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A Portfolio Approach for Purchasing Systems: Impact of Switching Point

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Abstract

In operations management different ordering policies, such as, economic order quantity, lot for lot and periodic ordering, are used in various combinations without deeper considerations for the likely consequences on cash flow and profitability. The success of these techniques is analyzed through inventory levels and/or total cost. In this paper, we present results of simulation which uses three different product groups with varying demand characteristics, changing product margins and also considers product quality failures (due to ordering, engineering change or customer requests). Based on our results, we suggest a portfolio approach where lot for lot policy may be useful in an early phase of the product life-cycle and later it may be an advantage to change over to economic order quantity (EOQ) based ordering. However, demand sustainability and failure rates create instances where orders in larger economical lots may reduce profitability. Therefore, manufacturing may benefit from a portfolio of different purchase order policies and may evaluate the successful balance of policies using cash flow as a parameter. Accuracy of demand forecasting is vital to switching point estimation. Further research on real-world applications of advanced forecasting tools is advocated as well as a framework to develop the portfolio for intelligent purchasing systems.

Keywords: Lot for lot, EOQ, mixed ordering policy, life-cycles, cash flow, VAR, GARCH, RFID

1. Introduction

The purchasing process has received increasing scrutiny in manufacturing companies during the last two decades. On an average, nearly half of the total revenue is spent on purchasing and a significant part of these purchases are direct end-product related. The proportion of revenue spent on indirect purchases may be 20% to 33% (Kaplan 1984; Adler 1987; Kapoor & Gupta 1997; Sumanth 1998; Sheffi 2003; Hilmola 2005). Currently, most purchase order approaches are based on minimizing total cost and/or inventory levels. These generic approaches have been developed to serve deterministic business environments with minor stochastic variation, for example, in demand. Just-in-time (JIT) techniques succeeded in decreasing in-process inventories and lead time but raw material and end-product inventories remained unchanged and the volumes are large (Chen *et al*. 2005; Holweg 2005). The latter stems from multiple factors: (1) demand is dynamic as well as uncertain, (2) product life-cycles are quite different (Fisher 1998; Helo 2004), (3) product development (design) and fulfilment processes (supply network) for new products lack coordination during the early life-cycle (these may have harmful effects on shareholder value, see Hendricks & Singhal 1997), (4) product margins vary with sales price as well as direct material purchase price (Grimm 1998), (5) cost over-runs and (6) advance payments from customers and payment for suppliers are based on different parameters (Ma & Hilmola 2007; Farris & Hutchison 2002). Due to these and others factors, it may not be pragmatic for organizations to use the same quantities or order policies over the product life-cycle. Thus, the need for a portfolio approach in purchasing systems (Martinez-de-Albeniz & Simchi-Levi 2003).

Hence, developing a framework for purchasing systems may be helpful. The proposed system, eventually, may *sense* the environment and *respond* with improved decision(s) to trigger alternative purchasing order policies in accordance with business dynamics as well as key performance indicators (KPI). Based on the results of the work presented in this paper, it is apparent that use of single purchasing policy systems in dynamic environments may erode profits. Purchase orders may not be optimized with respect to total costs alone but must consider cash flow performance as a critical parameter for future decision support that is integrated with a portfolio of options.

This study draws from a high growth manufacturing start-up acquiring most sub-components through its supply network with assembly and testing as its main responsibility. This approach is common for electronics manufacturers (Curry & Kenney 1999; Papadakis 2006: Jammernegg &

Reiner 2007). Auto manufacturers may also adapt this process for assembly-to-order strategies (Holweg & Miemczyk 2002).

In addition to real-world observations of manufacturing systems, in this work, empirical material is generated through hypothetical parameter values of system dynamics simulation model. System dynamics (Forrester 1958; Roberts 1964) simulation can model complex relations (Ma *et al*. 2007) such as feedbacks and feed forwards between parameter values, stocks, flows and delays that can be created in different layers to aid the management of complex systems.

The problem space in this paper may be described as follows: (1) what is the most suitable purchasing policy during the early product life-cycle and (2) does purchasing system using a portfolio of different ordering policies during the product life-cycle perform better than a single strategy. We expect the simulation study to reveal partial answers and we shall strive to offer some guidelines for purchase order policies. In addition, we shall suggest a systems approach to purchasing for manufacturing companies, which may be 'automated' based on advances in creating intelligent software.

This study is structured as follows: in section 2 we will review the two important purchase order theories, discuss their assumptions and implications on purchasing function. Section 3 reviews the challenges faced by manufacturing with short to shorter product life-cycles. In section 4 we present the system dynamics simulation model using three different scenarios (demand characteristics, profit margin and cost). Results are discussed in section 5 and in section 6 we arrive at some tentative conclusions based on our study and propose further research directions.

2. Implications of Different Ordering Policies

The Economic Lot Size Model was introduced almost a century ago (Harris 1913). Economic Order Quantity (EOQ) optimization method was derived from this model. In this method, purchasing decisions are completed with standardized quantities, which would minimize total costs with respect to inventory holding cost and order cost. This approach was soon extended to make-to-stock production decisions. In EOQ framework, demand for purchased components is considered to be independent and varies with parameters which are acknowledged to be uncertain. This assumption enables the calculation of sufficient order points for optimal order quantities to guarantee the prevention of out of stock situations (Figure 1).

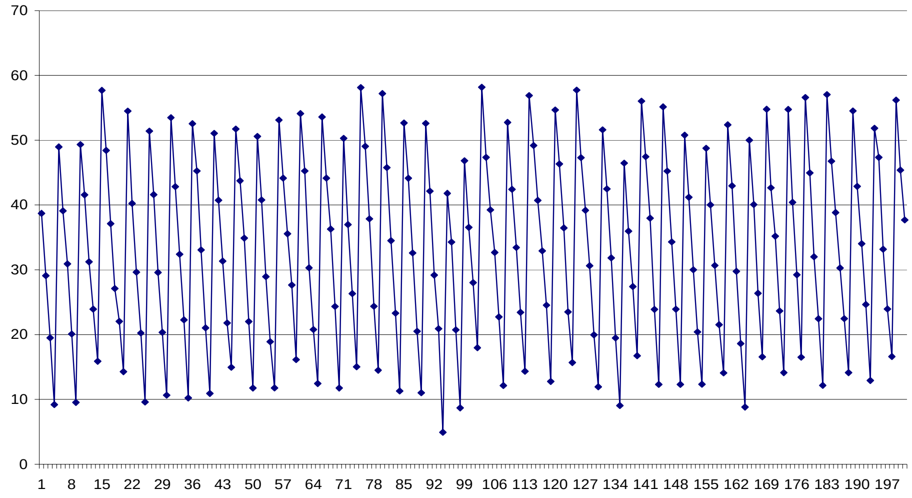

Figure 1. Inventory of purchased item with stochastic demand (normal distribution; average of 10 units per period with standard deviation of 2 units per period). Purchasing lot size is 50 and safety stocks are used to prevent out-of-stock.

EOQ strategy was challenged by the net requirements logic of Material Requirements Planning (later referred to as Manufacturing Resource Planning which became a part of Enterprise Resource Planning). Figure 2 and Table 1 illustrates how MRP net requirements was designed to handle production and material requirements in keeping with JIT practices without loss of efficiency (Plossol 1994; Vollmann *et al.* 1997; Ptak 2000). In this paper, the example concerns only one end product (item A), one semi-finished product (item C) and one purchased component (item D). It requires two item C and six item D to produce one item A. In this study, the ERP system manages only one item (A) and displays the following selected parameters (Table 1):

1. Safety stocks are emphasized on an end-item level, which has inventory from previous periods (not allocated)
2. In every case, lot sizes are based on the principle of 'lot for lot'
3. Manufacturing/assembly as well as purchasing lead times for all items are 1 time period

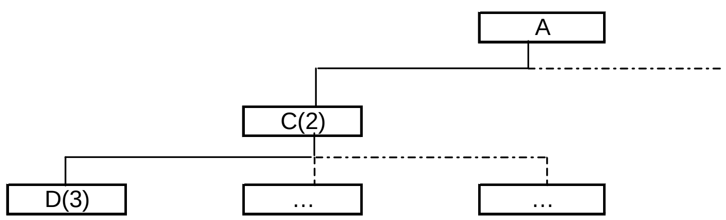

Figure 2. Three stage bill of material (BOM) used in net requirements.

As Table 1 reveals, customer demand is anticipated to increase in 6th period from 200 to 300 units. This significant change is duly handled by net requirements logic which estimates that 1200 units of purchased item D should be ordered in periods of one and two, and in the two periods thereafter this amount will increase to 1800 units. In this example, it may be argued that MRP logic performs adequately and is able to synchronize supplier in the manufacturing system. If LFL (lot for lot) policy is used without MRP logic at the single item level, then operations may somewhat resemble make-to-order type of production where orders are placed after receiving customer order (no advanced assembly or manufacturing scheduling).

Table 1. Net requirement calculations

Item ID	A	Low lvl	0	On Hand	600	Lot Size	LFL
Lead Time	1	Alloc	0	Safety Stock	200		

	1	2	3	4	5	6	7
Customer Forecast	200	200	200	200	200	300	300
Scheduled Receipts	200						
Projected on Hand	600	400	200	200	200	200	200
Planned Order Receipts				200	200	300	300
Planned Order Releases			200	200	300	300	

Item ID	C	Low lvl	1	On Hand	0	Lot Size	LFL
Lead Time	1	Alloc	0	Safety Stock	0		

	1	2	3	4	5	6	7
Gross Requirements			400	400	600	600	
Scheduled Receipts							
Projected on Hand	0	0	0	0	0	0	0
Planned Order Receipts			400	400	600	600	
Planned Order Releases		400	400	600	600		

Item ID	D	Low lvl	2	On Hand	0	Lot Size	LFL
Lead Time	1	Alloc	0	Safety Stock	0		

	1	2	3	4	5	6	7
Gross Requirements		1200	1200	1800	1800		
Scheduled Receipts							
Projected on Hand	0	0					
Planned Order Receipts		1200	1200	1800	1800		
Planned Order Releases	1200	1200	1800	1800			

However, small changes in parameters, even in case of a single product, will result in distortion of demand signals in a MRP system (for example, increasing safety stock requirements, inventory in-hand, using lot size in manufacturing/assembly process). By using lot size, the system may be more economical as set-up and ordering costs may have lower significance. However, inventory holding cost and demand distortion are the potential negative outcomes of applying lot sizing.

Prior research on distortion of demand signals and "nervousness" of ordering systems has outlined some of the causes, summarized below (Carlson *et al.* 1979; Kropp *et al.* 1984; Blackburn *et al.* 1986; Minifie *et al.* 1990):

- Increasing bill of material (BOM) quantity requirements multiplies the demand and adding stages to the BOM will create greater distortion.
- Excess inventory in-hand is too high in the beginning of calculations due to excess inventory in previous periods.
- Safety stocks are held at each stage (not only at the end-item level)
- Lot sizing is used at all levels to increase the efficiency of system through improvement of local efficiencies, but this ignores the performance of the system as a whole.

In previous studies of MRP systems, researchers have been proposed solutions to manage this instability. These include such issues as (Blackburn *et al*. 1986): (1) freezing production schedule for longer planning horizon, (2) apply lot for lot ordering policy and (3) forecast beyond the planning horizon, and change orders completed in the end of the period accordingly. These work well to prevent MRP instability, but in the end their cost considerations are rather complex (without considering delivery performance and eventually revenues), since schedules are always instable, and changing optimal and static solution during period of action could eventually lead to higher costs, and impact cash flow and profitability. It is interesting to note that larger scale distortion or amplification in the supply chain environment, often referred to as the *Bullwhip Effect*, is still a problem in search of solutions (Lee *et al.* 1997). Lot for lot ordering with short reaction times is still viewed as one remedy for the problem (Moyaux *et al.* 2007). Standardized order quantities often create excess inventory in the supply chain (Nienhaus *et al.* 2006).

3. Product Life-Cycles and Managerial Process

Product life-cycles have decreased considerably during the last few decades, to the point where electronic goods may have a sales life of 4-8 months while some music and clothing may be even shorter. The automobile industry and also pharmaceutical products may follow this trend. Hence response and lead-time minimization are important strategies compared to the traditional cost efficiencies or outsourcing (with long lead-time for manufacturing). Rubesch & Banomyong (2005) observes that in the US auto industry the labour-intensive seat manufacturing is outsourced to the Far East with a 28 day transportation lead time. A similar strategy for an electronic product with only 4-8 month life-cycle is inappropriate. Warburton & Stratton (2002) proposed, based on the US textile industry, that manufacturing may contain a network of units, both in low labour cost countries as well as high cost areas adjacent to large markets that can offer rapid response and flexibility. Zara has adopted this strategy (Fraiman & Singh 2002; Christopher *et al.* 2004).

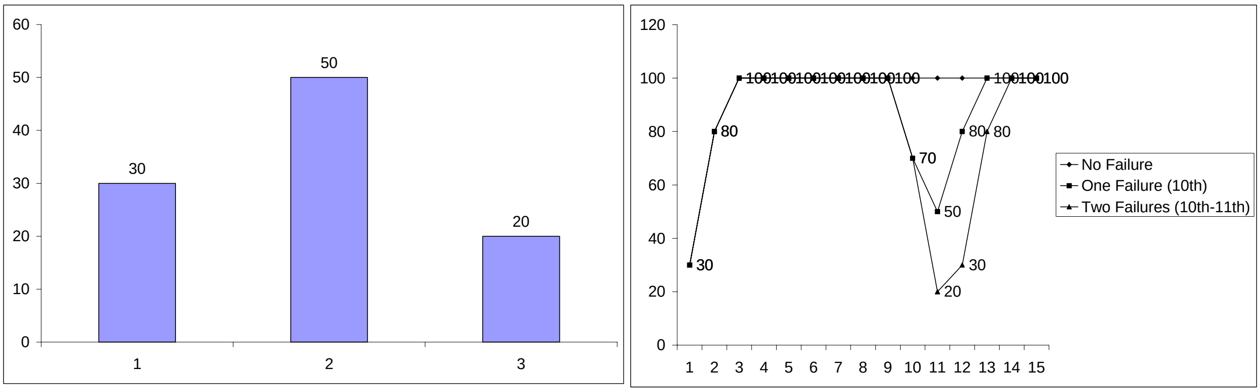

Figure 3. Three month product life-cycle (left-side), and consequences as one failure (10th period) and two failures (10th and 11th period) are being faced. Source: Von Braun (1990, adapted).

Von Braun (1990) showed that decreasing product life-cycle has positive effects on increasing sales within short period of time if consumption remains unchanged. Figure 3 illustrates the negative impact of this observation, as sales of total life-cycle is 100 units (left-side of Figure 3), and weighted towards first and second period (total 80 units), then total sales of hypothetical product is in trouble, even if only one product introduction failure occurs (One Failure scenario). In case of two consecutive failures, sales will decrease from 100 to 20 units. For example, sales of mobile phones by Ericsson decreased from 15.1% in 1998 (Gartner 1999) to 6.7% in 2001 (Gartner 2002). This failure was one reason for the merger that created Sony-Ericsson.

4. Simulation Model to Test Purchase Order Policies for Products with Different Life-Cycles

Set-up

Several ‘manufacturing’ companies simply do not own any manufacturing capacity. They assemble subcomponents to generate the end product to fulfil demand. Start-ups may apply such strategy but it may become difficult for small companies to manage its cash flow. Hence, to optimize cash flow, the company seeks ordering policies best suited for each kind of product. To explore this problem, we deploy a system dynamics simulation model, in which the subassembly purchasing and end product assembly processes are modeled, and the corresponding cash flow and ordering policies are studied (numbers and payment terms in the simulation model are hypothetical).

We focus on three products: product 1, product 2 and product 3. The BOM (Bill of Material) for all three products are similar: each end product needs 1 electrical system and 2 mechanical systems. Product 1 is a mature product with high demand and grows steadily in the beginning. After a period, the demand reaches its peak and begins to decline. Product 2 is a relatively new product. Its demand grows rapidly and soon reaches a peak but then declines because of its short life-cycle. Product 3 is a speciality product. Its demand is low, uncertain, and fluctuates. In this case study, we examine the cash flow for these three products and determine the best subassembly ordering policy.

Different payment programs for suppliers and customers impact medium-term cash flow. In the simulation we have assumed that customers for product 1 pay without delay on delivery. Customers offer advance payments of 20% for product 2 and 40% for product 3 on the value of the order (payments with 3 week delay) and after actual delivery they pay the remaining (with delay of 2 weeks). For suppliers, all orders are paid as components are delivered, (payment delay is 8 weeks). Due to the high price of products 2 and 3, customers may receive a discount for late delivery (0.5% per week, from sales price of products) or if order exceeds 1 unit (1% batch discount).

Assumptions

Demand generation was random (according to stochastic distributions such as normal distribution and empirical table). Based on current inventory status, subassemblies are ordered from suppliers according to ordering policies. The ordered components are delivered to the company's inventory after the lead time. When all subassemblies are available (assembly capacity permitting) end product is assembled and inventory shifts to end product category. Both subassembly delivery lead time and end product assembly lead time are random (gamma distribution). Orders are shipped to meet customer demand when there is inventory of end product(s).

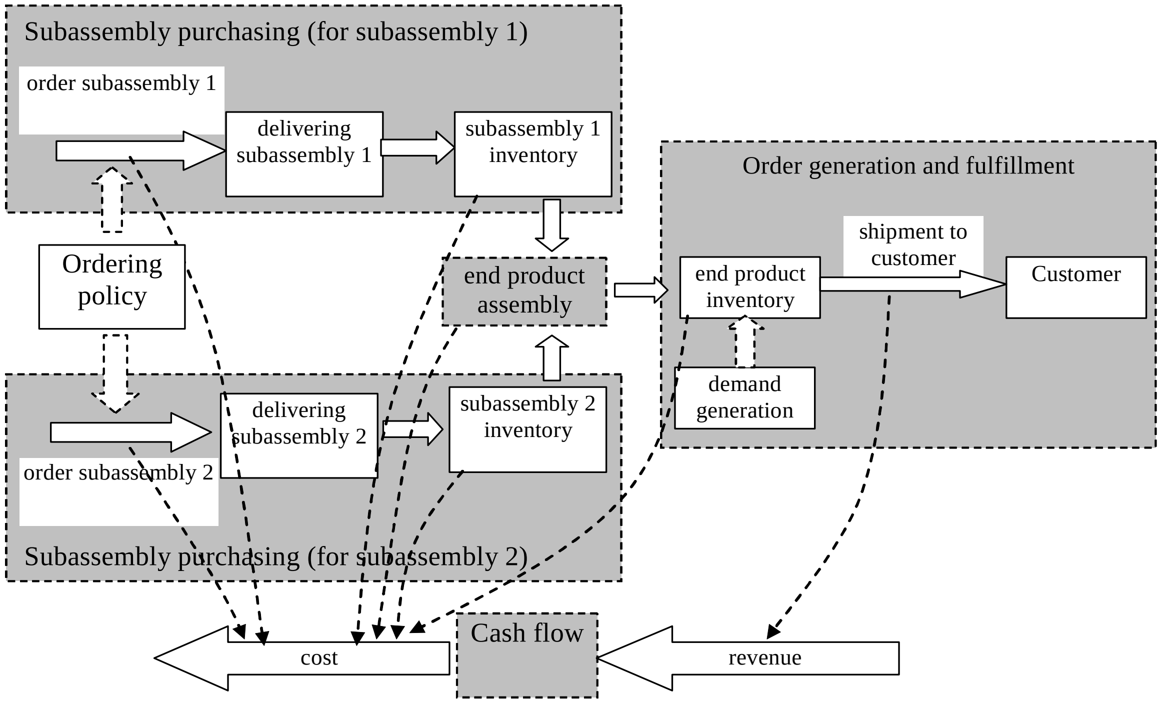

Figure 4. Simulation Model.

In this model, we consider a time period of 400 weeks (approximately 8 years). As mentioned above, the demand for the three products are different. The demand for product 1 is generated according to normal distribution, shown in Figure 5. In the beginning, demand for product 1 grows steadily. At about week 300 (6th year), it reaches a peak ad then begins to decline. As the demand for different order policies is the same, here we illustrate the demand for LFL (without failure).

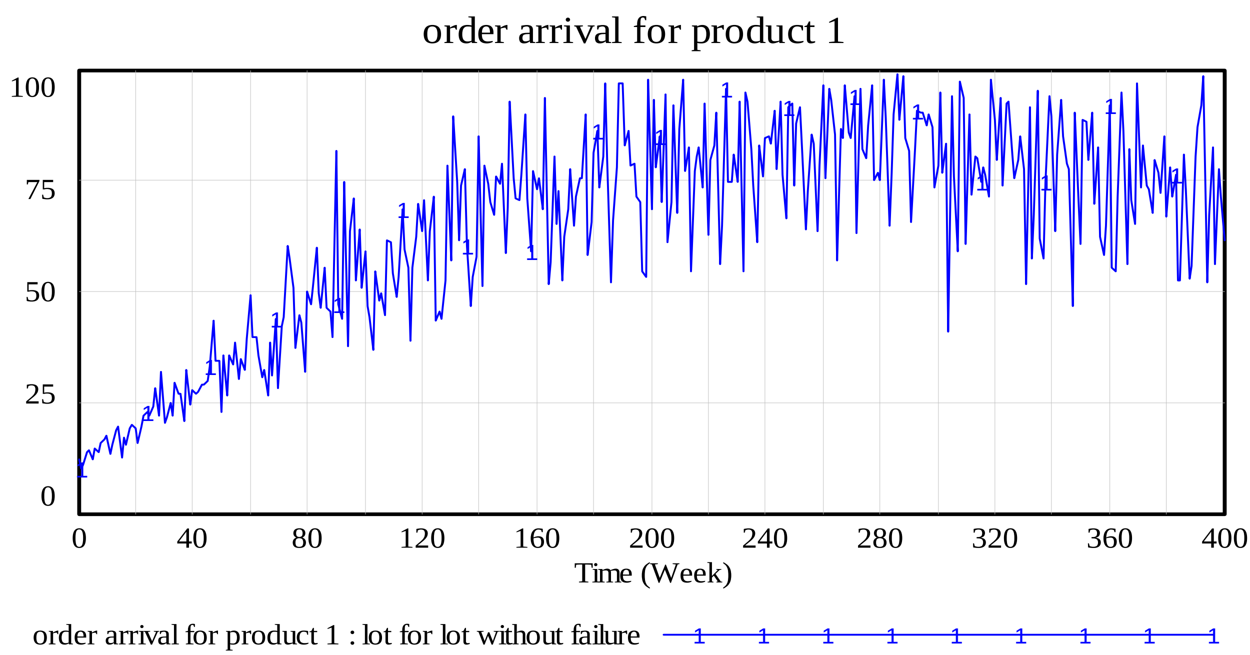

Figure 5. **D**emand generation for product 1.

Demand for product 2 is generated according to empirical table. At different time points, the empirical table is different. For example, Table 2, show empirical demand at week 100.

Table 2. Empirical table for demand of product 2 at week 100.

Items		Probability (%)
probability of having order in this week		50
order size	probability of 1 product order	10
	probability of 2 product order	50
	probability of 3 product order	40

The demand for product 2 at any given time is generated according to a corresponding empirical table. Figure 6 shows the generated demand for product 2, which is a relatively new product. In the beginning, the demand grows quickly. It peaks at week 100 and thereafter declines, rapidly. After week 200, the demand for product 2 is very low. Generally, the demand for product 2 is lower than that for product 1. During 400 weeks, average demand for product 1 changes from 10 to 100 units per week. However, the average demand for product 2 is 0 to 1.5 units per week.

The demand generation for product 3 is similar to product 2. The main difference between them is that, the demand for product 3 is lower and fluctuates. Figure 7 shows the generated demand for product 3 in this simulation model. During week 40 and 80, the average demand is relatively high (around 0.4 units per week). During week 240 and 330, the average demand is 0.3 units per week. For other periods, the demand for product 3 is very low.

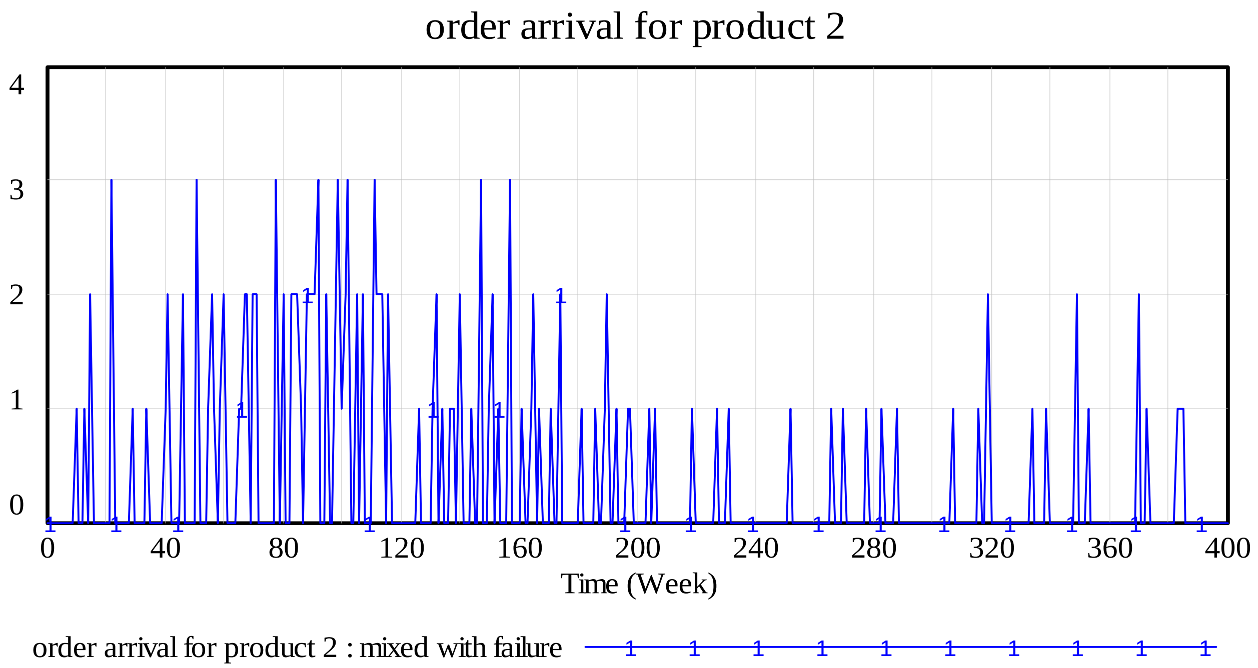

Figure 6. Generated demand for product 2.

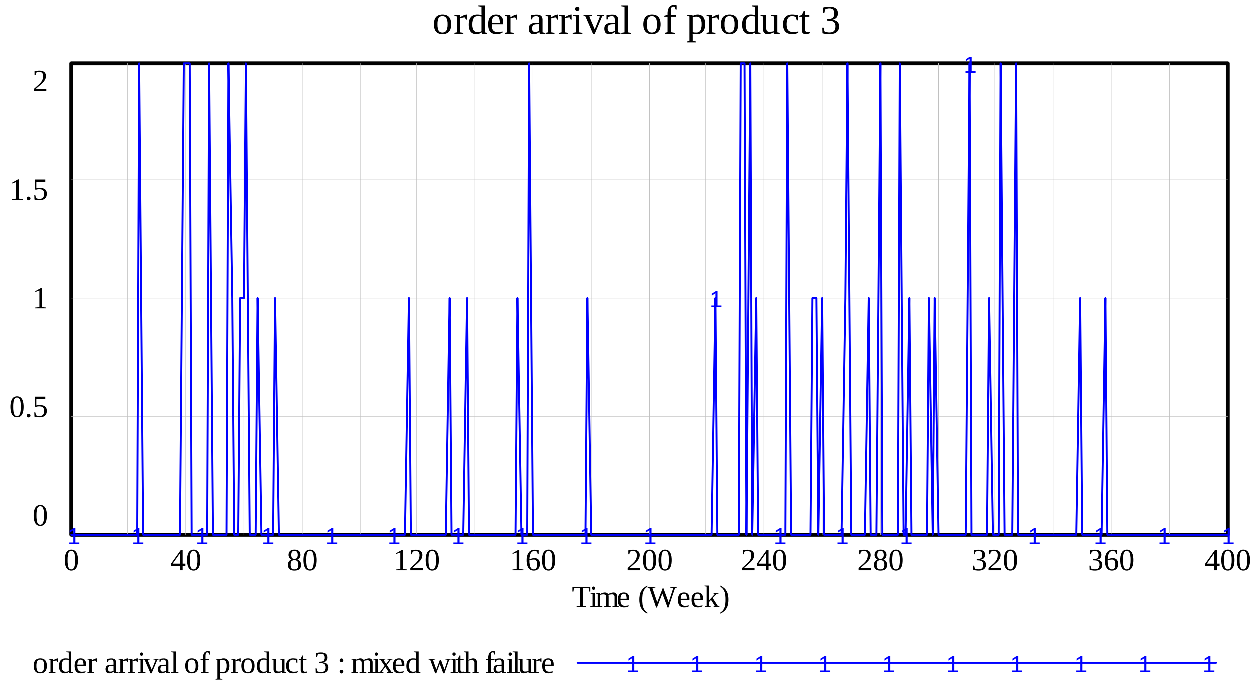

Figure 7. Generated demand for product 3.

Relative to cash flow, which ordering policy is most suitable for which product? Cash flow equals total revenue (based on payment program) minus total cost. Total cost includes subassembly purchasing cost (based on payment program), end product assembly cost, and inventory holding cost for subassemblies and end products. Here, three ordering policies are considered: LFL (lot for lot), EOQ (Economic Ordering Quantity) and mixed ordering policy (combination of these two). LFL is the simplest to implement whereby purchasing department only orders sub-assemblies based on customer demand. EOQ takes into account fixed costs and demand, as follows:

(1) cost per order fixed at €5000 and transportation is €300 per truck (fill-rate of different products is 30-50 in electrical systems and 60-100 in mechanics)

(2) demand is mean demand rate of each product.

In a mixed ordering policy, when demand is low and available cash is limited, LFL is used and later, when demand is high, policy switches over to EOQ model. Mixed logic is based on the careful observation of the mean demand of particular product. For product 1, if mean order rate is above 50 units per week, system favours EOQ over LFL. For product 2, EOQ is triggered by a demand of 0.5 units per week and in a case of product 3 the value of 0.1 units per week. The switch between LFL and EOQ may be built into the logic of the system using a variety of approaches.

Results

Product 1 is a mature product with low profit. At the selling price of €500 per unit, about 65% of revenue is cost of sub-assemblies. Annual inventory holding cost for products and subassemblies is 20% of the value. Cash flow of product 1 for three ordering policies is shown in Figure 8.

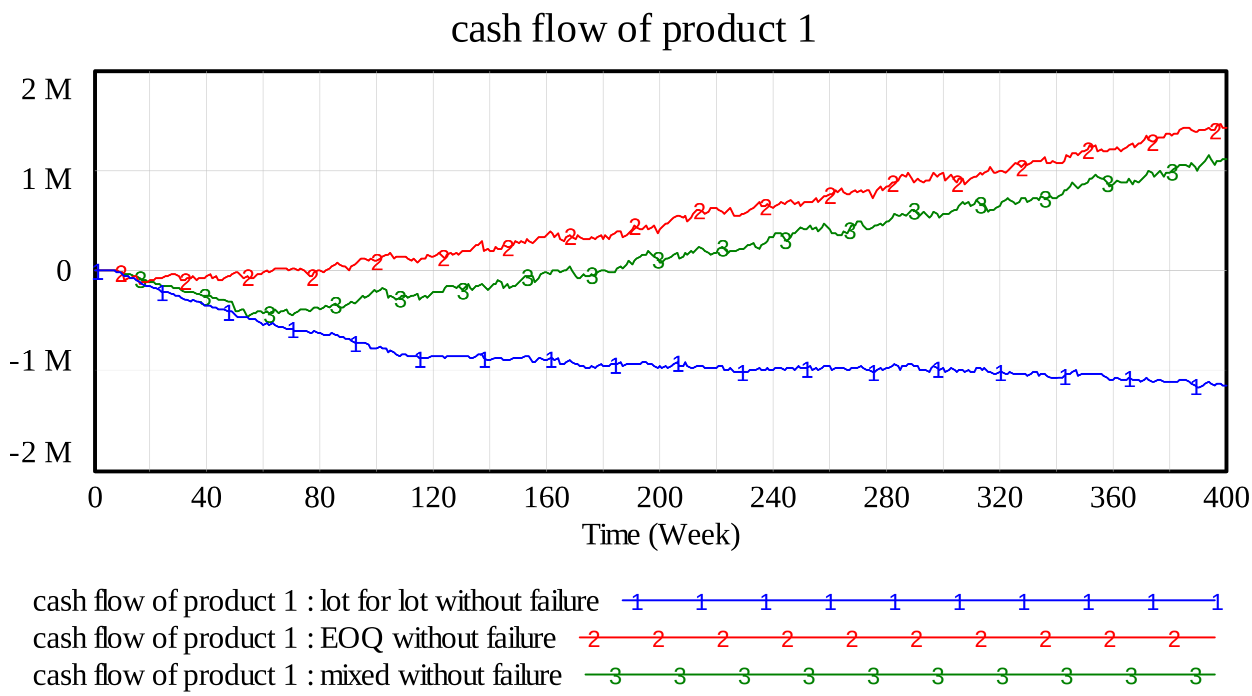

Figure 8. Cash flow of product 1 for three ordering policies: LFL, EOQ and mixed policy (failures in placing orders for subassemblies are <u>not</u> considered).

Figure 8 shows that LFL is the worst policy in this case. The cash flow declines and is negative for the period. In LFL, the company orders subassemblies frequently, increasing the ordering cost without economies of scale. Among these 3 ordering policies, EOQ appears best.

Cash flow performance shown in Figure 8 may suggest to use only EOQ policy, for product 1, but in practice, it is not recommended. In start-ups errors in ordering may be unavoidable due to technical specifications, communication, change in customer preference and engineering change. If only EOQ is applied, an error may lead to a loss due to large lot size. Hence, it may be prudent to use LFL. When operations are more stable, EOQ may be applied, as illustrated through simulation.

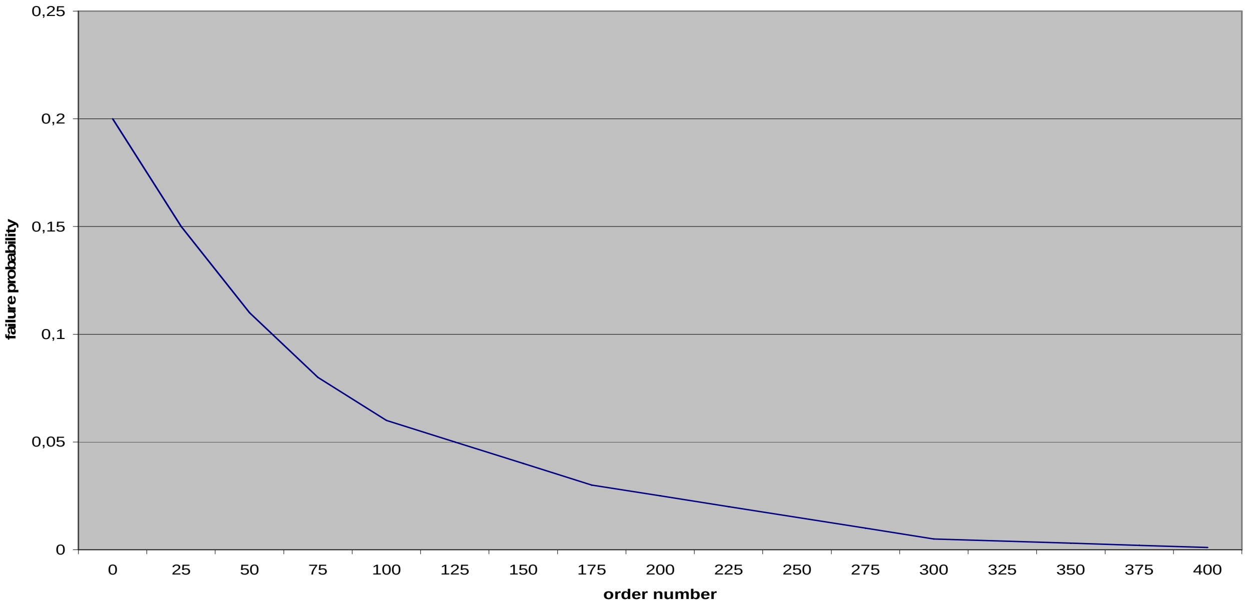

Figure 9. Learning curve: failure probability for varying order numbers.

Figure 9 shows the basic learning curve used in the simulation model. In the beginning when placing orders to suppliers, the probability for failed ordering is 20% (failure costs, that is, material, transportation and ordering, are at the manufacturer's disposal). As order number grows, this probability declines. The x-axis in Figure 9 is order number rather than time (because people get experienced in the ordering process, not by time). In the simulation model, following schemes are arranged concerning the failure probability: each time there is a failed order, the probability of failure in the later ordering process is reduced by 2% (from the learning curve). When the company places a wrong order for one reason or another, it will pay following costs: transportation cost and processing cost for returning the ordered subassemblies to the suppliers and a part of the material cost for manufacturing these subassemblies. After taking into account these costs, the cash flow of product 1 changes (compare Figure 8 with Figure 10).

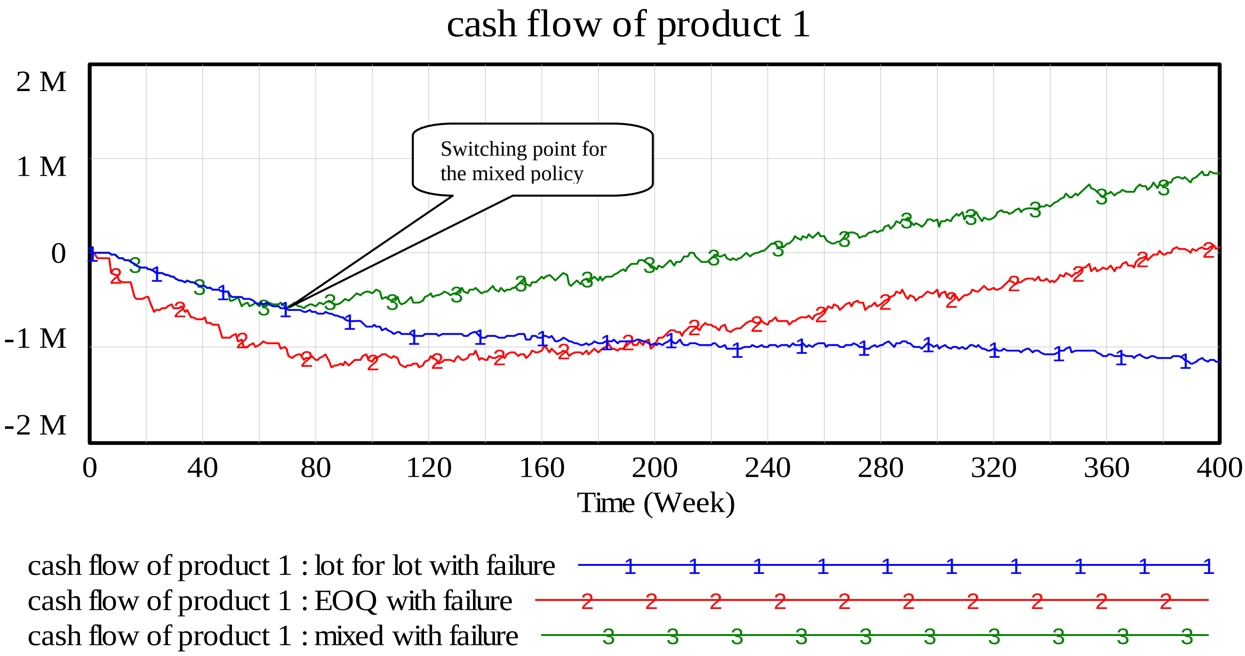

Figure 10. Cash flow of product 1 for three ordering policies: LFL, EOQ and mixed policy (failures in placing orders for subassemblies are considered).

As shown in Figure 10, in the beginning, due to the cost of failed ordering, EOQ appears worst among three policies. After considering ordering failure probability, mixed policy is the optimal one for product 1. Initially LFL is suitable while ordering for subassemblies. Later, when the company is confident of the process, the ordering policy can be switched to EOQ. When to switch depends on the learning process of the company. In this case, the switching point is at week 60, i.e., beginning of the second year.

The inventory behaviour for holding subassemblies (components) and end products is shown in Figures 11 and 12, respectively.

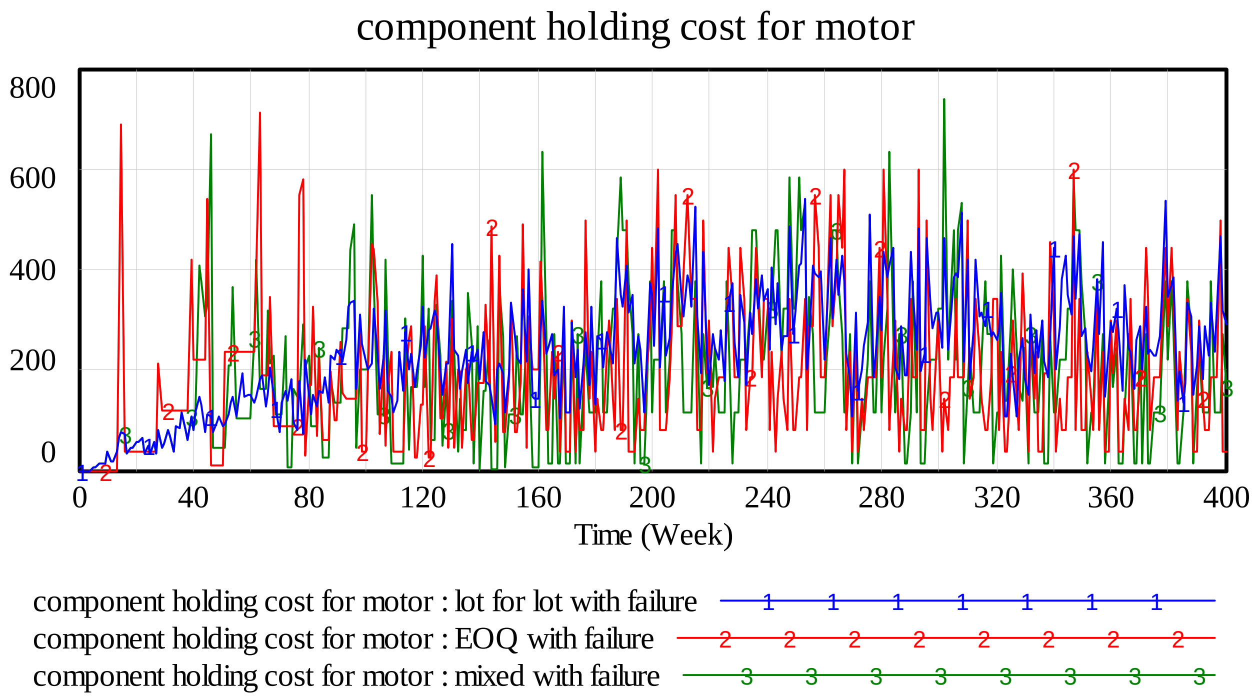

Figure 11. Component holding cost (€) for motor (product 1).

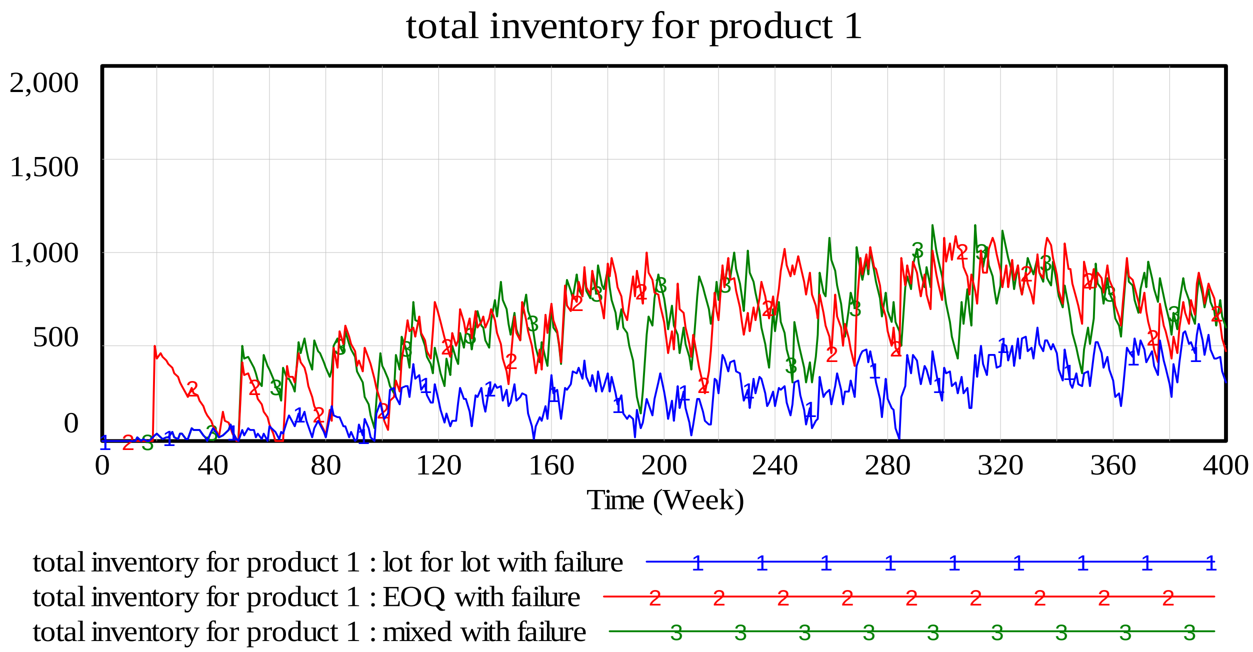

Figure 12. Total end product inventory (unit) for product 1.

In Figure 11, we use inventory holding cost (€) of all components (or subassemblies) of product 1 to show its inventory behaviour. The reason is that, for one product, there are several types of components, such as mechanical and electrical system. It is difficult to measure the general inventory by number of units. We assume 20% of the product value as the inventory holding costs per year. In the illustration, it shows inventory holding cost per week (inventory holding cost is about 0.4% of the product value). Sum of all inventory holding costs for the components generates the total component inventory cost for product 1. Concerning the component holding cost, at some points, especially in the low demand period, EOQ and mixed policy have higher inventory cost than lot for lot, but, on average, there is not a significant difference between three ordering policies. This is due to the fact that, in this model, we assumed enough assembly capacity and proper organization in the production process to prevent material flow blockage and excess inventory build up.

In Figure 12, to make the inventory behaviour more visible, we use unit to measure the end product inventory. EOQ and mixed policy have higher inventory than LFL, especially, during low demand period. In these two ordering policies, to benefit from economies of scale, the company needs to purchase more than necessary in one order. This builds up excess inventory (holding cost).

Product 2 is relatively new and selling price is €5000 per unit with 50% material margin. The cash flow of product 2 for three ordering policies is shown in Figure 13.

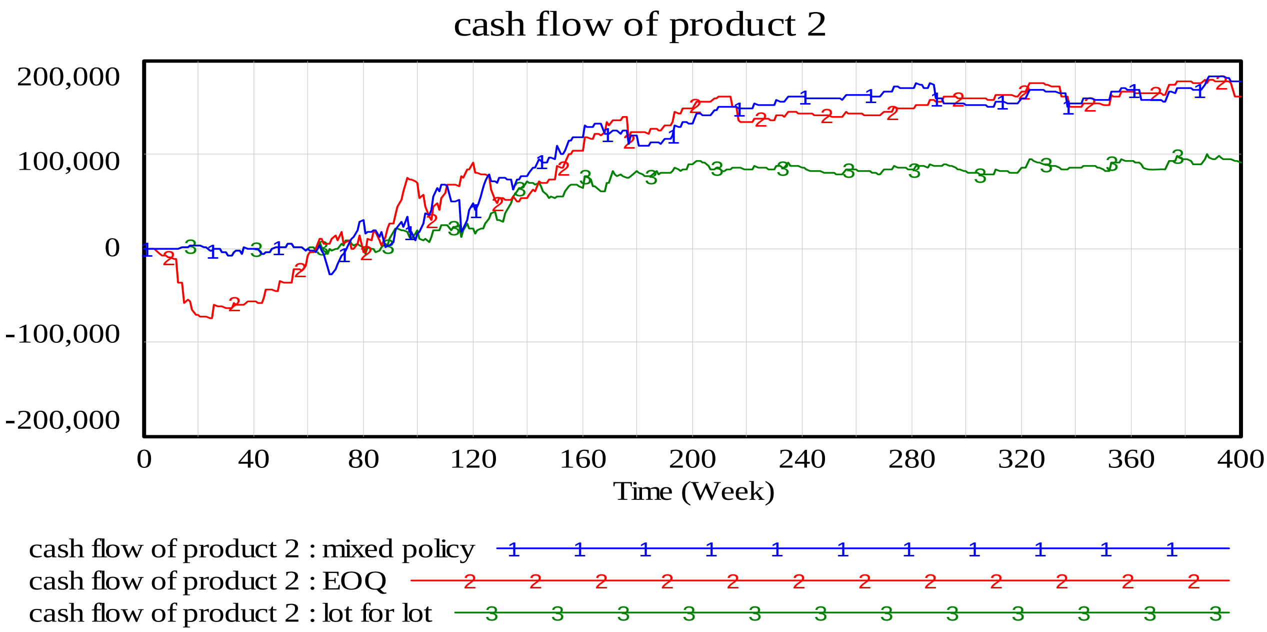

Figure 13. Cash flow of product 2 for three ordering policies: lot for lot, EOQ, and mixed.

As shown in Figure 13, in the early growth period (week 0 to 80), cash flow for both lot for lot policy and mixed policy is around zero. But for EOQ policy, the cash flow is negative. The lowest point is around - €80,000 with grave consequences for cash flow. Hence, in the beginning, both lot for lot and mixed policy are better than EOQ. After week 80, there is no significant difference between EOQ and mixed policy. Both are better than LFL. Over the entire period, mixed ordering policy may be optimal solution for product 2.

When the failed orders are considered, the cash flow for product 2 changes (compare Figure 13 to Figure 14). Illustrations suggest that, mixed ordering policy is appropriate for product 2 (LFL in the beginning followed by EOQ). The switching point from LFL to EOQ depends on cash flow performance and the learning process at the company. In Figure 14, the switching point is around week 70, a little bit later than product 1 (for product 1, this switching point is around week 60). The possible reason is that, for product 2, company orders less (due to less demand) and consequently it may require longer time to learn. In practice, it may be judicious, when switching from LFL to EOQ, to apply small lot size (partly EOQ) as a compromise. When the condition at the company is ready for applying new ordering policy, EOQ can be applied without reservations or compromise. Interestingly, as smoothed demand declines below 0.5 units per week, during week 230, mixed system starts to favour LFL. Therefore, in case of product 2, we have two switching points and it results in a better performance (as failure is being considered).

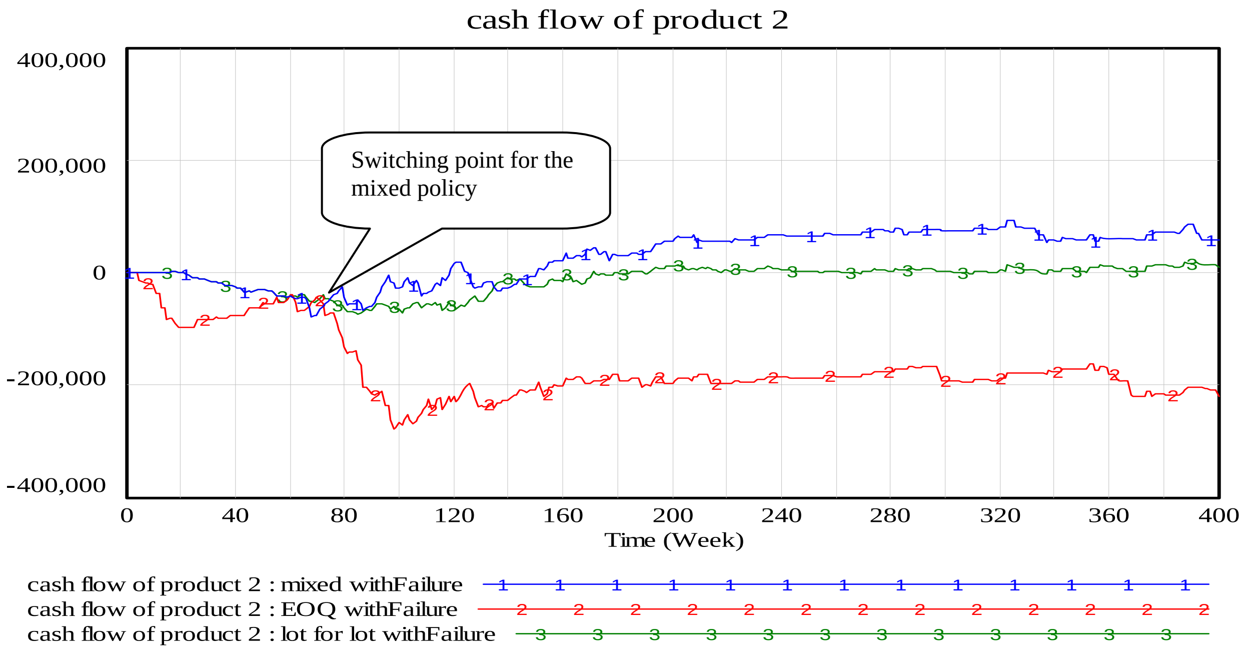

Figure 14. Cash flow for product 2 after considering ordering failure probability.

For product 2, the inventory behaviour for holding the components and end products are shown in Figure 15 and Figure 16, respectively.

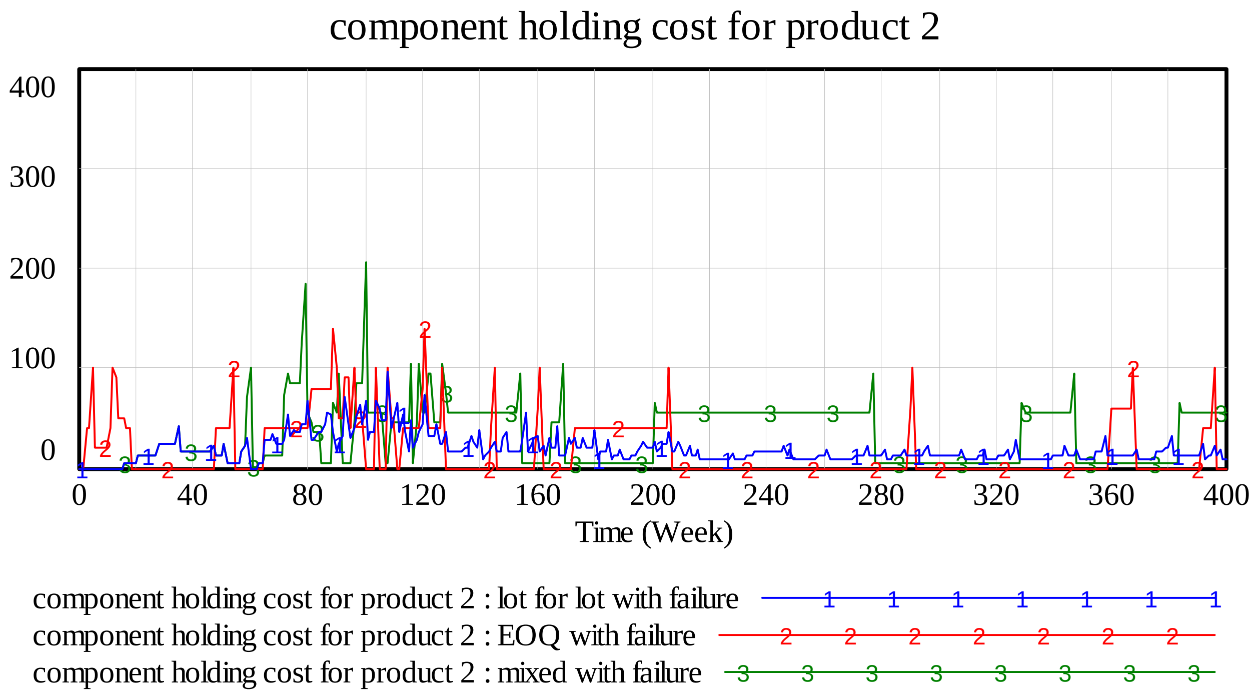

Figure 15. Component holding cost (€) for product 2.

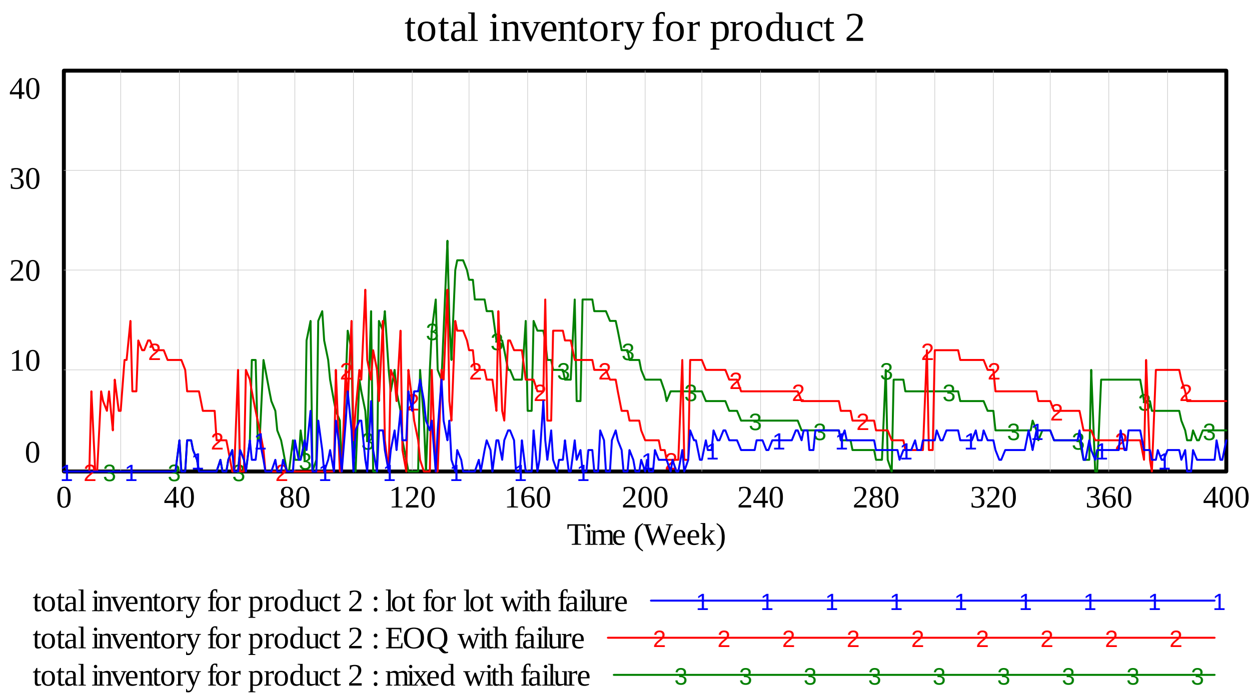

Figure 16. Total end product inventory (unit) for product 2.

For components, we use inventory holding cost (€) to show its inventory behaviour; but for end product, we use units. For both, LFL offers better inventory behaviour. In LFL, the company orders components after receiving customer demand (no extra inventory, no holding cost). But, LFL does not exploit economies of scale, hence, ordering costs and transportation costs are high. In general, mixed policy performs better, from a cash flow perspective.

At €10,000 per unit selling price for product 3, the material margin is 70%. The cash flow of product 3 for three ordering policies is shown in Figure 17. In this case, lot for lot policy is always better than the other two. Demand for product 3 is low and fluctuates. If EOQ policy is applied, the inventory will be high. Therefore, LFL enables ordering subassemblies when demand for product 3 materialises. Since LFL is always applied for product 3, it is unnecessary to explore failed ordering. The inventory behaviour for components and end product of product 3 are shown in Figures 18 19, respectively. For both of them, lot for lot policy offers better performance, as explained above.

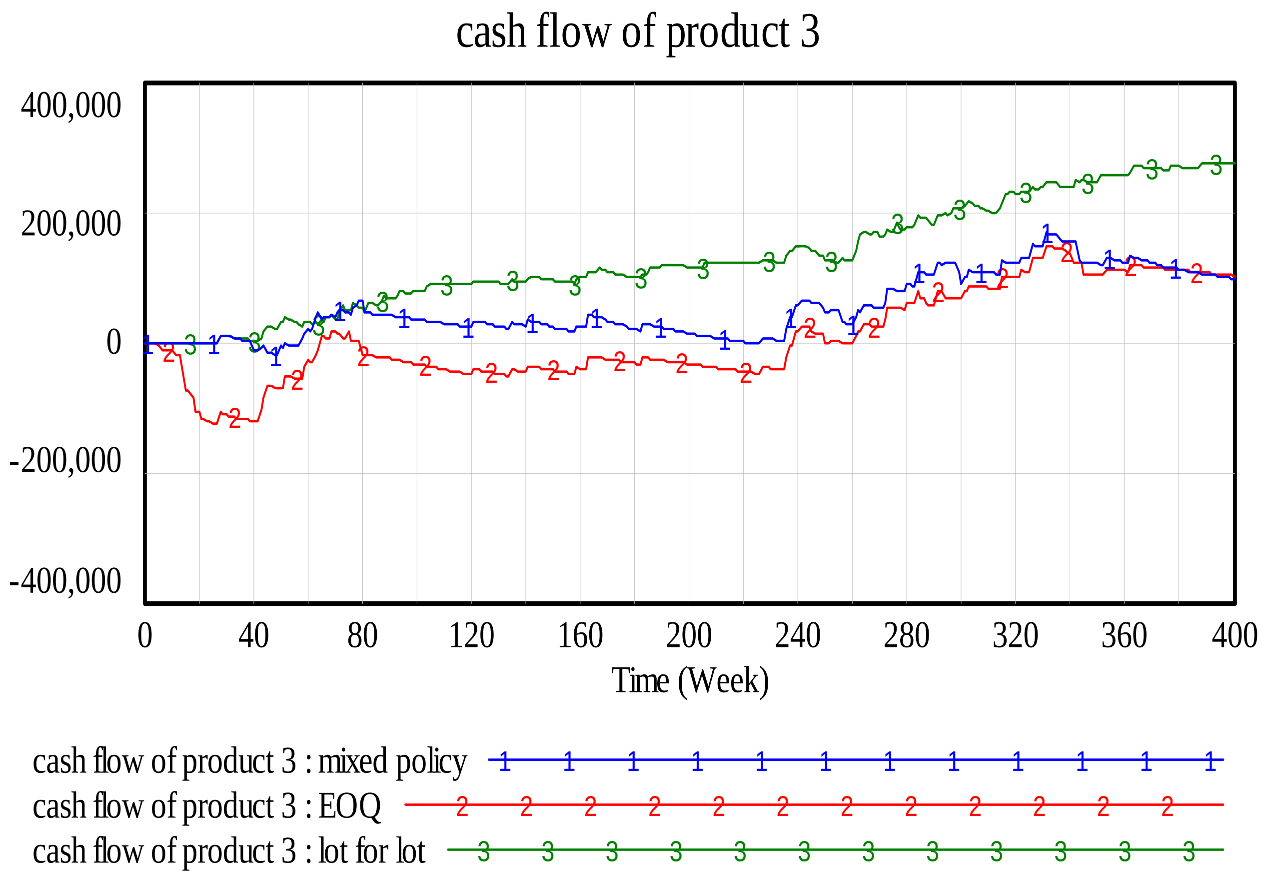

Figure 17. Cash flow of product 3 for three ordering policies: lot for lot, EOQ, and mixed policy.

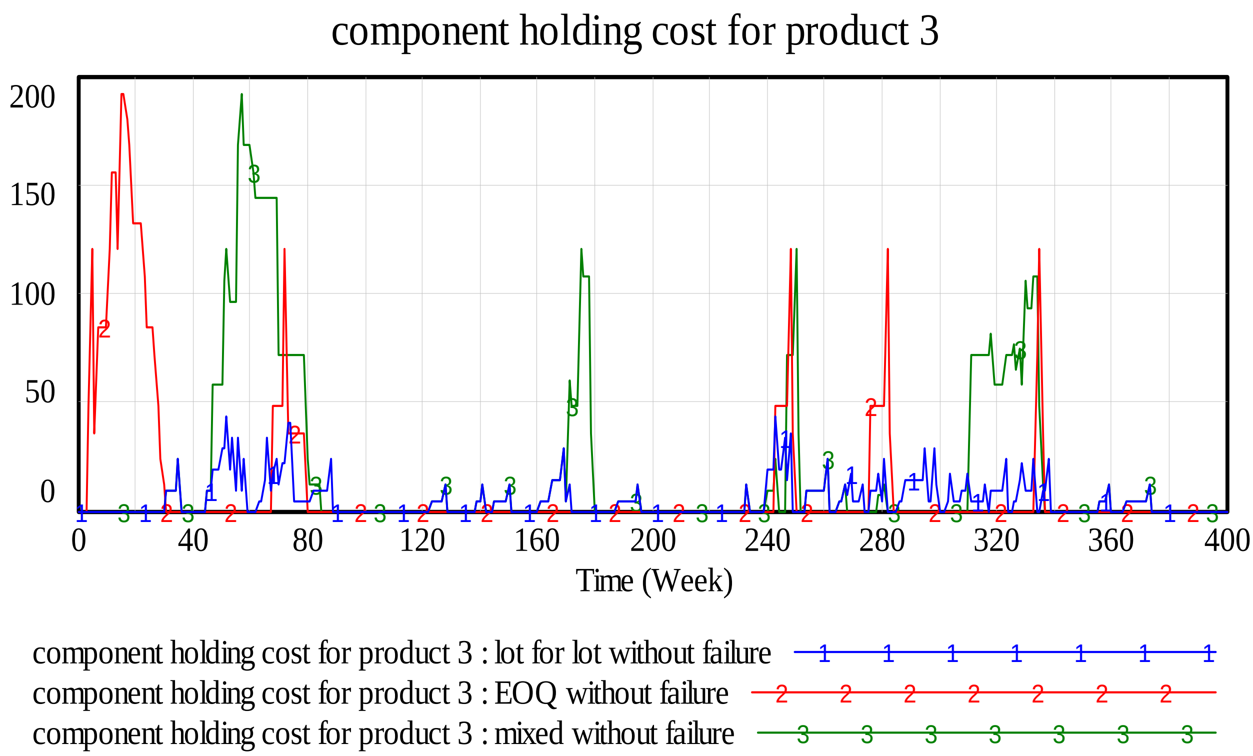

Figure 18. Component holding cost (€) for product 3.

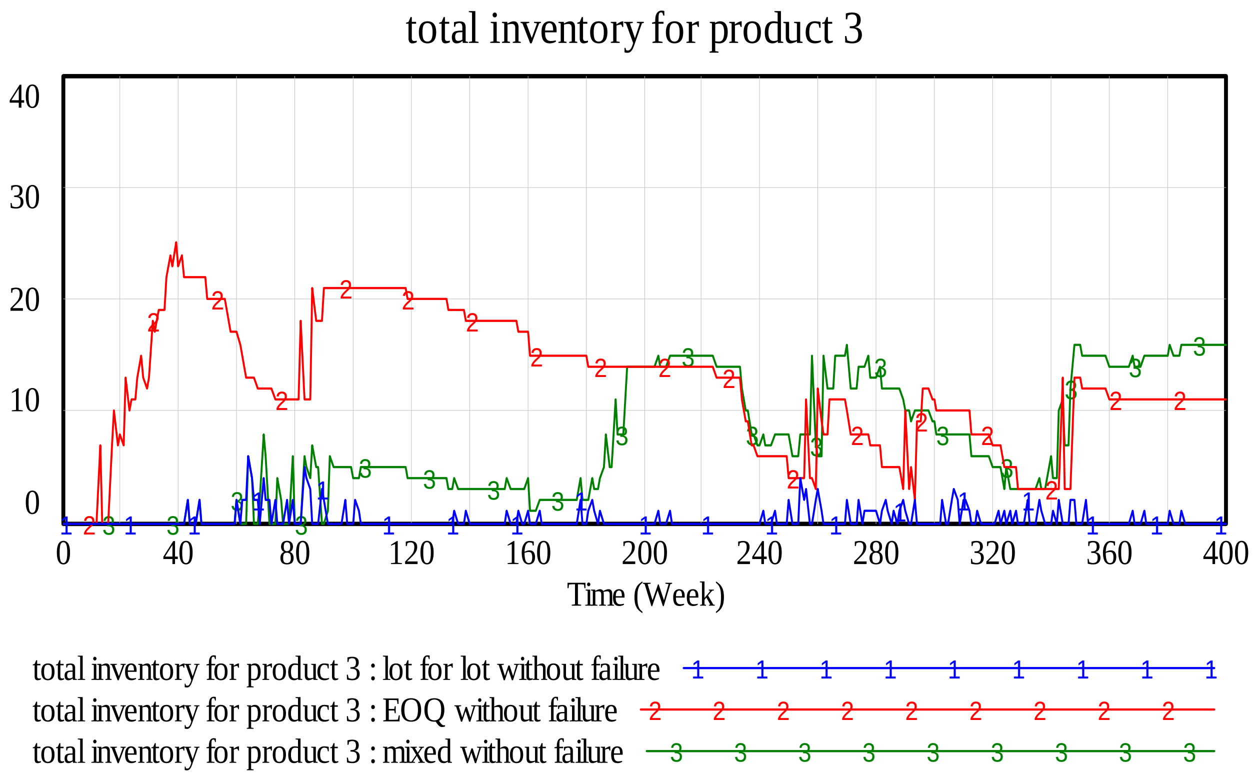

Figure 19. End product inventory (unit) for product 3.

5. Discussion

In an assembly system, a firm purchases subassemblies and assembles them into end products. In this study, a simulation model was used to analyze challenges faced by start-up companies pursuing make-to-order assembly with outsourced subassemblies. In this three product model, product 1 is a mature product with relatively high demand which grows steadily in the early stage but declines after it peaks. Product 2 is a new and short life-cycle product. In the beginning, its demand grows rapidly and soon reaches a peak. Its decline is also rapid. Average demand for product 2 is lower than product 1. Product 3 is a speciality product. Demand for product 3 is much lower with fluctuates significantly.

In an assembly system, subassembly ordering policy plays important role in managing the company. In this simulation model, different ordering policies were tested for all products, and following are some conclusions:

- For mature and relatively high demand product (such as product 1 in this study), cash flow performance suggests EOQ ordering policy is appropriate when purchasing subassemblies. But, in practice, due to unfamiliarity with operations in a start-up environment, it may be better to apply lot for lot (or small lot size), initially. When general conditions are stable, a switch to EOQ is suggested. If mean demand starts to decline, reverting to LFL allows to hedge the risk of obsolescence risk of components nearing the end of product life-cycle. The latter reversal point in ordering policy was not identified in this study since mean demand of product did not decline below stated switch level.

- For new and relatively low demand product (product 2), mixed ordering policy may be applied during the initial stages of low demand. Use of LFL may prevent negative cash flow. With increasing demand, switch to EOQ is preferred. In the switching period, small lot size EOQ should be applied as a buffer between two policies. End of life-cycle order management is important and reversal to LFL may be warranted.

- For a high cost product with low demand and high fluctuation (product 3), LFL is advised during the entire product life-cycle.

The decision to switch depends on the mean order rate (limit was approximated from mean or smoothed demand levels of end product demand). Since LFL is preferred in the initial stages for all three product types, the decision making process for an appropriate switching point may be made after early sales figures are at hand from the initial 10-20 weeks (in this case).

In simulation experiments we observed that EOQ ordering results in large orders in early phases of product life-cycle, due to the lesser volume of products in the assembly (despite optimization of fixed costs). However, as order backlog in assembly clears and demand increases, the benefits of EOQ are appreciable. We conclude that organizations may wish to avoid using standardized order quantity approach with economic considerations in the early phases of life-cycle. Although, this may impact availability of products, the greater risk of obsolescence risk is also high in the initial phase, hence a risk averse approach to purchasing may be considered. If demand forecast is not realised, then EOQ policy will lead to excessive inventory and reduce cash flow to a trickle.

It is quite apparent that the volatility of inventory development, stemming from the impact of different ordering policies, directly influences inventory carrying cost and may contribute to decreasing cash flow and eventually will reduce profitability. As a conventional response to stochastic demand patterns, a normal or uniform distribution is the assumption in most of the generated demand types, in this and other studies. Thus far, it is the standard approach to assume homoskedastic distribution for parameters with demand volatility. However, in recent years there is growing acknowledgement in research circles that heteroskedasticity is better representative of real-world scenarios (Datta *et al.* 2007). Therefore, it may be logical to explore whether these types of analyses can be performed with heteroskedastic distributions and employ advanced econometric VAR-GARCH type of combined tools (Datta *et al.* 2007) to model systems and improve accuracy of demand forecasts. In such research, business process engineering and simulation will be important. But, in contrast to the *modus operandi* outlined in Section 4, in the simulation model of the future, the 'demand' may not be generated randomly according to conventional statistical distributions (normal distribution, empirical tables). Instead, accurate real-time demand data (customer forecast in Table 1) based on high volume data analysis will be part of the input (for the simulation). At present this may not be pragmatic, since high volume data is scarce and most data acquisition systems are still reliant on batch upload of data. However, with increasing diffusion of automatic identification tools, such as radio frequency identification (RFID), it is likely that an abundance of data may become available to better model the volatility and quantify the variance of the error (Datta *et al*. 2007). This improvement in accuracy may impact decisions and increase profitability. For example, as illustrated in a number of figures in simulation results section, the decision when to switch from lot for lot to EOQ depends on cash flow performance and the learning process. The latter is a heuristic measure that introduces risk and uncertainty in the decision making process because ‘learning’ may vary by company. It is the accumulation of these types of errors that leads to increased probability of out-of-stocks (OOS) or excess inventory carrying costs, which impact profitability and manifests itself as the *Bullwhip Effect*. Other studies (Chen *et al.* 2000) have shown that higher amount (with shorter observation frequency) of demand observation points may decrease the *Bullwhip Effect*. Taken together, we propose that future research directions may explore the application of advanced econometric tools to improve accuracy of predictive analytics (Datta *et al.* 2007).

6. Conclusions

Purchasing has experienced a number of changes during the last century. In this study we suggest why a portfolio approach of using different purchasing policies may be central to new purchasing systems. The latter may better sense and respond to the demanding impact of global manufacturing competition to help ensure profitability. With decreasing product life-cycles there is a concomitant rise in the frequency of new product introductions and that makes purchasing an extremely complex operation that must continually adapt to changing preferences. Our study suggests that product life-cycle types, demand development evaluation and product failures play significant role in the final decision process. Therefore, it is critical to define which ordering approach should be used in each of these situations, which, collectively, is the principal function of the purchasing system. It appears that early in the product life-cycle, purchasing based on lot for lot (LFL) policy is suitable but as quality failure probability decreases and demand strengthens, then the switch to standardized order batch sizes may improve performance. Current tools of operations management do not offer insight for advanced decision making. One potential method for tracking these signals may be the development of the GARCH technique (proven useful in financial risk management and awarded the 2003 Nobel Prize in Economics). Improving precision in predictive analytics may help in better execution of the switching point decision making (among other things) for much larger and more complex operations with vast number of decision parameters. The incorporation of ambient intelligence or algorithms from artificial intelligence may help purchasing systems *learn* how to be autonomous and/or help human operators to decide between portfolio of approaches by evaluating decisionable information extracted from data analytics (acquired from a plethora of business processes). Taken together, these represent potentially interesting future steps.

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