Offshore Remanufacturing with Variable Used Product Condition

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ABSTRACT

We consider the acquisition and production decisions of a remanufacturer who acquires used products of variable condition and allocates remanufacturing activity to domestic and offshore facilities. The problem is formulated as a multicommodity network flow model with economies of scale and product obsolescence. We show that the remanufacturer's optimal strategy can be chosen from a finite set of simple policies in which each product is routed to a facility based on its condition. We then numerically investigate the impact of key parameters on optimal decisions regarding offshore remanufacturing.

INTRODUCTION

The use of low-cost offshore locations for manufacturing operations has recently received attention in the popular press and from academic researchers. While shifting production activities to low-wage offshore locations may provide a lower manufacturing cost without a significant difference in quality (Venkatraman, 2004), it can also increase logistics costs (Zhao, Flynn, & Roth, 2007; Lu & Van Mieghem, 2009). Thus, the tradeoff between production and logistics costs must be considered to determine if offshoring offers a net economic advantage.

In this article we investigate the offshoring decision from the perspective of a remanufacturer – that is, a firm that acquires used items, transports them to production facilities through a reverse logistics network, and restores them to saleable condition. The positive environmental impact and significant profit potential of remanufacturing has led to rapid growth in remanufacturing activities, supported by an active research community. For detailed

overviews of remanufacturing research, we refer the reader to Souza (2008), Atasu, Guide, & Van Wassenhove (2008), and Guide & Van Wassenhove (2009).

Given that remanufacturing is often very labor-intensive (Seitz & Peattie, 2004), the opportunity to access the lower labor rates available in some offshore locations can be an important strategic consideration for remanufacturers. Despite the potential benefits of offshore remanufacturing, it has received limited attention in the academic literature. An accurate decision model for the remanufacturing offshoring decision must incorporate the added complexity of variability in the condition of used items (i.e., raw materials). Condition variability has been well-documented in the literature and was mentioned by Fleischmann, Bloemhof-Ruwaard, Dekker, van der Laan, van Nunen, & Van Wassenhove (1997) as a distinguishing characteristic of reverse vs. forward distribution. Thus, the assumption of homogeneous raw materials in traditional offshoring models might not translate accurately to a remanufacturing setting.

In this article we examine offshoring decisions for remanufacturers facing condition variability, with the goal of informing high-level strategic decisions of firms regarding the appropriate role of offshoring (as opposed to presenting tactical decision-making tools). To this end, we present a stylized model of remanufacturing operations and use the model to derive strategic insights for remanufacturing firms.

AN OFFSHORE REMANUFACTURING DECISION MODEL

We consider a problem motivated by our experiences with CertiCell LLC, a U.S.-based remanufacturer of high-end cell phones, or "smart phones." At the time of this study, CertiCell operated both domestic and offshore production facilities, and they acquired used phones in various conditions. The firm's objective is to maximize profits given the lead times and cost

structures of the facilities, including the time-sensitive nature of costs for used items with high obsolescence rates. Achievement of this objective involves the following decisions: how many used items should be acquired, how many of these items should be remanufactured, where remanufacturing should take place, and at what price the remanufactured items should be offered. Variability in used product condition adds complexity to remanufacturing decisions and distinguishes them from conventional manufacturing.

At CertiCell, the cost of repairing an LCD screen on some smart phones is so high that it becomes the defining condition indicator. Thus, products can be classified as "high-touch" if the LCD is in need of repair and "low-touch" if only minor and cosmetic repairs are needed. Used products are sorted into one group for cosmetic repairs and another for major repair work (Guide, Muyldermans, & Van Wassenhove, 2005). Similar sorting systems are found in industries such as printer remanufacturing and toner cartridge remanufacturing. For toner cartridges, items are often categorized based on whether they have been previously remanufactured ("non-virgin" as opposed to "virgin"). To reflect such environments, we follow the approach used in previous research of modeling condition variability using two categories (Aras, Boyaci, & Verter, 2004; Galbreth & Blackburn, 2009), where both categories are remanufacturable, but at different costs. Because labor requirements for a given phone vary with condition, the optimal location to remanufacture can also depend on the condition category – for example, while offshoring might be justified for major repairs (as with LCD repair for a smart phone), additional shipping and handling costs can make offshoring an unattractive option if only low-touch repairs are needed.

Motivated by this smart phone remanufacturing problem, we consider the case where used items are in ample supply and can be sourced by the remanufacturer as needed – a common assumption in the literature (Souza, Ketzenberg, & Guide, 2002; Ferrer, 2003; Ferrer &

Ketzenberg, 2004; Galbreth & Blackburn, 2006, 2009; Zikopoulos & Tagaras, 2007, 2008). We model a remanufacturer facing a set of potential buyers in a one-period model (single sourcing decision, single demand), as is appropriate for short life cycle products (Robotis, Bhattacharya, & Van Wassenhove, 2005; Zikopoulos & Tagaras, 2007, 2008; Galbreth & Blackburn, 2006, 2009; Lu & Van Mieghem, 2009). Although some firms remanufacture to order, in this model we assume that demand in the marketplace for remanufactured items is price-dependent and consumers are heterogeneous in their willingness to pay. We explicitly model the impact of the production facility lead time by assuming that the value of the used items decreases as time passes – that is, the acquisition price is higher if items must be acquired earlier to account for longer shipping lead times to the production facility, as is the case when remanufacturing occurs offshore (both the supply of used phones and the demand for remanufactured phones are assumed to be domestic).

Consistent with practices followed in most reverse supply chains, all acquired items are processed through a central facility (Rogers & Tibben-Lembke, 2001). After acquisition, the items are sorted into two categories: low-touch (or lower remanufacturing cost) and high-touch. Similar to other remanufacturing studies (Robotis et al., 2005), we assume that sorting is costless (or, equivalently, that sorting costs are included in acquisition costs). The remanufacturer may choose to scrap a fraction of the acquired items at the central location. The remaining items are shipped to either a domestic or offshore facility for remanufacturing; at the domestic location, production costs are higher but lead times are shorter and shipping costs are lower. Consistent with observations at remanufacturing firms, the proportion of used items in each condition category is assumed to be known with certainty (Souza et al., 2002). Other remanufacturing models have also assumed that the proportion of used products in each condition category is

known (Guide, Muyldermans, & Van Wassenhove, 2005; Karaer & Lee, 2007), and a fixed proportion has been found to be a reasonable assumption in many cases (Galbreth & Blackburn, 2009). We denote the proportion of items in the low-touch category α . We take α as exogenous, contrasting our work to models that consider the condition of acquired items to be a function of acquisition price (Guide, Teunter, & Van Wassenhove, 2003; Karakayali, Emir-Farinas, & Akcali, 2007).

Parameter	Description				
с	cost to remanufacture a low-touch item at the domestic				
	facility				
uo	unit acquisition costs of used items when the offshore				
	facility is used				
β	% price decay of used items per unit time				
S	round trip shipping cost to/from domestic plant				
ρ	ratio of domestic remanufacturing costs to offshore				
-	remanufacturing costs (p>1)				
θ	ratio of offshore shipping cost to domestic shipping cost				
	(θ>1)				
L	round-trip lead time differential of offshore vs. domestic				
	facility (offshore lead time minus domestic lead time)				
λ	ratio of high-touch remanufacturing cost to low-touch				
	remanufacturing cost (λ >1)				
α	fraction of used items that are low-touch				
d	unit disposal cost of excess items (negative disposal cost				
	indicates a positive salvage value)				
$\overline{S_o}$	setup cost if production occurs at the offshore facility				
S_d	setup cost if production occurs at the domestic facility				

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Table 1 summarizes the parameters for our model. The parameter c is the baseline lowtouch domestic remanufacturing cost, where remanufacturing cost is broadly defined to include all factors that may differ by location, including materials, production, taxes, etc. The parameter *s* is the round-trip domestic shipping cost. Similar to Lu & Van Mieghem (2009), shipping costs include a variety of components, including tariffs, duties, etc. Three parameters in Table 1, ρ , θ , and L, capture the tradeoffs inherent in an offshoring decision. ρ represents the ratio of domestic remanufacturing costs to offshore costs. This cost savings is offset to some extent by the higher shipping costs to and from the offshore facility as indicated by θ , the ratio of offshore to domestic shipping costs. Finally, L is the difference in lead times between offshore and domestic locations, which can be an important factor when obsolescence is a concern.

Variable	Description				
Quantity Decision					
Q	quantity of used items acquired				
Price Decision					
р	price of remanufactured items				
Disposition Decisions					
f_{dl}	fraction of used items that are low-touch and				
· ur	are remanufactured domestically				
f_{dh}	fraction of used items that are high-touch and				
- 677	are remanufactured domestically				
f_{ol}	fraction of used items that are low-touch and				
- 00	are remanufactured offshore				
f_{ah}	fraction of used items that are high-touch and				
• 011	are remanufactured offshore				
f_{sh}	fraction of used items that are high-touch and				
~ 511	are scrapped				

Table 2: Decision variables.

As mentioned above, a remanufacturer with both domestic and offshore production facilities must make four related decisions: (i) how many used items should be acquired, (ii) how many of these used items should be remanufactured, (iii) where should remanufacturing take place, and (iv) at what price should the remanufactured items be offered. The decision variable Q indicates the number of used items to acquire. The disposition fractions f_{sh} , f_{dl} , f_{dh} , f_{ol} , f_{oh} indicate how many used items will be remanufactured and where. The first subscript of each fraction f denotes disposition (s, d, or o corresponding to scrap, domestic, or offshore, respectively) and the second subscript denotes the item category (h for high-touch, l for lowtouch). These fractions define the dispositions of all acquired items

(i.e., $f_{sh} + f_{dl} + f_{dh} + f_{ol} + f_{oh} = 1$). Finally, *p* is the price of the remanufactured items. Please see Table 2 for a complete listing of decision variables. Note that we assume low-touch items, which are in the best condition of any acquired items, are never scrapped.

The remanufacturer's decision is modeled as a multicommodity network flow problem with nonlinear production costs due to economies of scale and nonlinearly decreasing acquisition costs over time, capturing obsolescence costs. The network model for this problem is shown in Figure 1, which depicts a single source node (Acquisition) and two destination nodes (Scrap, Market). Production may take place at the domestic and/or offshore production nodes. Economies of scale are incorporated using setup costs, which are incurred at production nodes if flow through the node is positive. Given our focus on a single-period problem, these costs reflect order setup with an existing facility – as opposed to capital investments in new facilities, which would be more applicable in a multi-period problem. The price paid for used items is time-dependent because, as time passes, used items lose value and can be acquired for a lower price. If the offshore facility is to be used, the lot of used items must be acquired earlier to allow for longer lead times, at unit cost u_{a} . If all remanufacturing takes place domestically, then used item acquisition can be delayed, and the unit cost is $u_d = u_o e^{-\beta L}$, where L is the lead time differential and β is the % price decay per unit time. A similar approach to modeling the value of time is used in Guide, Souza, Van Wassenhove, & Blackburn (2006). This cost advantage from delaying acquisition can include cost of capital as well. In Figure 1, the flow on each arc is given as a function of the decision variables, followed by the unit cost in brackets.



Figure 1: A network flow representation of the offshore remanufacturing problem.

In this model, unit variable cost is comprised of two components: shipping costs and variable production costs. Combining the costs of flows along the four arcs leading into the production nodes in Figure 1 and dividing by Q gives the following unit variable cost:

$$r(\overline{f}) = (f_{dl} + f_{dh})s + (f_{ol} + f_{oh})\theta s + f_{dl}c + \frac{f_{ol}c}{\rho} + f_{dh}\lambda c + \frac{f_{oh}\lambda c}{\rho}$$

where \overline{f} is the vector of production options: $\overline{f} = (f_{dl}, f_{dh}, f_{ol}, f_{oh})$.

We model consumer willingness to pay as distributed uniformly in the interval [0,1], a common assumption in the literature that captures a wide range of variability in the marketplace (Ray, Boyaci, & Aras, 2005; Ferguson & Toktay, 2006). Without loss of generality, market size is normalized to 1, so revenues for price p are given by p(1-p). Optimal acquisition quantity and scrap rates are chosen such that market demand is met, that is, $Q(1-f_{sh}) = (1-p)$, or

$$Q = \frac{(1-p)}{(1-f_{sh})}$$
. Similar to Aras et al. (2004), Ferguson & Toktay (2006), and others, we assume

no capacity constraints at the remanufacturing facilities. Finally, we define two binary variables, I_o and I_d , which equal 1 if a production node has positive flow. These variables allow us to capture the appropriate acquisition cost (u_o if the offshore facility is used, u_d otherwise) as well as whether each facility's fixed setup cost, S_o or S_d , will be incurred. The problem is to maximize profits as follows:

Maximize
$$\Pi = p(1-p) - Q[r(\overline{f}) + f_{sh}d + I_ou_o + (1-I_o)u_d] - I_dS_d - I_oS_o$$

The first term in the above expression is total sales revenues. The first two terms in the square brackets are unit remanufacturing and unit scrap costs. The final two terms in the square brackets are unit acquisition costs – note that only one of these two costs will be incurred, depending on the value of I_o . The final two terms are the setup costs. Since Q is a function of p and f_{sh} , we substitute for Q to obtain the following:

$$\underset{p,f,I,I_{d}}{\text{Maximize}} \Pi = p(1-p) - (1-p) \left[\frac{r(\overline{f}) + f_{sh}d + I_{o}u_{o} + (1-I_{o})u_{d}}{1-f_{sh}} \right] - I_{d}S_{d} - I_{o}S_{o} \quad (1)$$

Subject to:

$$f_{dl} + f_{ol} = \alpha \tag{a}$$

$$f_{dh} + f_{oh} + f_{sh} = 1 - \alpha \tag{b}$$

$$0 \le p \le 1 \tag{c}$$

$$I_o \ge \left(f_{ol} + f_{oh}\right) \tag{d}$$

$$I_d \ge \left(f_{dl} + f_{dh}\right) \tag{e}$$

$$I_o \in \{0,1\} \tag{f}$$

$$I_o \in \{0,1\} \tag{g}$$

And the optimal acquisition quantity is given by $Q^* = \frac{1 - p^*}{1 - f_{sh}^*}$, where p^* and f_{sh}^* denote the

optimal values. Constraints (a) and (b) follow from the definition of α . Constraint (c) ensures that a feasible value of p is chosen. Constraints (d)-(g) define the indicator variable values for the two production nodes.

We will now analyze the problem presented above, developing properties of the optimal solution through a proposition and a series of observations. First we observe that, if setup costs are zero, the optimal solution to (1) can be found by solving a simple subproblem of (1): **Observation 1**: When $S_d = S_o = 0$, the optimal solution to (1) can be found by minimizing the cost term in the brackets of (1) subject to constraints (a)-(d) and (f). Denote the minimum value of the bracketed term in (1) as $g(\overline{f}^*, I_o^*)$. Then the optimal values of the other decision variables

are given by:
$$p^* = \frac{1 + g(\overline{f}^*, I_o^*)}{2}$$
, $Q^* = \frac{1 - p^*}{1 - f_{sh}^*}$, and $I_d^* = \begin{cases} 1 & \text{if } f_{dh}^* + f_{dl}^* > 0\\ 0 & \text{otherwise} \end{cases}$. In this case, note

also that $p^* > 0.5$.

When fixed setup costs are included in the model, we establish several properties of the optimal solution that hold in general. Observe that, due to the absence of capacity constraints at

either location and the concave remanufacturing costs, it is optimal for all items of a particular condition category to have the same disposition – either domestic or offshore remanufacturing, or scrap. In other words, if it is optimal for one item of a given condition to have a given disposition, it is optimal for all other items with that condition to have the same disposition. We need only consider policies in which items within the same condition category have identical dispositions, allowing us to restrict our attention to all-or-nothing policies for each condition category – that is, each of the disposition fractions $(f_{dl}, f_{dh}, f_{ol}, f_{oh}, f_{sh})$ can take on a finite number of values (e.g., $f_{dl} \in \{0, \alpha\}$). Given this fact, we can use Proposition 1 to develop a taxonomy of possible optimal strategies:

Proposition 1: There is an optimal solution to (1) such that $f_{ol} * f_{dh} = 0$.

Proof: see appendix.

Proposition 1 implies that, if it is optimal to produce low-touch offshore (i.e., f_{ol} is positive), then there will be no domestic high-touch production. Also, if it is optimal to produce hightouch domestically (i.e., f_{dh} is positive), then there will be no offshore low-touch production. We examine the structure of optimal policies that satisfy Proposition 1, keeping in mind our ability to restrict our attention to all-or-nothing policies, through a series of observations: **Observation 2**: If $f_{dh} > 0$, then $f_{dl} = \alpha$ and $f_{oh} = 0$.

If it is optimal to remanufacture any high-touch items domestically, then, because $f_{ol} = 0$ from Proposition 1 and considering the fact that low-touch items are never scrapped, all low-touch items are remanufactured domestically. Given the all-or-nothing property of the optimal solution, this implies that $f_{oh} = 0$, and the offshore facility is not used.

Observation 3: If $f_{dl} = 0$, then $f_{dh} = 0$.

If it is optimal to remanufacture no low-touch items domestically, then $f_{ol} = \alpha$, since low-touch items are always remanufactured. Then from Proposition 1 we find that no high-touch items will be remanufactured domestically

Observation 4: If $f_{ol} > 0$, then $f_{sh} + f_{oh} = 1 - \alpha$.

If it is optimal to remanufacture any low-touch items offshore, then, since $f_{dh} = 0$ from Proposition 1, all high-touch items will either be scrapped or be remanufactured offshore.

Observation 5: $f_{sh}(f_{dh} + f_{oh}) = 0$.

If the amount of scrapping is positive, then the sum of offshore and domestic high-touch remanufacturing will be zero, and vice versa.

Proposition 1 and the related observations allow us to enumerate a complete set of possible optimal strategies for a remanufacturer with both domestic and offshore facilities (Table 3).

Strategy	f_{dl}	f_{dh}	f_{ol}	f_{oh}	$f_{\scriptscriptstyle sh}$
Domestic Low Yield	α	0	0	0	1-α
Domestic High Yield	α	1-α	0	0	0
Offshore Low Yield	0	0	α	0	1-α
Offshore High Yield	0	0	α	1-α	0
Mixed	α	0	0	1-α	0

Table 3: optimal strategies for offshore remanufacturing.

In Table 3, the two possible domestic strategies and the two possible offshore ones are characterized by their "yield," which we define to be the fraction of acquired items that are remanufactured. We refer to strategies that scrap no items ($f_{sh} = 0$) as "high yield" and those that scrap items ($f_{sh} = \alpha$) as "low yield" (recall that Mixed is also a "high yield" strategy).

Proposition 1, its related observations, and the set of optimal strategies in Table 3 apply regardless of the cost structures of the remanufacturer. These results provide an intuitive framing of the offshoring decision and show that the optimal policy has a very simple structure. Although Table 3 shows that there is a finite set of strategies to be examined, more analysis is needed to determine how the problem parameters drive the optimal strategy within that set. Given the complex nature of the mixed-integer nonlinear program shown in (1), we use a numerical study to gain additional insights into which strategy is optimal under various industry conditions and cost structures. In the next section, we report the results of numerical analysis using Mathematica 7.0 to find the optimal offshoring strategy for a wide range of parameter values.

NUMERICAL ANALYSIS

In this section we report the key findings of an extensive numerical examination of the optimal offshoring policy under a range of parameter values. Given the challenges of optimizing a nonlinear function with integer constraints, we decomposed the problem into three subproblems, defined by all feasible combinations of integer variables values: { $I_d = 1$, $I_o = 0$ }, { $I_d = 0$, $I_o = 1$ }, { $I_d = 1$, $I_o = 1$ }. Each subproblem is a relatively simple nonlinear program without integer constraints, and we find the optimal solution as the subproblem with highest profit, along with the integer values corresponding to that subproblem.

Since the maximum willingness to pay in our model is scaled to 1, all unit variable costs are chosen such that remanufacturing is a profitable activity for the firm (i.e., total unit variable cost is less than 1). We begin by describing an example problem with unscaled cost parameters chosen to reflect realistic relative values, which are then scaled to be consistent with the setup of our model. The maximum price that any consumer is willing to pay for a remanufactured item is \$25. Acquisition costs are \$0.50 and disposal costs are zero. The inclusion of positive (negative) disposal costs would have the intuitive effect of making the low yield strategies less likely (more likely) to be optimal. Unit remanufacturing costs are \$1, and unit domestic roundtrip shipping cost is \$0.175. Scaling these cost parameters to reflect a maximum willingness to pay of 1, we have $u_0 = 0.02$, d=0, c=0.04, and s=0.007. The ratio of domestic to offshore production costs is $\rho=3$. The low-touch fraction α is initially set at 0.4 (other values of α are examined later in this section). The round-trip lead time differential L is 7 weeks. To capture the value of time, we chose $\beta=1\%$ per week as suggested by Blackburn, Guide, Souza, & Van Wassenhove (2004) for time-sensitive products (also used by Guide et al., 2006). Order setup costs, which depend on many factors including the difficulty of coordination with an offshore location, are set at $S_0=0.001$ and $S_d=0.0005$. Small values were chosen for fixed setup costs because market size has been normalized to 1, and these fixed costs must be of the same order of magnitude to make them meaningful (Ferguson & Toktay, 2006). For example, if the actual market size is 150,000, these setup costs would be \$150 and \$75. Recall that these are order setup costs as opposed to capital investments in new facilities.

The two parameters for which numerical analysis yields the most strategic insights are λ and θ , which capture the degree of variability in used product condition and the disparity in shipping costs between the domestic and offshore locations. We chose ranges for these variables that enable us to examine the full range of possible strategies given our other parameter settings. Specifically, λ is varied from 1.0 to 3.7 in increments of 0.1, and θ is varied from 4.5 to 7.0 in

increments of 0.05. We solved the problem for all combinations of λ and θ (28 possible $\lambda * 51$ possible $\theta = 1,428$ experiments) and noted where the optimal strategy changes, as shown in the phase diagram in Figure 2.



Figure 2: Optimal solution as a function of λ and θ (for $\alpha ==0.4$).

Figure 2 shows the impact of the ratio of high-touch costs to low-touch costs, λ , on the optimal strategy. For example, given θ =6.5, beginning with a very small λ and increasing it (moving left to right in Figure 2) would cause the strategy to shift from remanufacturing all low-touch and high-touch items domestically, to a mixed approach, and finally to only remanufacturing low-touch domestically and scrapping all high-touch items. In essence, this progression is a function of the changing disposition of high-touch items (from domestic to

offshore to scrap as the relative cost to remanufacture them, λ , increases). Changes in θ , the shipping cost penalty of offshoring, also have a predictable impact on strategy. For example, given λ =3.2, starting with a very large θ and decreasing it (moving down in Figure 2) would shift the strategy from no offshore remanufacturing (Domestic Low Yield) to remanufacturing high-touch items offshore (Mixed) to eventually remanufacturing all items offshore (Offshore High Yield) as the incremental shipping cost offshore becomes very small. Note that high-touch items are the first ones to be sent offshore as θ decreases, with low-touch following if θ continues to drop.



Figure 3: Optimal solution as a function of λ and θ (for α =0.6).



Figure 4: Optimal solution as a function of λ and θ (for α =0.8).

By varying α , we demonstrate how strategies change with the quality of the acquisition lot (Figures 3 and 4). Note that α =0.4 in Figure 2. In Figures 3 and 4, we see that the mixed strategy region shrinks as α increases (and has disappeared completely for the very high α in Figure 4). In other words, as the proportion of low-touch items increases, the viability of the mixed strategy is reduced. As expected, we also see that low yield strategies (i.e., strategies that involve scrapping all high-touch items) are more likely to be optimal as α increases. In fact, the offshore low yield strategy does not even appear in the relatively low α example in Figure 2 (although it does eventually become optimal for very large λ). Higher α makes it more likely that scrapping of high-touch items will occur, which is intuitive given that there are relatively few high-touch items for higher α (recall that the proportion of high-touch is simply 1- α). It is also interesting to examine the optimal strategy in terms of its yield. The labels of the regions of Figures 2-4 in which the optimal policy has a low yield have been shaded. Observe that, for very small λ , since high-touch items are not much more expensive to remanufacture than low-touch, the optimal solution has a high yield in all three figures. At the other extreme, for very large λ , the remanufacturing cost of high-touch items is so high that they will never be remanufactured, and a low yield strategy might be optimal. However, for lower α , such as in Figure 3, this low yield strategy is less attractive, since it involves scrapping a larger proportion of items.

We demonstrate other effects of α on the optimal strategy by choosing a fixed (λ , θ) pair and observing how the optimal strategy changes with α . Consider, for example, $\lambda = 2$, $\theta = 6$. The optimal strategy in this case can be found in Figures 2-4 for three specific α values (0.4, 0.6, 0.8). Figure 5 clearly shows how the optimal remanufacturing strategy migrates as α increases. Observe in that figure also that, as expected, profit strictly increases as α increases (i.e., as the condition of the used items improves).

Figure 5 provides insight into how a firm's optimal strategy might change as the proportion of low-touch items available in the marketplace changes over the life cycle of the product. As the time a product is on the market increases and product usage increases, the proportion of used items in good condition, α , tends to decrease. In the toner cartridge remanufacturing industry, this is seen in the diminishing proportion of virgin cartridges that can be acquired as time passes from the initial introduction of a cartridge. Similar decreases in low-touch returns can be expected over time with cell phones and other remanufacturable items. This life cycle effect is equivalent to moving from right to left in Figure 5 – a remanufacturer might initially be willing to scrap the (relatively few) high-touch items, but as the high-touch

proportion increases over time, it becomes optimal to remanufacture them offshore (a mixed approach). For sufficiently low α , the high-touch items dominate the acquired batch to the extent that that it no longer makes economic sense to use the domestic facility, and an offshore-only approach becomes optimal. Thus, managers should carefully monitor α and revisit these strategic decisions over a product's life cycle. Although Figure 5 was generated for a specific (λ, θ) pair, the progression from low yield to high yield strategies as α decreases over time occurs for any (λ, θ) pair, with the extent of the strategy shift depending on the values of (λ, θ) .



Figure 5: Profitability as a function of α .

To observe the impact of changes in another key parameter, the ratio of domestic to offshore costs ρ , we fix α and find the optimal solution for a wide range of ρ . With the same parameters used to generate Figure 5, and α fixed at 0.7, we show the impact of changes in ρ in Figure 6. Recall that, in all previous examples, ρ was fixed at 3. Figure 6 shows how an increase in ρ can improve profitability. Of course, no profit impact occurs until use of the

offshore facility becomes optimal, since ρ only affects offshore costs. In Figure 6, the optimal strategy is Domestic Low Yield for lower values of ρ , but it shifts to Offshore High Yield for sufficiently high ρ , at which point profitability is increasing in ρ , as expected.



Figure 6: Profitability as a function of ρ.

CONCLUSIONS

In this article we examined the optimal role of offshoring in a remanufacturing context, where variability in the condition of used items is an important decision driver. This work addresses the intersection of two emerging research areas of offshoring and remanufacturing. While our results were derived from a stylized model, we believe that this model captures the reality of the problem sufficiently to add value in framing strategic discussions.

We show that, when both domestic and offshore facilities are available, the optimal policy can be selected from a defined set of five strategies, and each condition category will be remanufactured in at most one facility. We also show how the optimal strategy is affected by

changes in key parameter values, and how it can evolve as the product matures and the proportion of low-touch items α declines. Extensions of this model to multi-period settings or cases involving multiple price/condition pairs represent interesting avenues for future research into the offshoring decision for a remanufacturer.

APPENDIX: PROOF OF PROPOSITION 1

Assume $f_{ol} > 0$, $f_{dh} > 0$. Then the following flow changes can be made to the network representation in Figure 1, which are capacity-neutral, maintain conservation of flow, and do not affect Q or p: decrease f_{ol} by ε , increase f_{dl} by ε , decrease f_{dh} by ε , increase f_{oh} by ε . The cost impact of these flow changes is

$$\varepsilon \left[-\left(\theta s + \frac{c}{\rho}\right) + \left(\theta s + \frac{\lambda c}{\rho}\right) + \left(s + c\right) - \left(s + \lambda c\right) \right]$$

which reduces to

$$\varepsilon c (1-\lambda) \left(1-\frac{1}{\rho}\right)$$

which is always negative since $\lambda > 1$ and $\rho > 1$. Thus, these changes would decrease costs,

increasing the firm's profits. Therefore the assumed solution of $f_{ol} > 0$, $f_{dh} > 0$ is not optimal.

REFERENCES

Atasu, A., Guide, V. D. R, & Van Wassenhove, L. N. (2008). Product reuse economics in closed-loop supply chains. *Production and Operations Management* 17(5), 483-496.

Aras, N., Boyaci, T. & Verter, V. (2004). The effect of categorizing returned products in remanufacturing. *IIE Transactions*, *36*(4), 319-331.

Blackburn, J. D., Guide, V. D. R., Souza, G. C., & Van Wassenhove, L. N. (2004). Reverse supply chains for commercial returns. *California Management Review*, 46(2), 6-22.

Ferguson, M. E., & Toktay, L. B. (2006). The effect of competition on recovery strategies. *Production and Operations Management*, *15*(3), 351-368.

Ferrer, G., (2003). Yield information and supplier responsiveness in remanufacturing operations. *European Journal of Operational Research*, *149*(3), 540-556.

Ferrer, G. & Ketzenberg, M. E. (2004). Value of information in remanufacturing complex products. *IIE Transactions*, *36*(3), 265-277.

Fleischmann, M., Bloemhof-Ruwaard, J. M., Dekker, R., van der Laan, E., van Nunen, J. A. E. E. & Van Wassenhove, L. N. (1997). Quantitative models for reverse logistics: A review. *European Journal of Operational Research*, *103*(1), 1-17.

Galbreth, M. R. & Blackburn, J. D. (2006). Optimal acquisition and sorting policies for remanufacturing. *Production and Operations Management*, 15(3), 384-392.

Galbreth, M. R. & Blackburn, J. D. (2009). Optimal acquisition quantities in remanufacturing with condition uncertainty. *Production and Operations Management*, forthcoming.

Guide, V. D. R., Teunter, R. H., & Van Wassenhove, L. N. (2003). Matching demand and supply to maximize profits from remanufacturing. *Manufacturing & Service Operations Management*, *5*(4) 303–306.

Guide, V. D. R., Muyldermans, L. & Van Wassenhove, L. N. (2005). Hewlett-Packard company unlocks the value potential from time-sensitive returns. *Interfaces*, *35*(4), 281-293.

Guide, V. D. R., Souza, G. C., Van Wassenhove, L. N. & Blackburn, J. D. (2006). Time value of commercial product returns. *Management Science*, *52*(8), 1200-1214.

Guide, Jr. V. D. R., & Van Wassenhove, L. N. (2009). The evolution of closed-loop supply chain research. *Operations Research*, *57*(1), 10-18.

Karaer, O., & Lee, H. (2007). Managing the reverse channel with RFID-enabled negative demand information. *Production and Operations Management*, *16*(5), 625-645.

Karakayali, I., Emir-Farinas, H., & Akcali, E. (2007). An analysis of decentralized collection and processing of end-of-life products. *Journal of Operations Management*, 25(6), 1161-1183.

Lu, L. X., & Van Mieghem, J. A. (2009). Multimarket facility network design with offshoring applications. *Manufacturing & Service Operations Management*, 11(1) 90-108.

Ray, S., Boyaci, T, & Aras, N. (2005). Optimal prices and trade-in rebates for durable, remanufacturable products. *Manufacturing & Service Operations Management*, 7(3), 208-228.

Robotis A., Bhattacharya, S. & Van Wassenhove, L. N. (2005). The effect of remanufacturing on procurement decisions for resellers in secondary markets. *European Journal of Operational Research*, *163*(3), 688-705.

Rogers, D. S. & Tibben-Lembke, R. (2001). An examination of reverse logistics practices. *Journal of Business Logistics*, 22(2), 129-148.

Seitz, M. A., & Peattie, K. (2004). Meeting the closed-loop challenge: The case of remanufacturing. *California Management Review*, 46(2), 74-89.

Souza, G. C., Ketzenberg, M. E., & Guide, V. D. R. (2002). Capacitated remanufacturing with service level constraints. *Production and Operations Management*, 11(2), 231-248.

Souza, G. (2008). Closed-loop supply chains with remanufacturing. In Z.L. Chen & R. Raghavan (Eds.). *Tutorials in operations research*. Washington, D.C.: INFORMS, 130-153.

Venkatraman, N. V. (2004). Offshoring without guilt. *MIT Sloan Management Review*, 45(3), 14-16.

Zhao, X, Flynn, B. B., & Roth, A. V. (2007). Decision sciences research in China: Current status, opportunities, and propositions for research in supply chain management, logistics, and quality management. *Decision Sciences*, *38*(1), 39-80.

Zikopoulos, C, & Tagaras, G. (2007). Impact of uncertainty in the quality of returns on the profitability of a single-period refurbishing operation. *European Journal of Operational Research*, *182*(1), 205-225.

Zikopoulos, C, & Tagaras, G. (2008). On the attractiveness of sorting before disassembly in remanufacturing. *IIE Transactions*, 40(3), 313-323.