The Non-Standard Lifecycle Pattern Effect on Capacity Planning of Reverse Logistics

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Abstract
The decision about how to handle their end-of-life products is a strategic issue of major importance for many firms. However, inaccurate demand forecasts along with the unknown usage period and reusability of a product make capacity planning in the reverse channel of a closed-loop supply chain (CLSC) a difficult task to accomplish. This paper studies the efficiency of a System Dynamics (SD) model, proposed by Georgiadis et al. (2006), in tracking near-optimal capacity planning policies for the collection and remanufacturing activities in a single product CLSC under various non-standard lifecycle patterns. We take into consideration the duration of the products' usage period, the percentage of collected products rejected for reuse after inspection, and specific lifecycle patterns that differ substantially from the standard growth–maturity-decline lifecycle pattern. The analysis of variance (ANOVA) of the results obtained from 648 such case-studies reveals the dependence of the near-optimal capacity planning policies to these factors. A very appealing feature stemming from the results is that the near-optimal capacity planning policies lie in a short range for almost all the examined cases. The results also verify a positive property of the proposed model about the robustness of the near-optimal capacity planning policies to moderate changes in actual total demand.

Keywords: Closed-loop supply chain, Remanufacturing, Capacity planning, Non-standard product lifecycles, System Dynamics, ANOVA.

JEL classifications: Industry Studies, Manufacturing, L600

Introduction

Reverse channels of closed-loop supply chains (CLSCs) are strongly characterized by uncertainties; the unknown demand pattern and the variability of a product's usage period along with the unknown reusability of the returned products, render the capacity planning for remanufacturing a challenging procedure. Moreover, a capacity alteration decision is associated with important questions such as "when", "where" and "how much" to expand/contract. Additional critical capacity planning issues include the volume and timing of returns which can be reused to satisfy new demand, owing to the dependence of their reusable part on both the demand and sales patterns.

In literature, the desired remanufacturing capacity levels are mainly determined indirectly, without considering any endogenous restrictions or adaptation mechanisms. Aksoy and Gupta (2001) consider the remanufacturing capacity through the variation of the remanufacturing rate of a flow shop system which is depended on the service rate, the breakdown and repair rate of the returned products and the buffer capacity of each station. Kekre et al. (2003) maximize the effective throughput of a remanufacturing system considering simultaneous line balancing and line length (number of production stations). Franke et al. (2006) present the case of mobile phones remanufacturing where the capacity planning in remanufacturing activities is examined using an endogenous continuous adaptation process. An endogenous process is also examined by Debo et al. (2006) for the study of diffusion of remanufactured products; the authors assume substitution between new and remanufactured products and study the optimal production and remanufacturing capacity levels. Other studies investigate the capacity planning of recovery and remanufacturing considering location-allocation modeling approaches; various methodological approaches have been applied such as steady-state simulation modeling (Schultmann et al., 2003) and nonlinear mixed-integer programming (Min et al., 2006; Lieckens and Vandaele, 2006).

The dynamic change of demand and of used product returns strongly characterize the CLSCs; therefore, capacity planning in CLSCs involves complex models in order to handle first, the large number of state variables and second, the cost structure. System Dynamics (SD) theory provides a simple and flexible modeling and simulation framework in adjusting the actual levels of capacity to the desired values using feedback mechanisms. The SD methodological approach in capacity planning issues of reverse logistics networks was firstly introduced by Sterman (2000) who presents the case of a pulp and paper industry. Georgiadis et al. (2003) introduce systematically the use of SD methodology in the analysis of CLSCs; they use a set of level of remanufacturing and collection capacities to study the effect of environmental issues on reverse channel’s activities. Vlachos et al. (2007) study capacity expansion policies in the reverse channel of a CLSC with remanufacturing activities assuming stationary demand. Georgiadis et al. (2006) develop a SD model for a single product CLSC with remanufacturing. They analyze the capacity planning policies both for collection and remanufacturing activities in the reverse channel, assuming that demand may follow different but standard lifecycle patterns consisted of the typical introduction, growth, maturity and decline stages. Specifically, they investigate how the lifecycle and return patterns of a product affect the near-optimal capacity policies regarding expansion and contraction of collection and remanufacturing capacities. The SD model includes an endogenous process for capacity planning which assumes nonlinear expansion costs; the capacity planning policies depend first, on economies scale and second, on both the volume of product returns and the quality of the used products.

This paper takes the last research further by studying the efficiency of the proposed capacity planning methodology in the reverse channel of a CLSC under lifecycles that differ substantially from the standard growth–maturity-decline pattern. In our study we further take into consideration the products’ usage period and the percentage of collected products rejected for reuse after inspection. Our contribution lies in the investigation of how an unpredictable lifecycle pattern and its consequences on product returns affect the near-optimal expansion and contraction capacity planning policies for the collection and remanufacturing activities. The system's response is studied throughout the product lifecycle, according to a residence time (usage period) distribution. Using the model in conjunction with an optimum-seeking grid procedure, we determine near-optimal capacity policies; as optimization criterion we employ the net present value of total supply chain profit for a long-term planning horizon.

The system under study

A simplified description

Figure 1 shows the CLSC under study in a simplified version. The actors involved in the forward channel are the producer and the distributor, while in the reverse channel are the collector and the remanufacturer. The forward channel comprises two echelons; the *Serviceable Inventory* and the *Distributor's Inventory*. The reverse channel starts at the end of the products' usage period and comprises also two echelons: *Collected Products* and *Reusable Products*. At the end of their usage period, the *Used Products* are either uncontrollably disposed of or collected and inspected for possible reuse. The inspection operations (just after collection) separate the part of returns that can be remanufactured into "as-good-as-new" products. The used products accepted for remanufacturing are directed to the remanufacturing facilities while the rejected products enter the reverse channel of other logistics networks (e.g. B class products) or they are disposed of controllably. To prevent economic obsolescence (Guide et al., 2006) or endless accumulation of reusable products, if a stock remains unused for more than *Reusable Stock Keeping Time* it is then directed to the reverse channel of other logistics networks (e.g. refurbishing). The reusable products after a remanufacturing process turn into remanufactured products. We assume that remanufacturing produces "as-good-as-new" products that conserve their original identity by carrying out the necessary disassembly, overhaul and replacement operations; the demand can therefore be satisfied by any mix of original or remanufactured products. Copiers (Krikke et al., 1999), toner cartridges (Ginsburg, 2001), single use cameras (www.kodak.com) are representative examples that fit the above description. The loop closes through the flow of remanufactured products to the serviceable inventory. Inventories are managed by means of a combined "pull-push" policy. A "pull" policy is adopted in the forward channel to maintain better stock control, while a "push" policy is adopted in the reverse channel first to express, indirectly, the pressure of legislation on manufacturers for end-of-life-products management and the pressure to reduce the used product flows going into landfills and second to satisfy more demand with less costly remanufactured products.

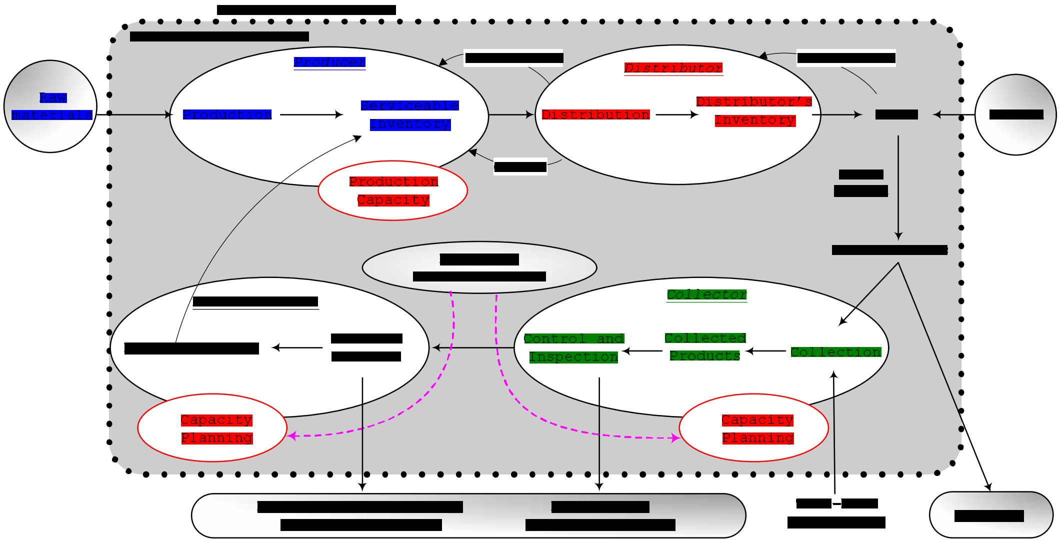

Figure 1: The system under study (simplified)

Generic stock and flow diagram of the two-product model

Figure 2 illustrates the generic stock and flow diagram (Sterman, 2000) of the CLSC under study. According to SD mapping notation, stocks are represented by rectangles and inflows/outflows by arrows pointing into/out of the stocks. Valves (⧖) control the flows, depending on decision rules and mechanisms. Causal links (→) represent causal influences among variables; the direction and polarity ("+" or "-") of a causal link explains the respective effect. Variables expressing forecasts are shown in small italics while parameters are in small plain letters. In this study, rules controlling the flows are indicated in ellipses. The control rules of *Production Rate* and *Distributor's Orders* are based on the structure suggested by Sterman (1989) and are presented analytically in Georgiadis et al. (2006).

In the forward channel, *Production Rate* of new products using *Raw Materials*, along with *Remanufacturing Rate* of *Reusable Products* increase *Serviceable Inventory* which is depleted by *Shipments to Distributor*. *Shipments to Distributor* deplete his *Orders Backlog* and increase *Distributor's Inventory*, which is in turns depleted by *Sales* to satisfy *Demand for Products*. We assume that all unsatisfied distributor's orders (*Orders Backlog*) and demand (*Demand Backlog*) are backlogged and satisfied in a subsequent period.

The rest of the stock and flow diagram is described in the following three subsections. Specifically, in the next subsection we develop a methodology used to produce the different product lifecycle patterns taken into consideration in this study. The lifecycle and product characteristics used in this process are presented in subsection 2.4, while in subsection 2.5 we present the evolution over time of stocks and used products flows in the reverse channel of the CLSC.

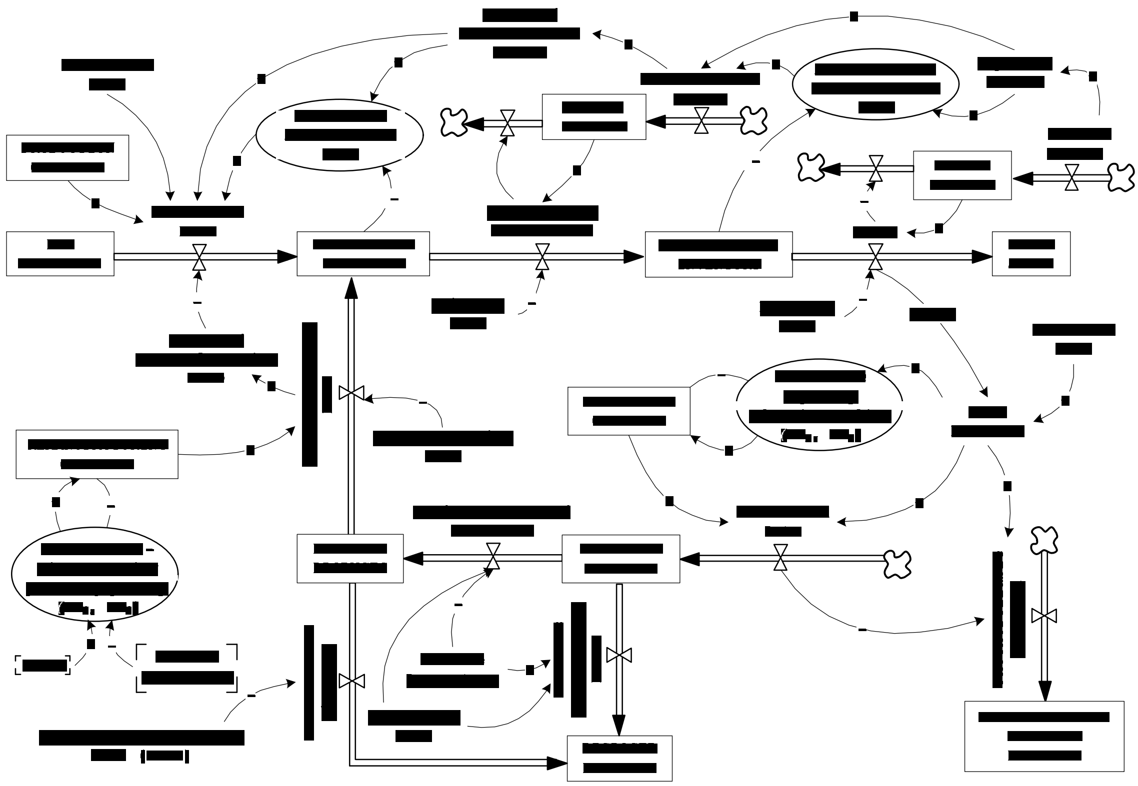

Figure 2: Stock and flow diagram of the two-product model.

Design of different product lifecycles

In order for our results to be comparable, we develop a methodology that produces different lifecycle patterns that do not follow the standard growth-maturity-decline form, but also have a specific link between them. In short, we produce a non-standard lifecycle pattern by adding the demand of two identical standard lifecycle patterns but with a differentiation in their timing, stemming from the variable *Timing Points*. Specifically, we consider six different *Timing Points* for the initiation of the second standard lifecycle pattern during the first one. As shown in Figure 3, these *Timing Points* are the middle and the end point of the growth stage of the first lifecycle pattern (*Timing Point* “a” and “b” respectively), the middle point of the maturity stage (*Timing Point* “c”), and the beginning, the middle and the end point of the decline stage (*Timing Point* “d”, “e” and “f” respectively). The two identical standard lifecycle patterns used in this procedure are generated by taking into consideration specific lifecycle characteristics (always the same between the two standard product lifecycles) presented in the following section.

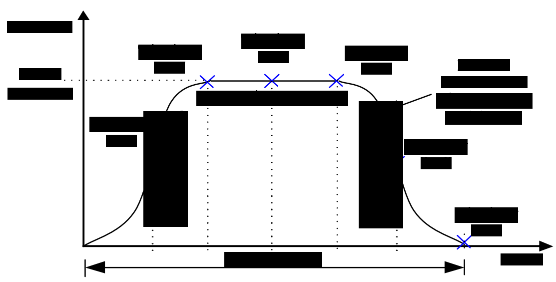

Figure 3: Alternative *Timing Points* for the second lifecycle pattern.

The summation of the two identical standard lifecycle patterns subject to the six alternative *Timing Points* “a” to “f” gives the general form of the different *Lifecycle Patterns* “a” to “f” respectively, as shown in Figure 4. These general forms of the *Lifecycle Pattern* are used in our study as the alternative demand patterns of the single existing product. However, since the two identical standard lifecycle patterns depend on the product lifecycle considerations (discussed in the following section), the in particular form of a *Lifecycle Pattern* further depends on the values of the product-lifecycle considerations that form the two standard lifecycle patterns.

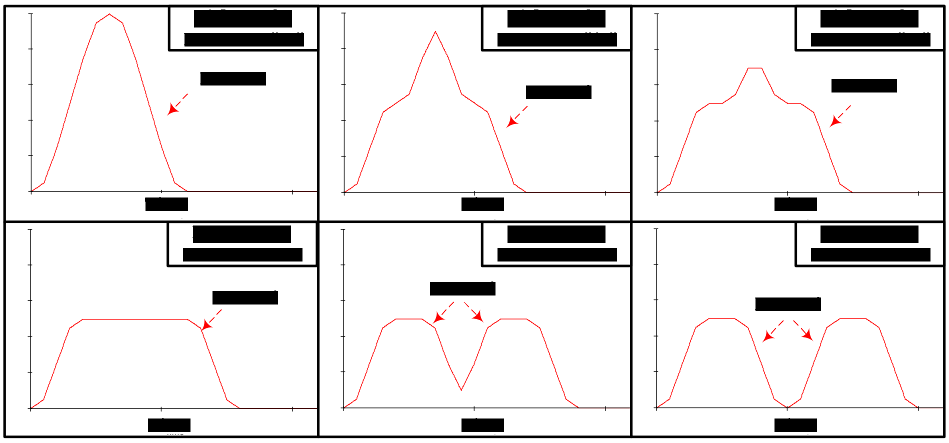

Figure 4: *Lifecycle Patterns* under study

Lifecycle and product characteristics

To form the in particular pattern of the two standard lifecycles, we use the lifecycle characteristics introduced by Georgiadis et al. (2006): the lifecycle length (*Lifecycle*), the length of the maturity stage in a *Lifecycle* (*Pattern*) and the maximum demand value during the *Lifecycle* (*Peak Demand*). The usage period is taken into consideration by the deviation of residence time with *Lifecycle* (*Residence Index*). The quality level of product returns is described by *Failure Percentage*, which is the percentage of collected products rejected for reuse. The two standard lifecycle patterns used to form the *Lifecycle Pattern* of each case are considered to be exactly the same inter se.

Stocks and used product flows in the reverse channel

Sales (see Figure 2) is given by equation 1:

$$Sales = \frac{min\left[(Distributor's\ Inventory,\ Demand\ Backlog)\right]}{Delivery\ Time} \qquad (1)$$

where, *Distributor’s Inventory* and *Demand Backlog* are given by:

d(Distributor’s Inventory)/dt= (Shipments to Distributor) – (Sales) (2)

d(Demand Backlog)/dt= (Product Demand) – (Sales) (3)

Sold products after a *Residence Time* turn into *Used Products*. Figure 5 shows the dynamics of *Total Demand*, *Sales* and *Used Products* of a case.

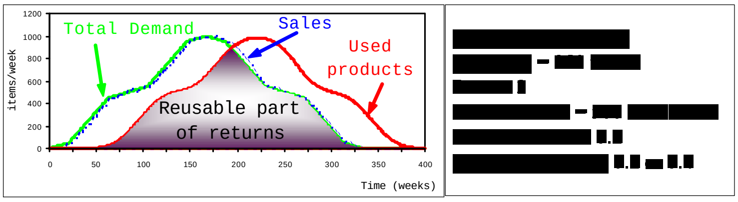

Figure 5: Dynamics of *Total Demand*, *Sales* and *Used Products*

The flows of product returns in the reverse channel depend on used products' pattern, the quality level of returns and the adequacy of collection and remanufacturing capacities. As shown in Figure 2, *Used Products* are either collected (*Collection Rate*) adding to *Collected Products*, or disposed of uncontrollably (*Uncontrollably Disposed Products*). According to *Failure Percentage*, *Collected Products* are either accepted for remanufacturing thus increasing *Reusable Products*, or rejected and are controllably disposed of (*Disposed Products*). *Reusable Products* are decreased both by *Remanufacturing Rate* and by *Controllable Disposal*; the last rate is activated only if a reusable product remains unused for more than *Reusable Stock Keeping Time*. *Collection Rate* is restricted by *Collection Capacity* while *Remanufacturing Rate* is restricted by *Remanufacturing Capacity*. Capacity policies include both expansion and contraction decisions for the collection and remanufacturing capacities. We consider the same modeling approach presented analytically in Georgiadis et al. (2006). In brief, the rates of collection capacity expansion (*CC Expansion Rate)* and contraction (*CC Contraction Rate*) depend on the discrepancy (*CC Discrepancy*) between *Collection Capacity* and its desired level (*Desired CC*), arising as an exponential smoothing of *Used Products*. *CC Expansion/Contraction Rate* is proportional to *CC Discrepancy*; specifically, *CC Discrepancy* is multiplied by the capacity planning control parameters Kc_1 (for expansion) and Kc_2 (for contraction), defining the magnitude of each decision. The values of Kc_j characterize the collection capacity planning policies that can either be trailing ($Kc_j<1$), matching ($Kc_j\approx 1$) or leading ($Kc_j>1$). To capture the needed lead-time between a decision and its realization, the model uses the variables *CC Adding Rate* and *CC Depleting Rate* which are the delayed values of *CC Expansion Rate* and *CC Contraction Rate* respectively. *Collection Capacity* is therefore defined as by the following equation:

d(Collection Capacity)/dt= (CC Adding Rate) – (CC Depleting Rate) (4)

Similar modeling approach is applied for *Remanufacturing Capacity*; the only difference is that its desired level arises as an exponential smoothing of *Sales* multiplied by [1-(*Failure Percentage*)]. Thus, Kc_1/Kc_2 (for collection capacity expansion/contraction) *and* Kr_1/Kr_2 (for remanufacturing capacity expansion/contraction) are the capacity planning control parameters (Ki_j) that fully describe the capacity policies. Figure 6 depicts the evolution over time of *Sales*, *Used Products*, *Collection Rate* and *Remanufacturing Rate* for the case of Figure 5; Figure 6a corresponds to aggressive capacity planning policies while Figure 6b corresponds to less aggressive ones.

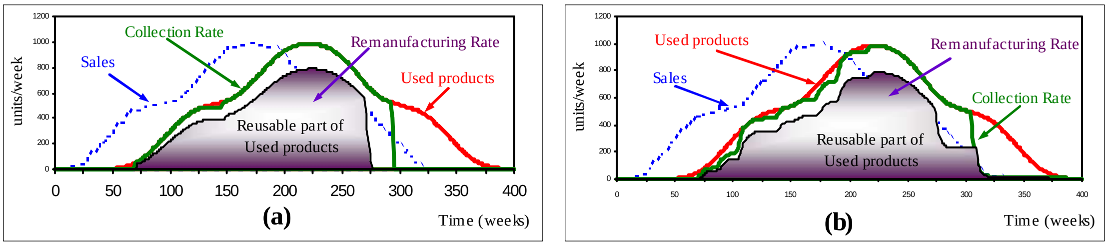

Figure 6: Dynamics of Collection and Remanufacturing Rate.

Numerical investigation and discussion

Experimental design

In this study we focus on the lifecycle and product characteristics' effect on the optimal capacity planning policies. Our research studies a full factorial experiment of the following six control factors: *Lifecycle Pattern*, *Lifecycle*, *Pattern*, *Peak* Demand, *Residence Index*, and *Failure Percentage*. In order for our results to be comparable with those of Georgiadis et al. (2006) we use the same sets of level for the control factors, shown in Table 1. The three *Patterns* mentioned in Table 1 are generated by the different length of the maturity stage, as illustrated in Figure 7. The remaining values of the model parameters are set equal to those given in Georgiadis et al. (2006). All possible combinations of these control factors are $2^2 * 3^3 * 6 = 648$, giving a total of 648 experimental runs. In each combination, we track the near optimal values of Kc_1, Kc_2, Kr_1 and Kr_2.

Table 1: Control factors and sets of level

Control factors	Sets of Level					
Lifecycle Pattern	a	b	c	d	e	f
Lifecycle (weeks)	250 (Medium)				500 (Long)	
Pattern (see Figure 7)	Pattern 1		Pattern 2		Pattern 3	
Peak Demand (units/week)	500 (Low)		1,000 (Medium)		1,500 (High)	
Residence Index	0.2 (Low)		0.35 (Medium)		0.5 (High)	
Failure Percentage	0.2 (Low)		0.4 (Medium)			

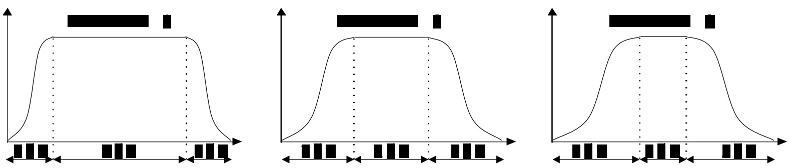

Figure 7: Different Patterns of a lifecycle

Experimental results and ANOVA

The ranges of the near optimal Ki_j's for each case are illustrated in Table 2 in twelve different cases of 54 experiments. Each case is represented as $l_{i.j}$, where i (i=a...f) indicates the *Lifecycle Pattern* and j (j=0.2, 0.4) indicates the value of *Failure Percentage*.

Table 2: Optimal value ranges of capacity planning control parameters

Case	Capacity Planning Control Parameter			
	Kc_1	Kc_2	Kr_1	Kr_2
$l_{a,0.2}$	17.8-23.2	Insensitive(1) 3 experiments(2) /Kc_2=3.2	29.0-31.8	No systematic behavior (<6.0 or insensitive(4))
$l_{a,0.4}$	17.6-22.2	Insensitive(1) 3 experiments(2) /Kc_2=2.0	22.4-24.0	No systematic behavior (<6.0 or insensitive(4))
$l_{b,0.2}$	17.2-20.0	Insensitive(1)	27.0-32.8	No systematic behavior

		3 experiments(3) /Kc_2=1.6		(<6.0 or insensitive(4))
$l_{b,0.4}$	17.2-20.0	Insensitive(1) 3 experiments(2) /Kc_2=2.0 3 experiments(3) /Kc_2=1.4	20.4-24.4	No systematic behavior (<6.0 or insensitive(4))
$l_{c,0.2}$	13.2-14.8 and 17.8-19.6	Insensitive(1) 3 experiments(2) /Kc_2=1.8 3 experiments(3) /Kc_2=1.2	21.0-21.8 and 25.0-32.4	No systematic behavior (<6.0 or insensitive(4))
$l_{c,0.4}$	15.2-20.6	Insensitive(1) 3 experiments(2) /Kc_2=1.0 3 experiments(3) /Kc_2=1.0	10.6-12.0 and 15.8-22.2	No systematic behavior (<6.0 or insensitive(4))
$l_{d,0.2}$	19.0-22.4	Insensitive(1)	15.0-17.2	No systematic behavior (<6.0 or insensitive(4))
$l_{d,0.4}$	19.0-22.4	Insensitive(1)	10.8-12.8	No systematic behavior (<6.0 or insensitive(4))
$l_{e,0.2}$	18.8-22.6	Insensitive(1)	15.2-17.8	No systematic behavior (<6.0 or insensitive(4))
$l_{e,0.4}$	18.6-22.8	Insensitive(1)	11.4-12.8	No systematic behavior (<6.0 or insensitive(4))
$l_{f,0.2}$	19.0-22.2	Insensitive(1)	14.8-17.2	No systematic behavior (<6.0 or insensitive(4))
$l_{f,0.4}$	18.8-22.2	Insensitive(1)	11.6-12.8	No systematic behavior (<6.0 or insensitive(4))

(1)Different values of Kc_2 affect the Total Supply Chain Profit less than 1%
(2)Lifecycle=250 weeks, Pattern 3, Residence Index=0.2, Peak Demand=500 or 1,000 or 1,500 units/week
(3)Lifecycle=500 weeks, Pattern 3, Residence Index=0.2, Peak Demand=500 or 1,000 or 1,500 units/week
(4)Different values of Kr_2 affect the Total Supply Chain Profit less than 2%

In order to examine the sensitivity of the near-optimal values of Kc_1, Kc_2, Kr_1, and Kr_2 to the six control factors, we use the Analysis of Variance (ANOVA). Table 3 illustrates the results of ANOVA for the dependence of the response variables to the control factors, up to third order interactions. The p-value column shows the probability of making error if the null hypothesis (the control factor affects the response variable) is accepted (type II error). The partial Eta-squared column (PES) shows the magnitude of the effect of each control factor on the response variables (always between 0 and 1); the higher the PES value of a control factor, the higher the magnitude of its effect on the response variable. For brevity, we depict only the second and third order interactions that have PES value above 0.30.

Table 3: Effects of the control factors on the response variables

Response Variable	Kc_1		Kc_2		Kr_1		Kr_2	
Control Factors and their Interactions	p-value	PES	p-value	PES	p-value	PES	p-value	PES
Lifecycle Pattern	.000	.826	.000	.390	.000	.982	.000	.132
Lifecycle	.077	.008	.365	.002	.252	.003	.000	.686
Pattern	.000	.680	.000	.510	.000	.312	.000	.887
Residence Index (RI)	.000	.137	.000	.510	.020	.019	.002	.030
Peak Demand	1.00	.000	1.00	.000	1.00	.000	1.00	.000
Failure Percentage	.000	.038	.037	.011	.000	.945	.000	.328
Lifecycle* Pattern	.000	.139	.440	.004	.000	.093	.000	.711
Pattern* RI	.000	.201	.000	.675	.004	.037	.011	.032
Pattern* Failure Percentage	.007	.024	.013	.021	.000	.417	.000	.202
Pattern* Lifecycle Pattern	.000	.652	.000	.561	.000	.534	.000	.420
RI * Lifecycle Pattern	.000	.115	.000	.561	.000	.102	.001	.069
Failure Percentage* Lifecycle Pattern	.000	.088	.044	.028	.000	.738	.000	.175
Pattern* RI* Lifecycle Pattern	.000	.378	.000	.719	.000	.126	.000	.246
Pattern* Failure Percentage* Lifecycle Pattern	.000	.146	.012	.054	.000	.641	.000	.346

Considering three classes for the power of significance (strong for PES>0.7, medium for 0.7≥PES>0.5, and weak for PES≤0.5), turns back from Table 3 that *Lifecycle Pattern* has a strong effect both on Kc_1 and Kr_1. *Lifecycle* affects only Kr_2, with a medium effect. *Pattern* has a medium effect on Kc_1 and Kc_2, a weak effect on Kr_1, and a strong effect on Kr_2. *Residence Index* affects only Kc_2, with a medium effect. *Peak Demand* has no effect on Ki_j's. *Failure Percentage* affects only Kr_1, with a strong effect. The second order interactions do not have any strong effects on Kc_1; however, the interaction of *Pattern* with

Lifecycle Pattern has a medium effect on Kc_1. Similarly, Kc_2 is affected by the medium effects of the three second order interactions between *Pattern*, *Residence Index* and *Lifecycle Pattern*. Kr_1 is affected by the strong effect of the interaction of *Failure Percentage* with *Lifecycle Pattern*, and by the medium effect of the interaction of *Pattern* with *Lifecycle Pattern*. Finally, Kr_2 is affected only by the strong effect of the interaction of *Lifecycle* with *Pattern*. The third order interactions have no strong effects on Ki_j's, except the interaction of *Pattern* with *Residence Index* and *Lifecycle Pattern* on Kc_2. Similarly, Kr_1 is affected by the medium effect of the interaction of *Pattern* with *Failure Percentage* and *Lifecycle Pattern*.

The joint examination of Tables 2 and 3, and of the detailed simulation results (not shown for brevity), lead to the following observations regarding the capacity planning control parameters:

- The optimal Kc_1 value-range 17.2 to 23.2 is insensitive to the studied factors, except for *Lifecycle Pattern* "c" and only for *Pattern* 3, where its values are close to 13.2 for $l_{c,0.2}$ and close to 15.2 for $l_{c,0.4}$. In most cases of the numerical experiments the economies of scale associated with capacity expansion dictate one or two expansion decisions due to the fact that their driving force is the used-product information; this forces the system to expand collection capacity quickly, explaining the rather high Kc_1 values.
- The values of Kc_2 have no effect on the system's profitability for medium and high values of residence indices. Specifically, from the detailed results and for *Residence Index* values equal to 0.5 and 0.35 is observed that different values of Kc_2 affect the system's profitability less than 1%. The explanation of this insensitivity is that the optimal decision to contract *Collection Capacity* is made near the end of the lifecycle, thus having no impact on the profitable part of collection activities. On the contrary, for *Residence Index* 0.2 the profitability is sensitive to the values of Kc_2 but only for *Pattern* 3 and *Lifecycle Pattern* "a", "b" and "c".
- The optimal Kr_1 values are affected by *Failure Percentage*; the lower the value of *Failure Percentage*, the more the supply of remanufacturable products in the reverse channel. Hence, lower values of *Failure Percentage* indicate higher values for Kr_1.
- The optimal values of Kr_2 do not exhibit a systematic behaviour; for all experiments with *Pattern* 3, for about 95% of the experiments with *Pattern* 2 and for about 40% with *Pattern* 1 the optimal values of Kr_2 are less than 6. Although the usefulness of this information is limited, the interesting characteristic is that for the rest of the cases where Kr_2 is greater than 6, the system's profitability is affected less than 2% if Kr_2 receives values less than 6.

The examination of the results obtained by the numerical investigation suggests the following, regarding the *Lifecycle Pattern* of demand:

- The optimal capacity planning policies for a given *Failure Percentage* are almost the same for the sets of lifecycle patterns *Lifecycle Pattern* "a" and "b", and *Lifecycle Pattern* "d", "e" and "f", while exhibit instability for *Lifecycle Pattern* "c".
- The most favorable *Lifecycle Pattern* for the system's profitability is *Lifecycle Pattern* "d", either for *Failure Percentage* 0.2 or 0.4. *Lifecycle Pattern* "e" follows, having almost the same profitability for *Failure Percentage* 0.2 but a lower one for *Failure Percentage* 0.4, compared to the respective cases of *Lifecycle Pattern* "d".

Lifecycle Pattern "a" appears to perform worse than all others, by diminishing profitability (compared to that of *Lifecycle Pattern* "d") by 25.61% for *Failure Percentage* 0.2, and by 20.22% for *Failure Percentage* 0.4 (mean value of the differences between the same cases). These results show that the system performs best when the *Lifecycle Pattern* has a trapezoid form with a long maturity stage.
- Due to the irregularities that introduces to the system's behavior, *Lifecycle Pattern* "c" appears to be avoided, if possible.

Additionally, the analysis of the results obtained by the numerical investigation lead to the following observations of major importance:

- If the *Peak Demand* of 1000 units/week is considered as the middle value, the near-optimal values of Ki_j are exactly the same to those for a 50% increase or decrease of *Peak Demand*, equal to 1500 and 500 units/week respectively. This insensitivity is observed in all experiments for all combinations of the characteristics shown in Table 1. Although it is in principle risky to generalize on the basis of numerical examples, the embedded capacity planning policy leads to the conjecture that the optimal values of Ki_j are indeed robust to "moderate" changes in the actual total demand.
- From all the control factors and their interactions, only a few have a significant effect on the response variables. This response shows that the embedded capacity planning modeling approach is qualified for use in systems characterized by uncertainty.
- The most favorable *Residence Index* is 0.2 (shorter usage period that gives greater opportunity for remanufacturing), followed by 0.35, whereas 0.5 performs worse than the first two.

Concluding Discussion

In this paper, we present an experimentation on the SD model for capacity planning in CLSC networks introduced by Georgiadis et al. (2006). In particular, we track near-optimal capacity planning policies for the collection and remanufacturing activities, taking into consideration six quite different lifecycle patterns and specific lifecycle and product characteristics; the 648 studied experiments cover a broad area of possible cases about the lifecycle of a product.

The results presented in this paper certainly do not exhaust the possibilities of investigating all the aspects of capacity planning in remanufacturing networks. The model's versatility allows, with suitable modifications, the systematic examination of the efficiency of alternative types of capacity planning modeling. A possible extension could also be the study of the impact of the residence time to the remanufacturability level of the used products.

References

Aksoy, H.K., and S.M. Gupta, 2001, "Capacity and buffer trade-offs in a remanufacturing system," *Proceedings of the SPIE International Conference on Environmentally Conscious Manufacturing II*, 167-174.

Debo, L.G., L.B. Toktay, and L.N. Van Wassenhove, 2006, "Joint life-cycle dynamics of new and remanufactured products," *Production and Operations Management*, 15, 498-513.

Franke, C., B. Basdere, M. Ciupek, and S. Seliger, 2006, "Remanufacturing of mobile phones - capacity, program and facility adaptation planning," *Omega*, 34, 562-570.

Georgiadis, P., G. Tagaras, and D. Vlachos, 2003, "Long-term analysis of closed-loop supply chains," in R. Dekker, M. Fleischmann, K. Inderfurth, and L.N. Van Wassenhove (eds.), *Reverse Logistics: Quantitative Models for Closed-loop Supply Chains*, Springler-Verlag, 2003, 313-332.

Georgiadis, P., D. Vlachos, and G. Tagaras, 2006, "The impact of product lifecycle on capacity planning of closed-loop supply chains with remanufacturing," *Production and Operations Management*, 15, 514-527.

Ginsburg, J., "Manufacturing: Once is not enough", *Business Week*, April 16 2001.

Guide, V.D.R. Jr., G. Souza, L.N. Van Wassenhove, and J.D. Blackburn, 2006, "Time value of commercial product returns," *Management Science*, 52, 1200-1214.

Kekre, S., U.S. Rao, J.M. Swaminathan, and J. Zhang, 2003, "Reconfiguring a remanufacturing line at Visteon, Mexico," *Interfaces*, 33, 30-43.

Krikke, H.R., A. Van Harten, and P.C. Schuur, 1999, "Business case océ: reverse logistics networks re-design for copiers", *OR Spektrum*, 2, 381-409.

Lieckens, K., and N. Vandaele, 2006, "Reverse logistics network design with stochastic lead times", Computers and Operations Research, 34, 395-416.

Min, H., H.J. Ko, and C.S. Ko, 2006, "A genetic algorithm approach to developing the multi-echelon reverse logistics network for products returns", Omega, 34, 56-69.

Schultmann, F., B. Engels, and O. Rentz, 2003, "Closed-loop supply chains for spent batteries", Interfaces, 33, 57-71.

Sterman, J.D., 1989, "Modeling managerial behavior: Misperceptions of feedback in a dynamic decision making experiment," *Management Science*, 35, 321-339.

Sterman, J.D., 2000, *Business Dynamics: Systems Thinking and Modeling* for *a Complex World*, McGraw-Hill.

Vlachos, D., P. Georgiadis, and E. Iakovou, 2007, "A system dynamics model for dynamic capacity planning of remanufacturing in closed-loop supply chains," *Computers & Operations Research*, 34, 367-394.