in screening non-conforming items at each stage has been incorporated.

The effects of the reworking of defective items on the economic production quantity (EPQ) model with backlogging as studied by Peter Chiu (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 lead 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.

There are few batch sizing models those explicitly take lead time into account in a stochastic manufacturing system. In these researches, the manufacturing facility is usually modelled by a queuing system. Karmarkar (1987) has examined the relationships between manufacturing lead times, WIP inventories and batch size. Karmarker et al. (1992) have presented a multi-item batching heuristic with the objective of minimizing the queuing delay. They develop upper and lower bounds on the optimal batch size. Based on the bounds, three batch sizing heuristics are presented and tested.

Hong (1995) has developed a mathematical model to study the effect of reduction in manufacturing lead time and increase in process quality on lot size computation and total relevant cost. Kuik and Tielemans (1999) presented a batch sizing model that minimizes the average queuing delay for a multi-item, single-machine work-centre. Later, they investigated the relationship between batch size and lead time variability.

The major limitations of the earlier studies are (i) the combined effects of quality and lead time uncertainties in a multistage production system are ignored; (ii) None of the studies have considered a multistage production problem in determining the optimal lot size under the uncertainties; (iii) Most models are mathematical model which can address one type of uncertainty at a time;

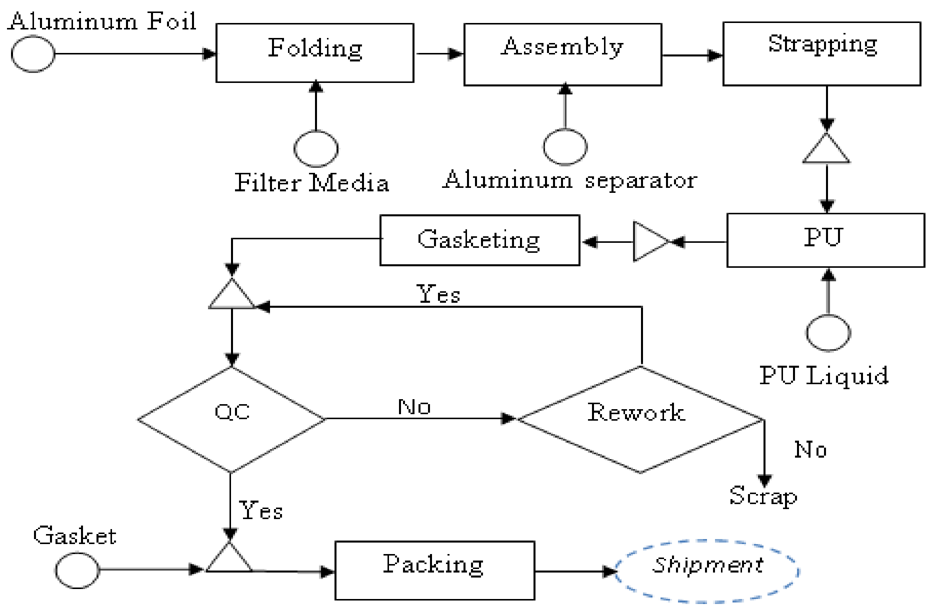

Figure 1. Manufacturing cell layout of the factory.

(iv) None of them brought out live case study. Thus this article deals with a multistage lot sizing model in an imperfect production process taking processing time as one of the decision variable. The lot size is optimized with the minimization of the two cost factors; WIP cost and long lead time cost in all stages in the production system.

RESEARCH/ EXPERIMENTAL DESIGN

In this article, various research scenarios are created based on a Malaysian company under quality and processing time uncertainties. The company, namely ABC (a given name), is producing air filter products for diverse air filtration system. ABC also produces chemical filtration system to filter the unwanted gases. The production line in the company can be divided into primary and secondary filter production lines. The secondary filter production line is under this research and the product is AAI (a given name) air filter. Parts and material required to produce AAI filters are media, separators, gasket, bond, cell sides and gel seal. The product undergoes eight stages; therefore, it represents a multistage production system. Fixed factors such as number of stages, mean processing time, average defective rate and other variables that are required in this research are collected from the floor and face-to-face conversation. The manufacturing cell layout of the system is shown in Figure 1.

Polishing unit (PU), quality control (QC) and packing stations process a batch of parts at a time. The main target of this article is to find optimum batch sizes at these stations. Efficiency test of the filters is done in QC station. If the filter is in good condition, the filter will be sent to the next buffer for packing process. Repairs on any defect are performed at rework station. The filter will scrap if the quality is not accepted or the repair work fails to ensure its efficiencies.

In this study, the decision variables are the production batch sizes in every stage (viz. PU, QC and packaging) and the noise or uncertain factors are processing time and defective proportion of items. The effects of these factors will give a more realistic and mimic to the real system because system is normally subject to these uncertainties. By varying the batch in stages, the waiting time and the WIP level are adjusted for an optimized total cost and reasonable machine productivity. Four levels of the factors are expected to have better chance of identifying the influence of both linear and nonlinear behaviors. The ranges of factor levels are selected based on capacity limitation and in consultation with the engineers in the company (Table 1).

Since this study contains three control factors of four levels and two noise factors of three levels for each, thus $\left(4^3 \times 3^2\right) = 576$ design points are required in case of full (or complete) factorial design. In order to reduce the size of experimentation, a partial factorial design is applied using orthogonal array. In this study, the $L_{16}4^5$ is the most suitable array, because it fulfills the requirement. This orthogonal array can accommodate five control factors of four levels each. It is possible to assign three control factors (batch size) to the first three columns and the remaining columns are left empty for the error of experiment. A total of $\left(16 \times 3^2\right) = 144$ simulation is needed to obtain optimum combination batch sizes in stages. Each experiment is simulated with nine replications (two noise factors of three levels each).

A second set of experiments are designed using the same method with only two control factors (viz. batch size in station PU and in station QC) to test their interaction effect on WIP level and lead time. The batch size in packing station is kept fixed at 5.

Mean value, signal to noise ratio and ANOVA are used to see the main and interaction effects. The average value and its signal to noise ratios of WIP level and lead times have been observed and analyzed. In order to evaluate the experimental results statistically, analysis of variance (ANOVA) is applied. Statistical significance tests of effects are made at 5% significance level. The smaller, the better the characteristic used for WIP and lead times.

When the optimum level of batch sizes is selected, a confirmation

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

Control factors (batch size)	Level 1	Level 2	Level 3	Level 4
PU	8	10	20	25
QC	16	20	24	28
Packing	1	3	5	8

Table 2. Defective fraction of the company for past few months.

Month	Reject	Output	Defective fraction (%)
January	1	712	0.140
December	2	930	0.215
November	10	1368	0.731
October	3	1439	0.208
September	0	905	0
Average: 0.259. Standard Deviation 0.278.			

Table 3. Manufacturing processing time for each station.

Station	Av. setup time per piece (s)	Av. setup time per batch (s)	Av. cycle time (s)
Folding	13.4	279.0	311.8
Assembly	-	-	122.6
Strapping	-	-	105.6
PU	9.3	355.1	345.2
Gasketing	-	-	374.5
Packing	-	36.0	75.4
QC	12.0	11.1	12

test is performed to see whether the level of batch sizes can offer any improvement. The result from confirmation test that lies within the range of the confidence interval is said to be reproducible and able to adapt in real situation.

Data collection and validation

In order to build the simulation model and to set the initial level of various factors in the model, data are needed to be collected. The data includes processing time at each stages, setup time, average defective proportion, manufacturing layout etc. Table 2 shows the number of rejected filter for September 2008 to January 2009 periods.

The time required to position each part into fixed places before operation is carried out 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 average setup time per piece/batch and the average cycle time are shown in Table 3.

Validation of data is 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 and adjustment has been taken.

The range of coefficient of variation (CV) of processing time is chosen in between the CV calculated from the historical processing time. Thus, three levels of CVs are tested: 0.05 (low stochastic), 0.1, 0.2 (high stochastic). Based on the historical data, three defective rates are considered: 0.26% (sample mean), 0 (perfect), 0.74% (highest).

Based on the manufacturing cell in Figure 1 and the collected data, a simulation model is developed in WITNESS (Figure 2). Finally, the authors used the WIP (the average number of product that has not been completed but has already undergone the first process) and lead time (average time a raw material needed to process before becoming a final product) for measuring the performance.

Model validation

The model validation is performed to test the overall accuracy of the model and the ability to meet the objectives. In this study, the simulation model is verified by historical data, face validity and analytical modeling. Part of historical data such as defective rate and processing time is used to build the model and the total number of throughput is used to determine whether the model behaves as the system does. Pre-simulation shows that the total number of throughput is about the same as in the real system. The authors have authenticated the models by an expert and authorized

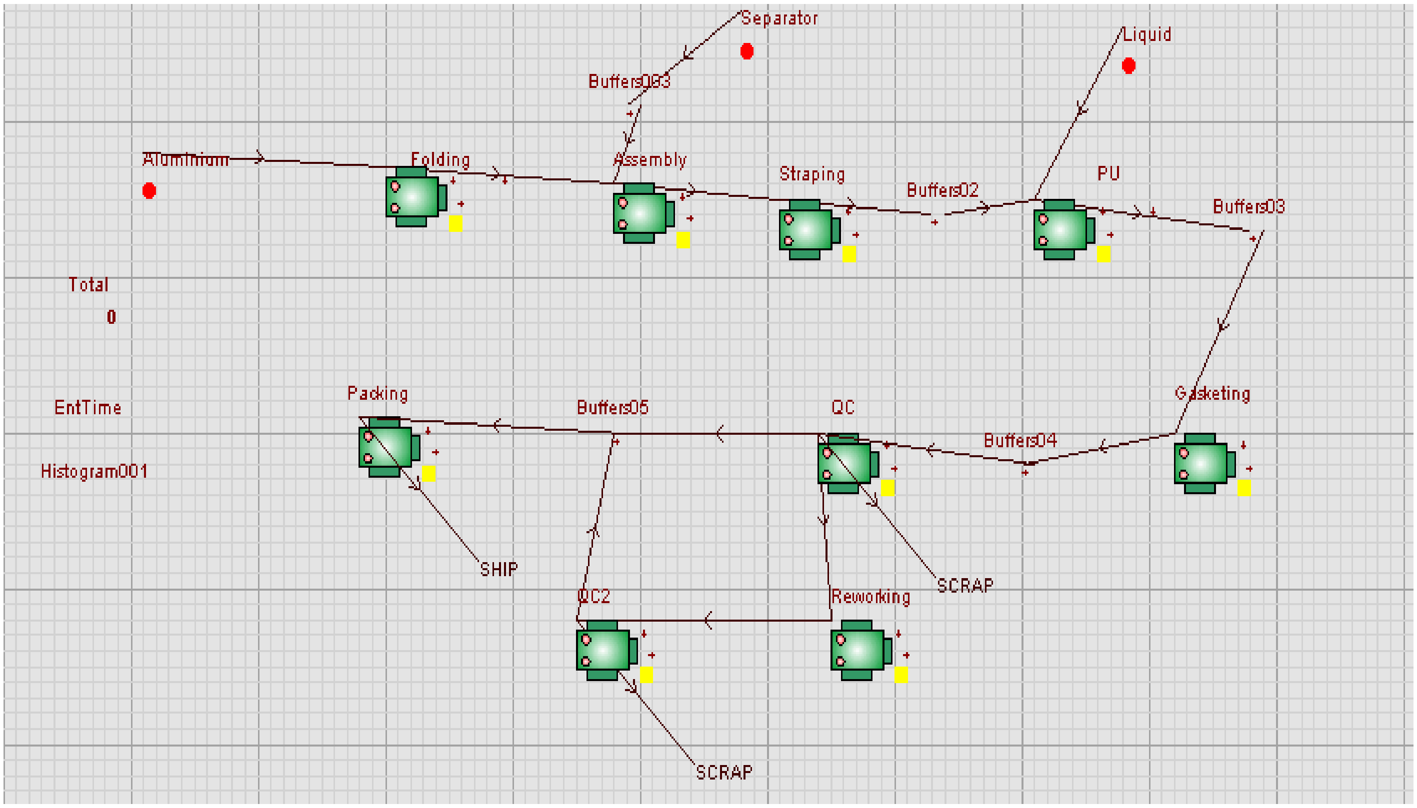

Figure 2. WITNESS model of entire assembly process.

Table 4. Comparison of throughput/day and lead time among real system/simulation/analytical model.

	Average throughput per day	Average manufacturing lead time (min)
Real system	50 - 60	
Simulation	55	29.74
Analytical model		31.52

WITNESS trainer for face validity. The suggestions and proposed corrections are adjusted and verified.

Since the manufacturing system is a set of elemental system composed of a number of various interconnected queues, thus these multi stages are modeled as network of queuing. This analytical model is used to calculate the waiting time in the system. The total manufacturing lead time for a part can be calculated by summing the total waiting time and processing time. This analytical solution is then compared with the simulation result. Table 4 shows the comparison of the outcomes of the models. The variation in average manufacturing lead time might be due to the assumptions made in analytical model.

DATA ANALYSIS AND DISCUSSION

The authors have conducted a total of 144 experiments for the first set of experiments. Table 5 shows the summary of experimental results for the average WIP level and lead time with corresponding S/N ratio for each setting. The average of lead time and WIP level are fall within 613 $\pm$ 61 and 60 $\pm$ 6 respectively.

Since the experiment design is orthogonal, the effect of batch size at each station for different levels is separated out. Table 6 shows the response for mean and S/N ratio for average WIP level and the same for average lead time is in Table 7. Since the characteristic of these factors are the smaller the better, the batch sizes are chosen based on smaller mean and larger the S/N ratio. Because, the larger the S/N ratio the smaller the variance are around the desired value.

Figures 3 and 4 shows the effects of variation in levels of control factors for (a) mean value and (b) S/N ratio of WIP level and lead time respectively. It is pellucid that an

Table 5. Experimental result for each sample.

	Batch size in station			Average lead time		Average WIP level	
Experiment	PU	QC	Packing	Mean	S/N smaller	Mean	S/N smaller
1	8	16	1	559.98	-54.96	55.37	-34.87
2	8	20	3	566.12	-55.06	55.98	-34.97
3	8	24	5	582.80	-55.31	57.62	-35.22
4	8	28	8	603.01	-55.61	59.62	-35.51
5	10	16	3	562.63	-55.00	55.63	-34.91
6	10	20	1	585.63	-55.35	57.90	-35.26
7	10	24	8	596.19	-55.51	58.95	-35.42
8	10	28	5	606.17	-55.65	59.93	-35.56
9	20	16	5	614.09	-55.76	60.72	-35.67
10	20	20	8	636.88	-56.08	62.97	-35.99
11	20	24	1	636.90	-56.08	62.98	-35.99
12	20	28	3	646.00	-56.20	63.88	-36.11
13	25	16	8	639.55	-56.12	63.24	-36.03
14	25	20	5	643.67	-56.17	63.64	-36.08
15	25	24	3	653.82	-56.31	64.65	-36.22
16	25	28	1	674.02	-56.57	66.65	-36.48

Table 6. Response Table for average WIP level.

Mean	PU	QC	Packing	S/N ratio	PU	QC	Packing
Level 1	57.15	58.74	60.72	Level 1	-35.14	-35.37	-35.65
Level 2	58.10	60.12	60.03	Level 2	-35.29	-35.57	-35.55
Level 3	62.64	61.05	60.48	Level 3	-35.94	-35.71	-35.63
Level 4	64.54	62.52	61.19	Level 4	-36.20	-35.92	-35.74
Max	64.54	62.52	61.19	Max	-35.14	-35.37	-35.55
Min	57.15	58.74	60.03	Min	-36.20	-35.92	-35.74
Diff	7.40	3.78	1.16	Diff	1.06	0.55	0.18
Rank	1	2	3	Rank	1	2	3
Opt	1	1	2	Opt	1	1	2

Table 7. Response Table for lead time.

Mean	PU	QC	Packing	S/N ratio	PU	QC	Packing
Level 1	577.98	594.06	614.13	Level 1	-55.23	-55.46	-55.74
Level 2	587.65	608.08	607.14	Level 2	-55.38	-55.67	-55.64
Level 3	633.47	617.43	611.68	Level 3	-56.03	-55.80	-55.73
Level 4	652.76	632.30	618.91	Level 4	-56.29	-56.01	-55.83
Max	652.76	632.30	618.91	Max	-55.23	-55.46	-55.64
Min	577.98	594.06	607.14	Min	-56.29	-56.01	-55.83
Diff	74.79	38.24	11.76	Diff	1.06	0.55	0.18
Rank	1	2	3	Rank	1	2	3
Opt	1	1	2	Opt	1	1	2

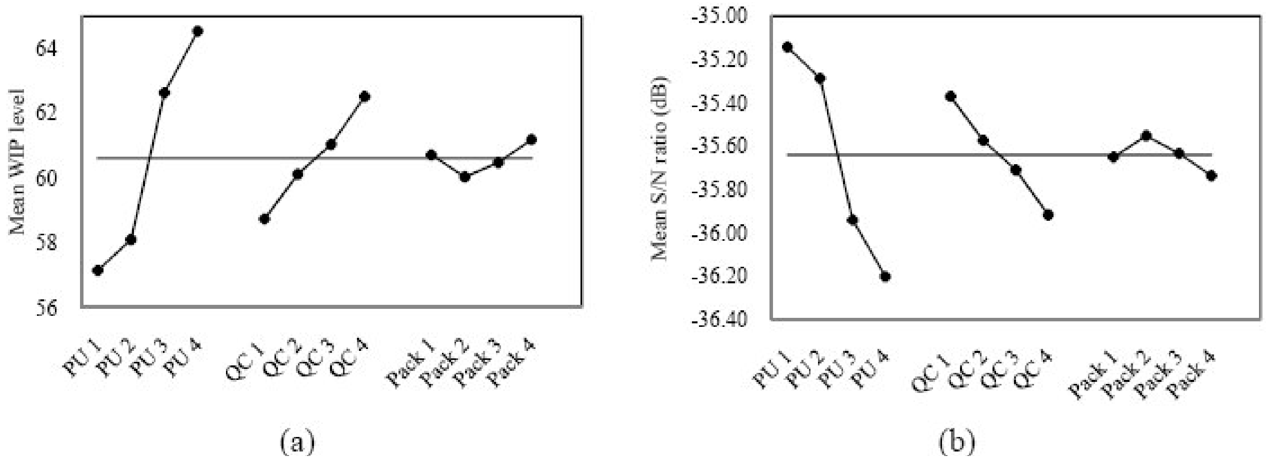

Figure 3. Response graph for (a) mean value and (b) S/Nratio of WIP level.

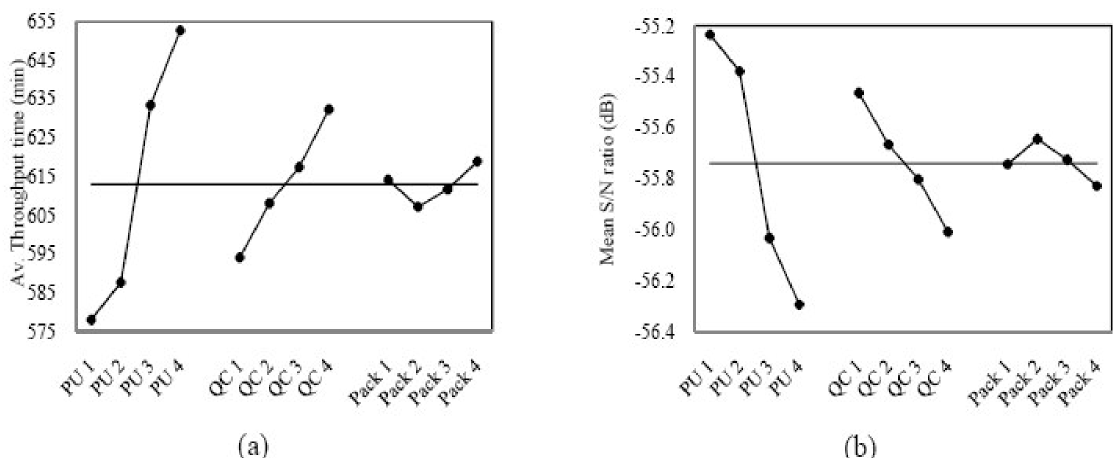

Figure 4. Response graph for (a) mean value and (b) S/N ratio of lead time.

Table 8. ANOVA for Mean value of WIP level.

Source	SSQ	DOF	VAR	Ftest	SSq	Rho (%)
PU	1362.74	3	454.25	88.33	1347.32	57.33
QC	272.91	3	90.97	17.69	257.49	10.96
Packing	25.35	3	8.45	1.64	9.92	0.42
Error	689.14	134	5.14	1.00	735.43	31.29
St	2350.15	143	16.43		2350.15	100.00
Sm	528955.59	1				
ST	531305.74	144				

increase in the batch size in both PU and QC stations yield an increase in WIP level (Figure 3a) and lead time (Figure 4a) in the system. For packing station, they decrease for level 1 to level 2 but increase for level 2 to 4 (Figure 3a and 4a). The scenarios are completely reversed, as it is expected, in case of S/N ratios (Figure 3b and 4b). Thus, based on the figures and response tables (Table 6 and 7), the batch sizes for PU, QC and packing stations are chosen as 8, 16 and 3, respectively.

Tables 8 and 9 show the ANOVA for average WIP level in mean and S/N ratio respectively. These tables show the relative importance of the control factors affecting

Table 9. ANOVA for S/N ratio for WIP level.

Source	SSQ	DOF	VAR	Ftest	SSq	Rho (%)
PU	3.118	3	1.039	805.613	3.114	81.33
QC	0.635	3	0.212	163.992	0.631	16.48
Packing	0.069	3	0.023	17.709	0.065	1.69
Error	0.008	6	0.001	1.000	0.019	0.51
St	3.829	15	0.255		3.829	100.00
Sm	20326.909	1				
ST	20330.737	16				

Table 10. ANOVA for mean of lead time.

Source	SSQ	DOF	VAR	Ftest	SSq	Rho (%)
PU	139284.79	3	46428.26	2095.50	139218.32	80.59
QC	27896.91	3	9298.97	419.70	27830.45	16.11
Packing	2599.30	3	866.43	39.11	2532.83	1.47
Error	2968.93	134	22.16	1.00	3168.33	1.83
St	172749.93	143	1208.04		172749.93	100.00
Sm	54104667.47	1				
ST	54277417.40	144				

Table 11. ANOVA for S/N ratio for lead time.

Source	SSQ	DOF	VAR	Ftest	SSq	Rho (%)
PU	3.11	3	1.04	788.67	3.11	81.30
QC	0.63	3	0.21	160.71	0.63	16.48
Packing	0.07	3	0.02	17.45	0.06	1.70
Error	0.01	6	0.00	1.00	0.02	0.52
St	3.82	15	0.25		3.82	100.00
Sm	49702.67	1				
ST	49706.49	16				

the WIP level. Both mean and signal to noise ANOVA indicates that batch sizes in stations PU and QC have impacts on average WIP level (for mean, 57.33 and 10.96% whereas for S/N ratio, 81.33 and 16.48%, respectively). However, the batch size in packing station shows a little influence on average WIP level (only 0.42% for mean and 1.69% in S/N ratio). The cycle time in Gasketing station (just after PU) is the highest among all stations. This station (that is, Gasketing) is the bottleneck of the system. Thus, the decision in choosing the right batch size in station just before the bottleneck (PU station in this case) is very crucial. This is why PU yields the largest percentage. F-values for PU and QC are exceeded the critical limits (2.67 and 4.67 for mean and S/N ratio, respectively), but it is within the limit in case of packing station. This confirms that the variance effect of these two individual factors (batch size for PU and QC) are significantly different from the error effect. Hence, the variation in WIP level is truly accounted by the change in the value of the batch size in stations PU and QC and the deviation due to experimental errors is small. Based on response table (Table 6) and ANOVA (Tables 8 and 9), the optimal batch sizes which yield the lowest WIP level are 8, 16 and 3 for stations PU, QC and packing in order.

Tables 10 and 11 show the ANOVA for mean and S/N ratio for lead time, respectively. The percentage contributions due to error are 1.47 and 0.52% for mean and S/N ratio in order. These low percentages indicate that no important factor is omitted from experiments. PU yields the highest contribution (80.69% for mean and 81.30% for S/N ratio) and followed by station QC (16.11 and 16.48% for mean and S/N ratio, respectively). The

Table 12. Experimental results of interaction effects for mean values of WIP and Lead time.

Experiment	Batch size used in station			Average	
	PU	QC	Packing	WIP level (quantity)	Lead time (min)
1	8	16	5	55.02	556.52
2	8	20		55.98	566.13
3	8	24		57.52	581.73
4	8	28		58.52	591.86
5	10	16		55.63	562.63
6	10	20		57.41	580.64
7	10	24		57.93	585.89
8	10	28		59.46	601.35
9	20	16		60.09	607.68
10	20	20		62.86	635.77
11	20	24		62.41	631.13
12	20	28		63.88	646.02
13	25	16		62.37	630.80
14	25	20		63.63	643.52
15	25	24		64.65	653.82
16	25	28		66.18	669.27

packing station shows little effect on lead time since its contribution is only 1.5%.

The critical F-values are 2.67 and 4.67, respectively for mean and S/N ratio, like earlier. The F values show that the batch sizes for three stations (i.e. PU, QC and Packing) are significant since the F values for these three stations are higher than the critical F value.

Based on ANOVA (Tables 10 and 11) and response table (Table 7), the optimal batch sizes which yield the lowest throughput time are 8, 16 and 3 for station PU, QC and packing respectively.

Interaction effect

As described earlier, a second set of experiments is developed with only the batch sizes in stations PU and QC as control factor to look into their interaction effects. Batch size in packing station is kept fixed (as the contribution is little) at 5 and other parameter remains same as in the first set of experiments. Like earlier, $L_{16}\,4^5$ orthogonal array is used. The mean values of average WIP level and average lead time with respect to their batch sizes in each experiment are shown in Table 12.

For both WIP level and lead time, there is a percentage difference of 13.4% when comparing experiments 1 and 13, whereas it is only 6.4% for experiments 1 and 4. Experiments 1 and 13 are performed with same batch sizes (16 units) in QC station but different in station PU (which are recorded as 8 and 25, respectively). Other hand, for experiments 1 and 4, the batch sizes (8 units) are same in station PU but varying in station QC (16 and 28 units). The percentage difference, higher in former than the latter case, indicates that change in batch sizes in PU station has more influence on WIP level compared to any change in batch size in station QC.

The ANOVA results for interaction effects of batch sizes (in stations PU and QC) for mean and S/N ratio for WIP level are in Tables 13 and 14 and the same for lead time are in Tables 15 and 16 in order. ANOVA shows that batch size in station PU contributes 59.5% for mean (Table 13) and 83% S/N ratio (Table 14). The same are 10.44% (Table 13) and 15.28% (Table 14) for the QC station. For lead time the contributions are 83 and 15% for batch sizes in stations PU and QC, respectively for mean and S/N ratio (Tables 15 and 16). It means that change in the batch size in station PU has a greater impact on the average WIP level and lead time compared to change in the batch size of station QC. These findings confirm the results of the first set of experiments.

For WIP level, the sum of square (SSQ) value for the interaction effect of PU and QC is very small (2.83) compared to the SSQ for error (670.93). Moreover, the F value for interaction effect is smaller than critical F value. For average lead time, the *F*-value of the interaction effect is significant but insignificant for error effect. The contribution of interaction effect is 0.14% only. These facts indicate that the contribution of the interaction effects of batch sizes in stations PU and QC are insignificant. Therefore, interaction effect of batch sizes in stations PU and QC can be omitted from the experiments. The result from the first set of experiments is thus can be confirmed to offer an optimum solution.

Table 13. ANOVA results for interaction effect for mean WIP level.

Source	SSQ	DOF	VAR	Ftest	SSq	Rho (%)
PU	1406.80	3	468.934	93.66	1391.78	59.50
QC	259.10	3	86.367	17.25	244.08	10.44
PU X QC	2.83	3	0.944	0.19		
Error	670.93	134	5.007	1.00	703.27	30.06
St	2339.67	143	16.361		2339.67	100.00
Sm	522223.02	1				
ST	524562.69	144				

Table 14. ANOVA results for S/N ratio for interaction effect for WIP level.

Source	SSQ	DOF	VAR	Ftest	SSq	Rho (%)
PU	3.249	3	1.083	306.54	3.24	83.36
QC	0.604	3	0.201	57.02	0.59	15.28
PU X QC	0.010	3	0.003	0.98		
Error	0.021	6	0.004	1.00	0.05	1.35
St	3.885	15	0.259		3.89	100.00
Sm	20263.057	1				
ST	20266.942	16				

Table 15. ANOVA results for interaction effect for mean lead time

Source	SSQ	DOF	VAR	Ftest	SSq	Rho (%)
PU	143710.81	3	47903.60	3431.23	143668.93	83.35
QC	26489.18	3	8829.73	632.45	26447.30	15.34
PU X QC	290.88	3	96.96	6.94	248.99	0.14
Error	1870.78	134	13.96	1.00	1996.43	1.16
St	172361.65	143	1205.33		172361.65	100.00
Sm	53415365.98	1				
ST	53587727.62	144				

Table 16. ANOVA results for S/N ratio for interaction effect for lead time

Source	SSQ	DOF	VAR	Ftest	SSq	Rho (%)
PU	3.240	3	1.08	302.59	3.23	83.32
QC	0.604	3	0.20	56.41	0.59	15.31
PU X QC	0.010	3	0.00	0.97		
Error	0.021	6	0.00	1.00	0.05	1.37
St	3.876	15	0.26		3.88	100.00
Sm	49602.704	1				
ST	49606.580	16				

Predicted values and expected gains

The second set of experiments confirmed that the effect of interaction of batch sizes in stations PU and QC is not significant. Hence, the optimum level of batch sizes in PU and QC are 8 and 16, respectively, as selected based on the individual average effect in the first set of experiments, are justified. The optimal level of the design parameters is used to predict and to verify the improvement of the quality characteristics. The predicted value for mean and

Table 17. Predicted values and expected gains for WIP and lead time.

	Average WIP level		Average lead time	
	Mean (units)	**S/N ratio (dB)**	**Mean (min)**	**S/N ratio (dB)**
Predicted value	54.704	-34.779	553.252	-54.871
Expected Gain	8.46	1.24	85.54	1.24

Table 18. Upper and lower limit for WIP level and lead time.

Average WIP level				Average lead time			
Mean		**S/N ratio**		**Mean**		**S/N ratio**	
Upper limit	Lower limit	Upper limit	Lower limit	Lower limit	Upper limit	Lower limit	Upper limit
53.130	56.280	-34.850	-34.710	549.980	556.520	-54.940	-54.800

Table 19. Average WIP level and lead time before and after optimization

Experiment	Average WIP level				Average lead time			
	Before (Opt.)	**After (Opt.)**	**Improvement**	**Units**	**Before (Opt.)**	**After (Opt.)**	**Improvement**	**Units**
1	61.11	53.43			635.67	555.76		
2	61.36	53.46			638.29	556.05		
3	60.95	53.47			634.06	556.16		
4	61.88	53.97			637.11	555.61		
5	62.16	53.97			639.95	555.61		
6	61.71	53.99			635.3	555.85		
7	66.39	57.62			642.5	557.63		
8	66.67	57.66			645.21	558.03		
9	66.24	57.65			641.04	557.93		
Mean	63.16	55.02	8.14	Min	638.79	556.51	82.28	units
Standard Deviation	2.483	1.977	0.505	Min	3.687	1.033	2.654	units
S/N Ratio	-36.02	-34.82	1.199	dB	-56.11	-54.91	1.198	dB
Gain in Loss Reduction			0.241				0.241	

S/N ratio for WIP level and lead time as well as expected gains using the optimal batch sizes are calculated. Table 17 shows the predicted values and expected gains for average WIP level and average lead time.

The upper and lower limits of estimated performance at optimum condition with 95% confidence level are shown in Table 18. The average results for population of samples tested at optimum condition is expected to be within these ranges. Since the confidence interval is calculated at 95%, if several such sets of experiments are performed, 19 out of 20 of the sets are expected to fall within these limits.

Confirmation experiment

A confirmation test is carried out to verify the experimental outcomes. Table 19 shows the comparison of the WIP levels and lead time before and after optimization. The result of confirmation experiments gives a mean value of 55.02 units and an S/N ratio of -34.82 dB for WIP level and 556.51 min and S/N ratio of 54.91 dB for lead time. The mean value and S/N ratio after optimization are fall within the limit of the confidence interval. Hence, it is believed that the significant factors as well as the appropriate levels for obtaining the desired result are properly chosen. From the result of confirmation experiment, the gain in mean is 8.14 units and in S/N ratio is 1.2 dB. Both the values are about the same as the conservative gain calculation in Table 17. The gain in loss reduction is 0.241. It implies that there would be a 24.1% improvement in the process.

Conclusions

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 system of the company under consideration are verified and validated as described. The comparison shows that simulated deliveries are acceptable for further investigations.

The results show that Gasketing station is the bottleneck of the system and selection of batch size in PU station is the most critical decision.

The interaction effect of batch sizes at PU and QC stations is not statistically significant. Therefore, the optimal batch sizes which yield the lowest WIP level and lead time are 8, 16 and 3 for stations PU, QC and packing in order.

The percentage contributions due to error (less than 2%) indicate that no important factor is omitted from experiments. The batch size at PU yields the highest contribution (80.69% and 57.33%) and followed by station QC (16.11% and 16.48%) on lead time and WIP level respectively. The packing station shows little effect on lead time (only 1.5%) and WIP (0.42%).

The confirmation test ensures that the significant factors (that is, the batch sizes in stations PU, QC and packing) as well as the appropriate levels for obtaining the desired result are properly chosen. Total of 24% improvement is possible if the optimum batch sizes are used in the system.

REFERENCES

Aas EJ, Klingsheim K, Steen T (1992). Quantifying Design Quality: A Model and Design Experiments. Euro ASIC '92. Paris, France.

Ben-Daya M, Rahim A (2003). Optimal lot-sizing, quality improvement and inspection errors for multistage production systems. Int. J. Prod. Res. 41: 65-79.

Chan WM, Ibrahim RN, Lochert PB (2003). A new EPQ model: integrating lower pricing, rework and reject situations. Production Planning and Control: The Management of Operations 14: 588-595.

Du X, Chen W (2000). Methodology for managing the effect of uncertainty in simulation based design. AIAA J. 38: 1471-1478.

Hadjinicola GC, Soteriou AC (2003). Reducing the cost of defects in multistage production systems: A budget allocation perspective. Eur. J. Oper. Res. 145: 621-634.

Hong JD (1995). The effects of manufacturing lead time and process quality in a multi-process production system. Production Planning and Control: Manage. Oper. 6: 311-319.

Karmarkar US (1987). Controlling W.I.P. and Leadtimes in Job Shops. Center for Manufacturing and Operations Management, William E.

Simon Graduate School of Business Administration, University of Rochester.

Karmarkar US, Kekre S, Kekre S (1992). Multi-item batching heuristics for minimization of queueing delays. Eur. J. Oper. Res. 58: 99-111.

Koo PH, Bulfin R, Koh SG (2007). Determination of batch size at a bottleneck machine in manufacturing systems. Int. J. Prod. Res. 45: 1215-1231.

kuik R, Tielemans PFJ (1999). Lead-time variability in a homogeneous queueing model of batching. Int. J. Prod. Econ. 59: 435-441.

Liu L, Liu X, Yao DD (2004). Analysis and Optimization of a Multistage Inventory-Queue System. Manage. Sci. 50: 365-380.

Makis V, Fung J (1998). An EMQ model with inspections and random machine failures. J. Oper. Res. Soc. 49: 66-76.

Oraifige IA (2006). Simulation Techniques Implementation to Reduce Lead Times in SMEs. *In:* ARABNIA, H. R. (ed.) THE 2006 International Conference ON Modeling, Simul. Visual. Methods Las Vegas, USA.

Ouyang LY, Chen CK, Chang HC (2002). Quality improvement, setup cost and lead-time reductions in lot size reorder point models with an imperfect production process. Comput. Oper. Res. 29: 1701-1717.

Ouyang LY, WU KS, HO CH (2007). An integrated vendor-buyer inventory model with quality improvement and lead time reduction. Int. J. Prod. Econ. 108: 349-358.

Peter Chiu Y (2003). Determining the optimal lot size for the finite production model with random defective rate, the rework process and backlogging. Eng. Optim. 35: 427-437.

Porteus EL (1986). Optimal lot sizing, process quality improvement and setup cost reduction. Oper. Res. 34: 137-144.

Wazed MA, Ahmed S, Nukman Y (2009a). Managing quality and lead time uncertainties using component commonality in a production environment. Engineering e-Transaction 4: 21-34.

Wazed MA, Ahmed S, NUKMAN Y (2009b). Uncertainty Factors in Real Manufacturing Environment. Australian J. Basic Appl. Sci. Res. 3: 342-351.

Yang JS, Pan JCH (2004). Just-in-time purchasing: an integrated inventory model involving deterministic variable lead time and quality improvement investment. Int. J. Prod. Res. 42: 853-863.

Zhang X, Gerchak Y (1990). Joint Lot Sizing and Inspection Policy in an EOQ Model with Random Yield. IIE Transactions 22: 41-47.