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Impacts of common components on production system in an uncertain environment

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In this paper, the authors have investigated the effects components commonality and uncertainty in lead time, machine breakdown, etc. in a manufacturing environment. The production is characterized by multiple end items for multi-period and multi-stage dependent demand. The delivery performances, throughput of the finished products and average production time in the system are examined for different experimental scenarios with reference to an existing manufacturing setting. A simulation package, namely WITNESS is used to simulate/analyze the situations of the production lines. Simulation models are developed and these are verified and validated with the historical data collected from the company. It is observed that inclusion of common components in the manufacturing system is generally beneficial over the non-commonality environment, especially i) in uncertain situations, ii) for long procurement lead time of components and iii) when the number of parts increase in the system. Impacts of machine breakdown on system outcomes are higher than that of the lead time variation. The combination of uncertain factors has more impact on outcomes (throughput and average production time) compared to the individual factor. Commonality has a better control over the machine breakdown than lead time uncertainty.

Key words: commonality, WITNESS, uncertainty.

INTRODUCTION

In manufacturing, components commonality refers to the use the same components for two or more products in their final assemblies. Commonality is an integral element of the increasingly popular assemble-to-order (ATO) production strategy where inventory is maintained for certain critical components – typically, involving long lead time and high cost – in a generic form (Mirchandani and Mishra, 2002). Commonality could be an approach in manufacturing, production and inventory management systems, where different components can be replaced by common component(s) for multiple products. Therefore, it can be used to simplify the management and control of the critical resources. Commonality thus can help improving the existing products' structures or processes or to develop a new product-mix at an optimized cost.

Heese and Swaminathan (2006) concluded that commonality substantially lowers the costs of proliferated product lines, mitigate the effects of product proliferation on product and process complexity. 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). Further, commonality facilitates quality improvement, enhances supplier relationship and reduces product development time (Mirchandani and Mishra, 2002). The commonality occurs in its own way in the system or can be planned for its preferred happening as well.

In most literatures, two sources of commonality are identified - the component part commonality and the process commonality. The formulation of the component part commonality is based on the mindset of counting the average applications per component part. It takes into account the product volume, quantity per operation and the price/cost of the component part. The process com-

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monality index incorporates such concerns as process flexibility, lot sizing, sequencing and scheduling common alarms into one analytical measurement (Jiao and Tseng, 2000). The number and diversity of compo-nent 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, 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. Thus, it is important for an analyst to determine whether the simulation model is an accurate representation of the system being studied. Further the model has to be credible; otherwise, the results may never be used in the decision-making process, even if the model is “valid” (Law and Mccomas, 1997). A few simulation models are used to analyze various effects of uncertain factors namely machine breakdown and lead time 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 wield a reduction of capacity level and delay 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 alter-native routing can be executed if an order needs to be expedited. Lead time is composed of processing, inspection, waiting and transportation times.

However, lead time may differ from early planned time due to one type or other uncertainties in the system. It may provoke either shortages or surplus in inventories which in turn increases backlogging or holding cost and thereby increases the total cost of the production (Wazed et al., 2008). Short manufacturing lead time is accepted as the central underlying factor for successfully accom-plishing the world-class manufacturing goals such as on-time delivery (Blackburn, 1985), quality (Schmenner, 1991; Schonberger, 1986), flexibility (Stalk, 1988) and productivity (Wacker, 1987). Manufacturing lead time is now often used as a measure of a firm’s competitiveness.

Under such circumstances, the authors studied the effects of component commonalities and two uncertain factors, namely machine breakdown and lead time variation in a multistage production system. The main objective of this study is to analyze the throughput and average production time of the assembly lines in a company, located in Singapore, consisting of two pro-ducts under commonality in a disturbed environment.

LITERATURE REVIEW

Review of the literature on manufacturing environment to examine its performance when disturbed by uncertainty has been carried out. This section discusses on past researches and then comments on the effectiveness of previous representation of such environment.

Uncertainty refers measuring the degree of differences between the models and the respective real systems’ values or between the estimation of variables and their true values. An uncertainty can be affected by errors associated with the model itself and the uncertainties of the model inputs. Modern manufacturing enterprises are facing increasing pressure to respond to production dynamics caused by disruption or uncertainty (Koh and Saad, 2003). Machine breakdown and lead time are two main uncertainty factors, though there are more as summarized in Table 1 (Wazed et al., 2009). Sometimes these act as sources of other unexpected events in the system.

Minifie and Davies (1990) developed a simulation model to study the interaction effects of demand and supply uncertainties. These uncertainties were modelled in terms of changes in lot-size, timing, planned orders and policy fence on several system performance measures, namely late deliveries, number of set-ups, ending inventory levels and component shortages. They used planned order release (POR) schedule to release order into the simulation model. It was concluded that the system performance is significantly affected when dis-turbed by demand and supply uncertainties. However, the simulation model developed by them allowed partial order release when some required parts at lower levels BOM chain are available on hand. This logic violates MRP principle in two folds: (i) order at the upper level BOM cannot be released until all parts at the lower level BOM are available, and (ii) this order cannot be released early or it can be released when its release date is reached or at the later release date (late release). Besides, the component commonality feature(s) is not included in the analysis.

Using a similar research methodology, Brennan and Gupta (1993) examined the performance of manufac-turing environment under demand and leadtime uncer-tainties. The effects from the use of different lot-sizing rules were also considered. It was concluded that these uncertainties could be tackled by using appropriate lot-sizing rules. A multi-product and multi-level dependent demand system was developed and the production orders execution was controlled by POR schedule. Additional algorithm was coded to control order release by checking availability of all the required components. Nevertheless,

Table 1. Uncertainty factors found in literatures.

Factor(s) of uncertainty	References
System uncertainty	(Sommer, 1981; Miller et al., 1997; Hsu and Wang, 2001; Reynoso et al., 2002).
Lead time uncertainty	(Ould-Louly and Dolgui, 2004; Mohebbi and Choobineh, 2005; Koh and Gunasekaran, 2006; Brennan and Gupta, 1993; Dolgui and Ould-Louly, 2002; Huang et al., 1982; Mayer and Nusswald, 2001).
Environmental uncertainty, Supply uncertainty	(Ho et al., 1995; Billington et al., 1983; Güllü et al., 1999).
Operation yield uncertainty	(Huang et al., 1985; Dalal and Alghalith, 2009; Kim and Gershwin, 2005).
Interrelationship between levels	(Kim and Hosni, 1998).
Demand uncertainty	(Bourland and Yano, 1994; Ho et al., 1995; Ho and Carter, 1996; Brennan and Gupta, 1993; Escudero and Kamesam, 1993; Vargas and Metters, 1996; Miller et al., 1997; Kira et al., 1997; Mohebbi and Choobineh, 2005; Grabot et al., 2005; Mula et al., 2006; Koh and Gunasekaran, 2006; Balakrishnan and Cheng, 2007; Mula et al., 2007; Anosike and Zhang, 2007; Arruda and Do Val, 2008; Ben-Daya and Noman, 2008; Grubbstrom, 1999; Agatz et al., 2008; Ahmed et al., 2003; Mukhopadhyay and Ma, 2009; Tang and Grubbström, 2002).
Probabilistic market demand and product sales price	(Lan and Lan, 2005; Mula et al., 2007; Leung et al., 2007; Dalal and Alghalith, 2009).
Capacity	(Mula et al., 2006; Mula et al., 2007; Kim and Hosni, 1998; Shabbir et al., 2003).
Resource breakdown/ uncertainty	(Koh and Gunasekaran, 2006; Balakrishnan and Cheng, 2007; Arruda and Do Val, 2008; Xu and Li, 2008; Sanmartí et al., 1995).
Changing product mix situation	(Anosike and Zhang, 2009).
Labor hiring, labor lay-offs	(Leung et al., 2007).
Quantity uncertainty	(Koh et al., 2002; Guide and Srivastava, 2000).
Cost parameters	(Mayer and Nusswald, 2001; Shabbir et al., 2003).
Quality	(Heese and Swaminathan, 2006; Mukhopadhyay and Ma, 2009; Kim and Gershwin, 2005; Mayer and Nusswald, 2001).

their order release logic ignored the feasibility of parts' early completion, which allowed it to order at the higher levels BOM chain to be released early. Similar simulation models have been developed by Enns (2001), Ho and Carter (1996) and Tito et al. (1999). The above omissions are the most common, made by the researchers.

John and Sridharan (1998) examined the effects of late delivery of raw materials, variations in process lead-times, interoperation (or switching) and waiting times in a manufacturing setting. To model such setting, they characterized demand by inter-arrival time rather than defined from the master production schedule (MPS). Matsuura et al. (1995) adopted the same approach to their demand modeling. This has resulted in the absence of an order release schedule to control production orders execution and there was no control over the release timing of the orders. The resource/machine failure and commonality issues are entirely derelict.

Liao and Shyu (1991) first presented a probabilistic inventory model in which the order quantity is predetermined and lead time is the unique decision variable. Ben-Daya and Raouf (1994) extended Liao and Shyu's (1991) model by considering both lead time and ordering quantity as decision variables where shortages are neglected. Ouyang et al. (1996) generalized Ben-Daya and Raouf's (1994) model by allowing for shortages with partial backorders. Moon and Choi (1998) and Hariga and Ben-Daya (1999) revised the Ouyang et al. (1996) model by including the reorder point as one of the decision variables.

Researches (Liao and Shyu, 1991; Ben-Daya and Raouf, 1994; Ouyang et al., 1996; Moon and Choi, 1998; Hariga and Ben-Daya, 1999) in this area often focused on the benefits of lead-time reduction where the quality-related issues are not taken into account. Ouyang et al. (2007) has developed an integrated inventory model which jointly determines the optimal order quantity, reorder point, process quality, lead time and the frequency of deliveries simultaneously. In these studies the machine breakdown and commonality related issues are not considered.

Porteus (1986) and Rosenblatt and Lee (1986) are among the first who explicitly elaborated on the relationship between quality imperfection and lot size. Keller and Noori (1988) extended Porteus's (1986) work to the situation where the demand during lead time is probabilistic and shortages are allowed. Hwang et al. (1993) developed/proposed multiproduct economic lot size models and found that setup time reduction and quality improvement could be achieved with a one-time initial investment. Hong and Hayya (1995) presented a model including a budget constraint and other types of continuous functions for quality enhancement and setup cost reduction. Ouyang and Chang (2000) investigated the impact of quality improvement on the modified lot size reorder point models involving variable lead time and partial backorders. Ouyang et al. (2002) extended Ouyang and Chang's (2000) model by investigating in process quality improvement and setup cost reduction simultaneously.

Tripathy et al. (2003) presented an EOQ model with an imperfect production process. They, however, assumed that instantaneous production, demand for the product exceeds supply and no backorder is allowed. The study observed that the unit production cost is directly related to process reliability and inversely related to the demand rate. The models developed by these authors (Porteus, 1986; Rosenblatt and Lee, 1986; Keller and Noori, 1988; Hwang et al., 1993; Hong and Hayya, 1995; Ouyang and Chang, 2000; Ouyang et al., 2002; Tripathy et al., 2003) tackled quality improvement and focused on the classical EOQ/EPQ model. These models ignored the impact of lead time variation and the opportunity of component commonality to obtain a better control in the system.

Zhang (1997) has studied a general multi-period, multiple product, multiple component model with deterministic lead times to minimize the acquisition costs. His model is subject to product-specific order fill rates. Deterministic lead time is not rational. Manufacturing system simulation is used for multi-items and multi stage imaginary systems for analyzing the vendor quality and vendor lead time uncertainty with and without commonality (Benton and Krajewski, 1990). This study has overlooked the failure of the production system.

Process models often use multi-stage procedures to conduct all or some portions of the design process when designing products with components commonality, platforms, or product families in mind. Jiao and Tseng (1999) presented a detail process to establish product families and Germani and Mandorli (2004) proposed a procedure leading to self-configuring components in a product architecture. Another five-step model for designing a product family was presented by Farrell and Simpson (2003). Yet a different approach to commonalize product subsystems has been suggested by Qin et al. (2005). In general, product engineering literature, tend to provide a detailed step-by-step procedure on how to proceed when designing modular products and products with common components (Kamrani and Salhieh, 2002; Ulrich and Eppinger, 2000). Nevertheless, uncertainties issues are not addressed in the descriptions.

Linking both product and process requirements, Jiao et al. (2000) proposed a data structure that integrates the bill-of-materials with the bill-of-operations. Jiao and Tseng (2000) developed a process commonality index that incorporates concerns like process flexibility, lot sizing and scheduling into their measurement instruments. Balakrishnan and Brown (1996) viewed 'commonality across products as shared set of processing steps from ingot casting to some intermediate hot or cold forming step' in their work. Heese and Swaminathan (2006) have analyzed a stylized model of a manufacturer who designs a production line consisting of two products. These are sold in two market segments with different valuations of quality. They investigated such circumstances that support component sharing as a profitable strategy and more specifically, the components that are the best candidates for commonality.

Lin et al. (2006) have setup a multi-period model of component commonality with lead time. They analyzed the quantitative relationship between lead time and the inventory level of common component. Nonas (2007) has considered the problem of finding the optimal inventory level for components in an assembly system where multiple products share the common components in presence of a random demand pattern. Jans et al. (2008) have proposed a mixed integer nonlinear optimization model to find the optimal commonality decision in an industrial production-marketing coordination problem. In these circumstances, although machine uprightness has paramount importance, but its maintenance or breakdown issue is not considered.

None of the earlier studies have considered the components commonality in a production system being affected by machine breakdown and lead time variations. Moreover, most of the previous models were not tested in real settings. In this research, the authors have put the real manufacturing facts for analyzing effects of uncertain factors (viz. machine breakdown and lead time variability), case-by-case and combined form on the production system with/without the inclusion of common components.

The production system

The XDE (a given name) is an electrical and electronic company located in Singapore. It is specialized in producing printed circuit board assembly. Two prominent production lines have been considered for the study. One production line manufactures PCBA PSU input 48V output 10V (line 1) and the other produces PCBA AUC28 V2 OCXO (line 2). The main sub-components to produce PCBA are capacitors, transistors, thermistor, diode and LED.

First of all, a number of sub-components are inserted in the PCBA using the chip placement machine. There are two chip placement machines in each production line (line 1: cp1 and cp2; line 2: cp3 and cp4). PCBAs are then passed to the solder printing machine (sp1 or sp2) for soldering. PCBAs are then baked using an oven (ov1 or ov2) which is available in the baking room. The baking

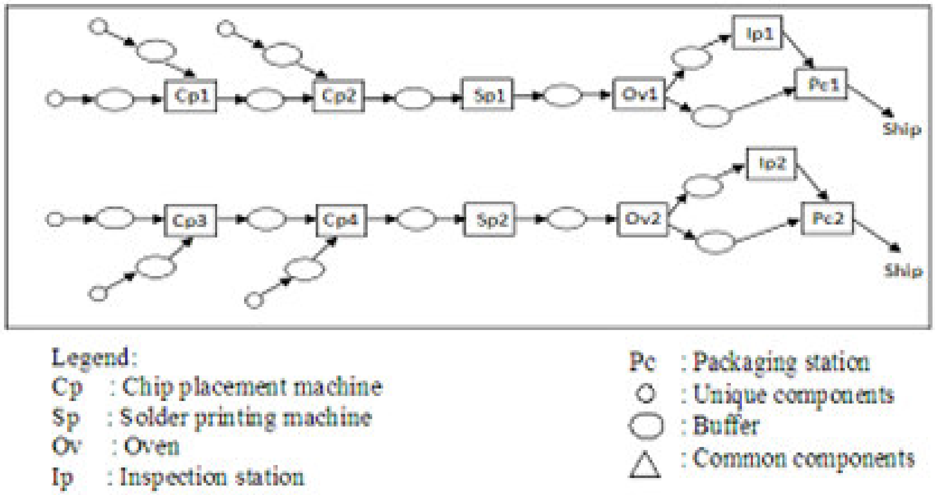


Figure 1. Existing layout of the company.

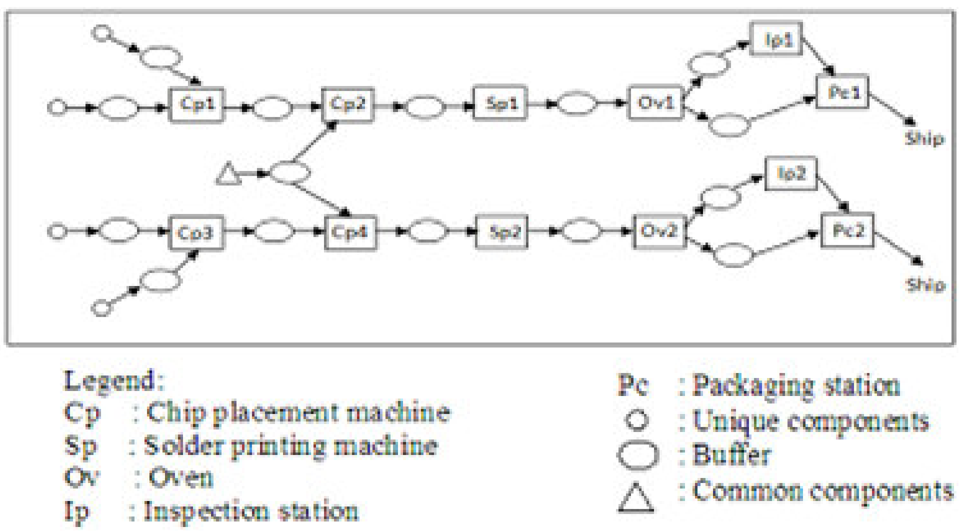


Figure 2. Proposed/modified layout.

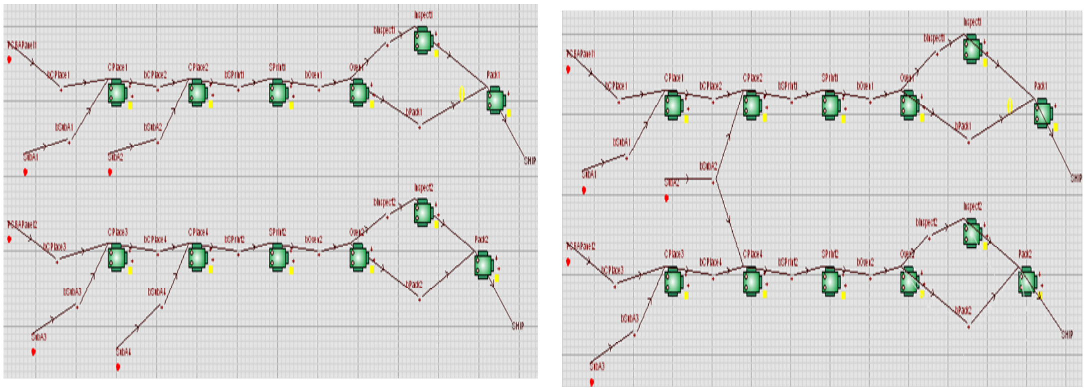
process takes about two hours and reduces the level of humidity. These parts are pushed to the Quality Assurance (QA) department (Ip1 or Ip2) for inspection. The QA staff use a fixed percentage sampling method to inspect the PCBAs. Inspection takes about fifteen to twenty minutes for one piece of PCBA. Finally, the finished products are packed and stored at the warehouse (Pc1 and 2). 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 a few simulation models based on the existing production layout (Figure 1) of the company. The existing layout is modified to introduce common components 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 lead time variability are applied separately and in combined form in simulation exercises with/without the inclusion of common components for analysis. Table 2 shows the various experimental scenarios.

Data generation/collection, analysis and discussion

Basically, in order to develop the useful simulation mo-



(a) (b)

Figure 3. Simulation models -(a) Base model and (b) Commonality model.

Table 2. Experimental scenarios of analysis for simulation.

Scenario	Machine breakdown	Lead time	Measured parameter
Case-1	No	No	Throughput
Case -2	Yes	No	and
Case- 3	No	Yes	Average production cycle
Case-4	Yes	Yes	

dels, parameters like bill of materials (BOM), components' procurement lead times, machine setup time, machine cycle time, machine breakdown, machine repair time, safety stock inventory, production system layout and the lines' buffer capacity are the important aspects. The authors have collected various data and information through the engineers of the company in order to figure out the exact scenarios. The demand under deterministic condition is shown in Table 3.

The Monte Carlo Simulation technique is used as 'demand generator' to produce the random demand under the probabilistic assumption. The basis of Monte Carlo simulation is experimentation on the chance (or probabilistic) elements through random sampling. The authors have collected the historical demands. The weekly distribution and the probability of occurrence are calculated. Then, the probability and cumulative probability are observed and then establish an interval of random numbers.

Finally generates random numbers and finds the actual simulating series of trials. The generated demand data for the same is shown in Table 4. 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 5 days after a warm-up period of 10 days and then the simulated

Table 3. Demand of products from both production lines in XDE.

Week	1	2	3	4	5	6	7	8
Line 1	150	150	150	100	100	0	200	150
Line 2	100	100	150	200	100	150	0	100

Table 4. Generated probabilistic demand for the production lines of XDE based on Monte Carlo Simulation.

Week	1	2	3	4	5	6	7	8
Line 1	150	0	50	50	200	100	250	200
Line 2	100	150	150	0	200	150	150	100

results are generated. The run time for a 9 h shift for 5 days is $9 \times 60 \times 5$ 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 5. The authors have authenticated the models by an expert and authorized WITNESS trainer for face validity. As the variation in the throughputs between the real system and simulation model is not large and also the face validation permitted with good recommendations, hence the simulation models are acceptable for analyzing the system. After validating the base model, various uncertainties are imposed to the models to investigate the case wise impacts.

Table 5. Real system and simulated weekly throughput.

	Real system		Simulation Model	
	Line 1	Line 2	Line 1	Line 2
Mean weekly throughput for base model	500	500	504	506

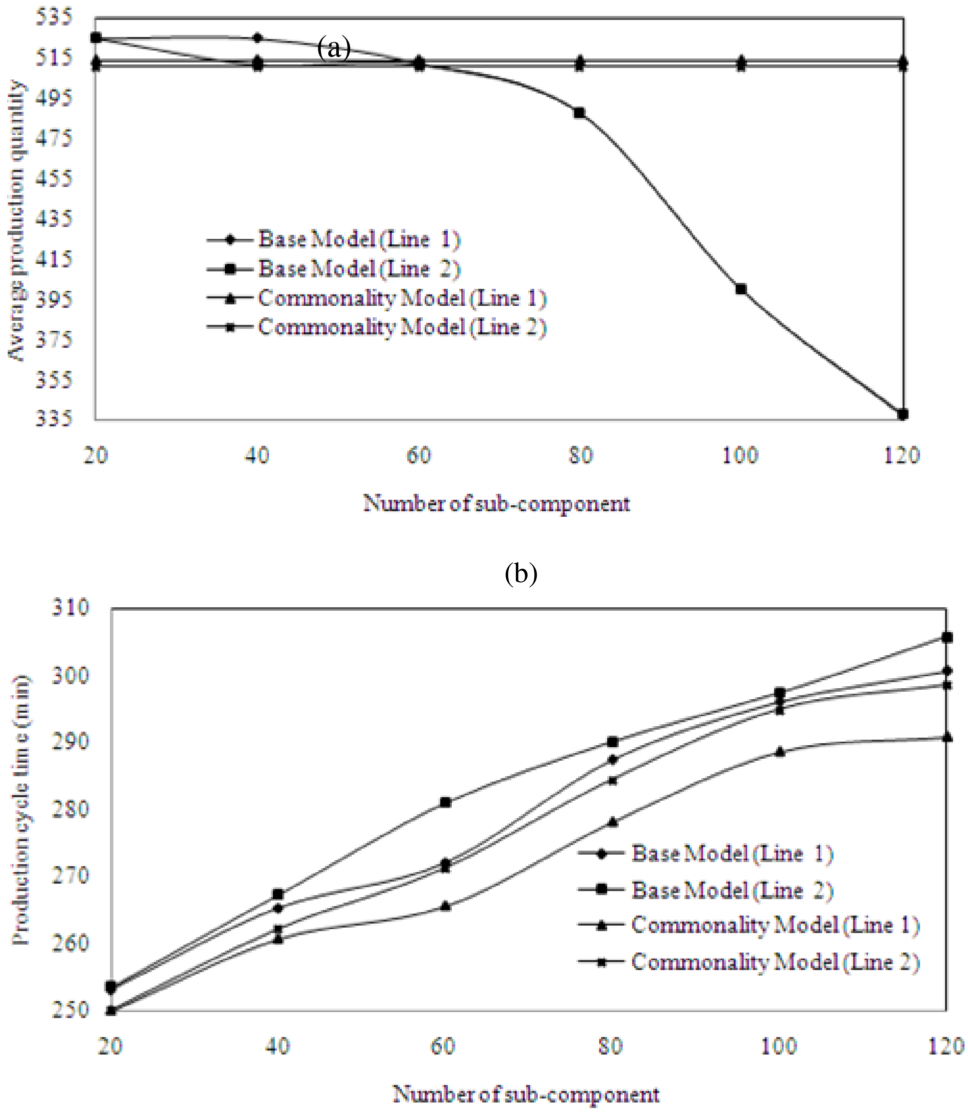


Figure 4. (a) Throughput quantity and (b) average time for base and commonality models for Case-1.

Figure 4 shows the (a) throughput quantity and (b) production cycle time respectively for both base and commonality models without machine breakdown and with 0 (zero) lead time. The 'average time' is the mean time the widget parts spent in the system. When the number of sub-components increases, the throughput quantity decreases for base models and maintains a stable level for commonality models. This means that the throughput quantity of the base models is inversely proportional to the number of sub-components inserted onto PCBAs. It is much higher for the commonality models compared to base models, especially when the number of parts increases in the system.

For all the cases the average production time follows an increasing trend with the number of components. It means that production time is directly proportional to the

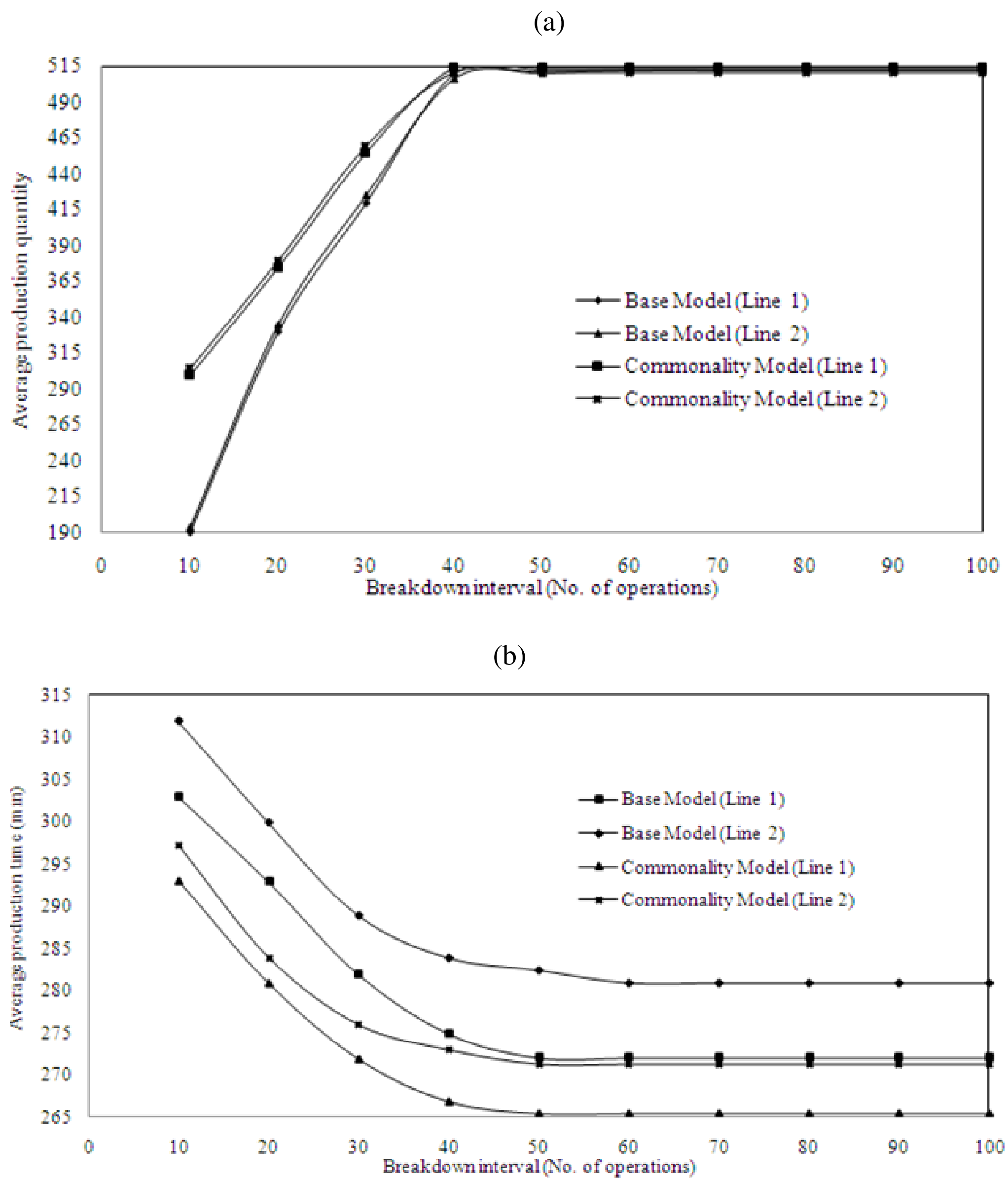


Figure 5. (a) Effect of machine breakdown on (a) production quantity and (b) cycle time when the number of sub-components is 60 and lead time is zero (Case-2).

number of sub-components to be inserted in a product.

The increase in production cycle time is higher in cases of base models than that of the proposed/commonality models. Therefore, use of common component can offer a stable output and tolerable production cycle time when the number of parts increase in the system.

The company is presently using 60 parts in their production system. Under the ideal condition (with no machine breakdown and zero lead time), the base models and the commonality models offer almost the same production quantity with little variation in their cycle times. Therefore, the authors have decided to use 60 sub-components/parts for investigating the other scenarios.

Figure 5 shows the effects of machine breakdown on (a) production quantity and (b) production cycle time for the base and commonality models. The production quantity increases and cycle time decreases sharply for both models when the break down interval increases. The present case under study shows that there are no effects of machine breakdown when the interval is 60 or more. Commonality offer least fluctuation in the production quantity and cycle time under the machine breakdown uncertainty. However, the average production quantity decreases and the cycle time increases in their level of numerical values when compared with case-1.

Figure 6 shows the throughput quantity and average production time for models under non-zero lead time but

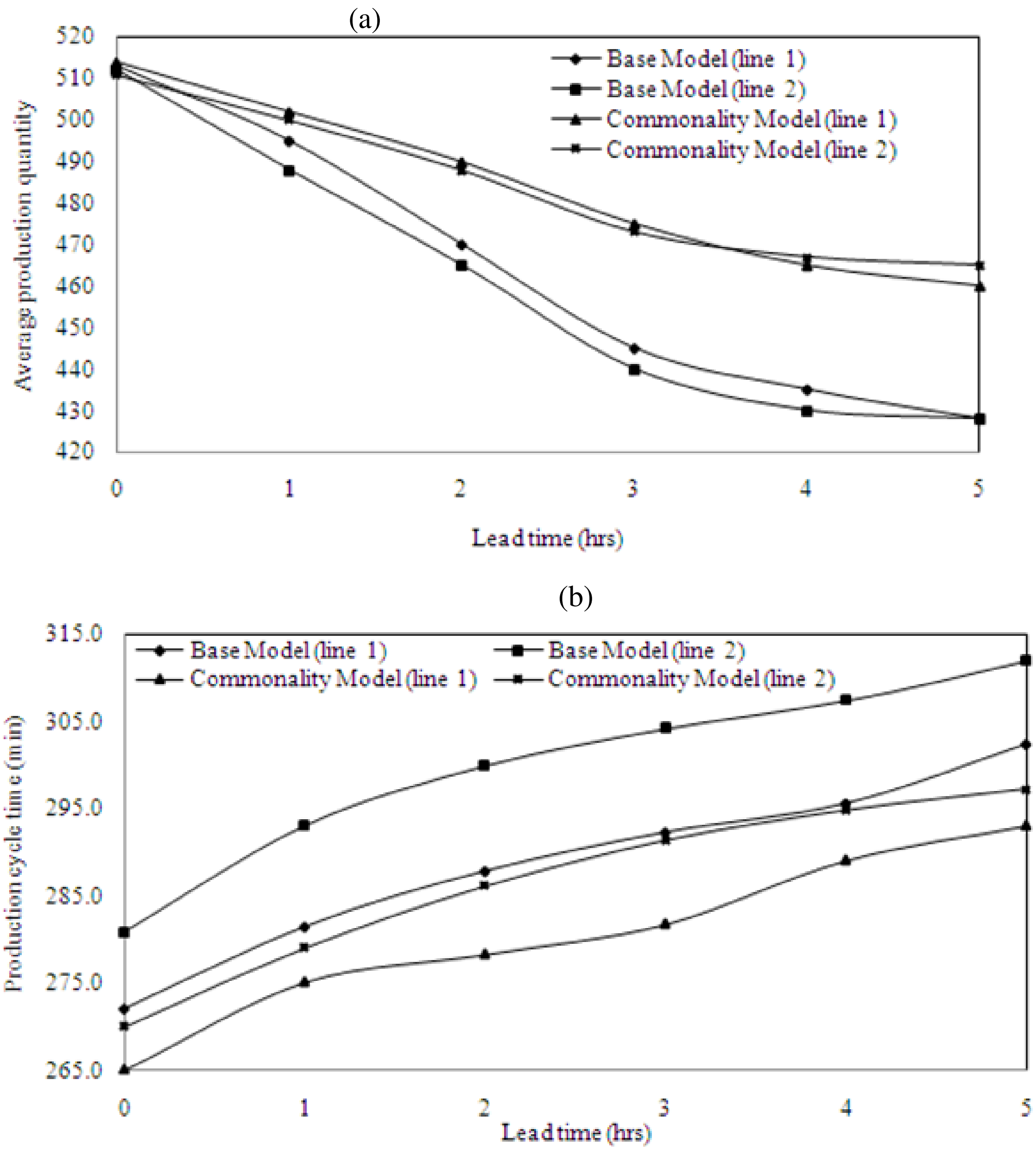


Figure 6. (a) Throughput quantity and (b) average time for base and commonality models for Case-3 when the number of parts is constant at 60 units.

without breakdown (Case-3) when the number of parts is 60. The throughput decreases and cycle time increases for all the models. The throughput quantity is reduced from 513 to 428 (line 1) and 512 to 428 (line 2) for the base models when lead time increases from 0 to 5 h. The values for the same are respectively 514 to 460 and 511 to 465 units for commonality models. It is observed that the throughput quantity for the commonality model is significantly higher compared to the base model. This resulted mainly due to the fact that the component commonality reduces the lead time uncertainty and supports achieving order quantity economics.

At zero lead time, the cycle times are 272.12 (line 1) and 280.91 min (line 2) for the base models and 265.10 (line 1) and 270.92 min (line 2) for commonality models. They reach to 302.50, 312.08, 293.12 and 297.30 min respectively when the lead time increases from 0 to 5 h. The cycle times for both models and for both production lines increases with the lead time but the fluctuation is less while the system uses common component(s).

Figure 7 shows the throughput quantity and average production cycle time for models under machine break down and nonzero lead time for the components (case-4). For both base and commonality models, the through-

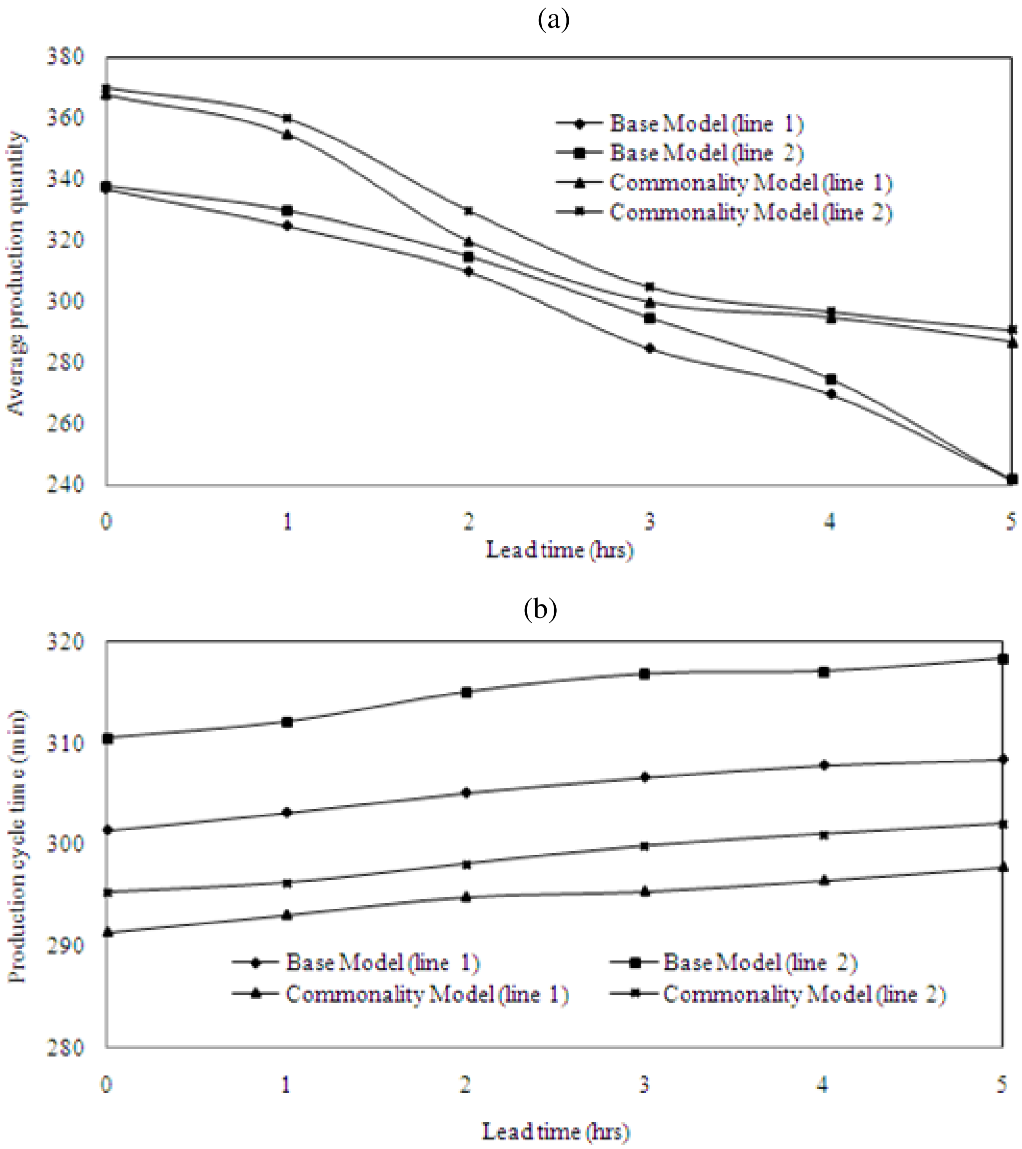


Figure 7. (a) Throughput quantity and (b) average time for base and commonality models for Case-4, when the number of parts is 60 units.

put follows a decreasing trend and cycle time follows an increasing trend for the production lines when the components' procurement time increases under the machine breakdown uncertainty. When there is no lateness (LT = 0) the throughputs for the base and commonality models are 337 and 368 for line 1 and 338 and 370 units for line 2. In other words, the throughput for those models is dropped from 337 to 242 and 368 to 287 units for line 1 and 338 to 242 and 370 to 291 units for line 2 when lead times increase 5 hours under the machine breakdown uncertainty.

The cycle times for base and commonality models are 301.89 and 291.40 min for line 1 and 310.50 and 295.32 min for line 2 respectively when LT = 0. The corresponding values are 308.40, 297.80, 318.35 and 302.10 when procurement lead time increases to 5 h. The results of the experimental scenarios are shown in Table 6.

Table 6 exhibits that the production volume reduces to at least 33 and 27% and the cycle times increases to 10 and 8% respectively for the base and commonality models when the system has encountered the machine breakdown only. The corresponding values are 16, 9, 11 and 9% when the system faces lead time uncertainty. The production quantity deceases to at least 52 and 43% and the cycle time increases to at least 13 and 11% for the base and commonality models respectively when the system suffers with both machine breakdown and lead time uncertainties.

From Table 4 and 6, it is clear that the base models are unable to meet the demand fluctuations. The periphery

Table 6. Summary of the experimental outcomes.

Test setup	Production quantity (in unit)				Cycle time (in min.)				Remarks
	Base Model		Commonality Model		Base Model		Commonality Model		
	Line1	Line2	Line1	Line2	Line1	Line2	Line1	Line2	
Case 1	513	512	514	511	272.12	280.99	265.57	271.28	LT = 0 and NP = 60 units
Case 2	337	338	368	370	301.96	310.63	291.38	295.12	LT = 0; NP = Constant = 60
Case 3	428	428	460	465	302.50	312.08	293.12	297.30	LT = 5 hrs and NP = Constant = 60 units
Case 4	242	242	287	291	308.40	318.35	297.80	302.10	

NP = Number of sub-component, LT = Lead time.

for the production quantities in commonality models is somewhat satisfactory for probabilistic demand distribution. In real system, it may not be practical to produce a particular product to its theoritical peak level. In addition, there may have customers who would request for extra units. As such, the commonality may able to cope up with the changing demand and the service level and thereby can minimize the stock out/shortage costs.

It is now pellucid that-

i. Machine breakdown has greater impact on the production quantity and the lead time uncertainty has more influence on cycle time, other hand.
ii. Combined effects of machine breakdown and lead time variation have greater impacts of the measured parameters than the individual factor.
iii. Component commonality has better control on machine breakdown uncertainty than the lead time variation.
iv. Insertion of common component(s) in the system can tackle the demand uncertainty as well.

Conclusion

This study developed a few simulation models for some production lines of a company located in Singapore producing electrical and electronics products. The models have been run for a reasonable warm-up period to assure the accurate results. The necessary data and information has been collected from the shop floor and through face-to-face conversations. The models and data 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 –

i. Uncertainties in model parameters, such as machine breakdown and lead time have great impact on the models outcomes. It is obvious that the throughput of the system decreases and average production time increases, when any of these uncertain factors is a reality in the system.
ii. The combinatorial impact of these uncertain factors is more prominent on the system deliveries than the individual factor. The analysis shows that the throughput is the least and the average cycle time is the highest when both of these uncertainties are functional in the production environment.
iii. Insertion of common components in production/ manufacturing system is constantly beneficial over the non-commonality environment, especially under i) uncertain situations, ii) for long procurement lead time of components and iii) when the number of sub-components increase in the system. The effect of the component commonality in the system shows the best improvements to the performances and this effect is more pronounced in the context of unexpected changes.

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