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ORIGINAL ARTICLE

Determining the optimal quantity and quality levels of used product returns for remanufacturing under multi-period and uncertain quality of returns

R. Aydin [1] · C. K. Kwong [1] · M. W. Geda [1] · G. E. Okudan Kremer [1]

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Abstract Managing product returns has been considered essential in the production planning and control of remanufacturing, as well as in the inventory control management of product returns. Uncertainties in the quantity and quality of returned products collected for remanufacturing could largely affect the profit generated from remanufactured products. However, determining the optimal quantity and quality levels of used products to be collected for remanufacturing in multiple periods under uncertain quality of the returns has not been properly addressed in previous studies. On the other hand, the effects of new product sales and demand for remanufactured products on used product returns, as well as the effect of quality of returns on the take-back and remanufacturing costs, have not been properly considered in previous studies. In this paper, a novel methodology is proposed to determine the optimal product returns for remanufacturing with consideration of the uncertainty in the quantity and quality of returns and study the effects of new product sales and demand for remanufactured products on used product returns, as well as the effect of quality of returns on the remanufacturing cost. A case study of determining the optimal returns of tablet PCs is conducted to illustrate the proposed methodology.

Keywords Remanufacturing · Uncertainty · Product returns · Multi-period models · Dynamic demand models

✉ C. K. Kwong
c.k.kwong@polyu.edu.hk

[1] Industrial and Manufacturing Systems Engineering, Iowa State University, Ames, IA 50011, USA

1 Introduction

With the increase in global consumption and technological development, countless products are discarded before their end-of-life (EoL) every year. These wasted products often lead to environmental pollution and the loss of the remaining value of the used products. For example, consumer electronics (e.g., cellular phones and tablet PCs) have particularly high demands but short product life cycles [1]. Therefore, numerous of such products have immense potential for product recovery, which could help protect the environment and recover the value of discarded products.

Recently, a growing focus on product recovery strategies has been observed throughout the entire product life cycle [2] because of stringent international legislations and government regulations, increasing social concerns on environmental protection, and profit generation [3]. End-of-use products can be collected, recovered, and sold in markets as remanufactured products. De Giovanni and Zaccour [4] and Chuang et al. [5] examined closed-loop supply chain models with consideration of environmental and operational performances in which product collection is undertaken by manufacturers, retailers, and/or third-party firms. Akcali and Cetinkaya [6] conducted a review of product return models for inventory and production planning in a closed-loop supply chain network under various demand conditions. Managing product returns has been considered to be essential for the production planning and control and inventory control of remanufacturing [1, 7, 8]. Shaharudin et al. [8] conducted an empirical study to investigate the management of product returns in terms of manufacturing, distribution, and customer returns. Overall, considerable uncertainty exists in the quantity, timing, and quality of the returned products [9–11], which could largely affect the profit generated from remanufactured products.

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Leasing new products and trade-in programs are two common methods of collecting used products from customers [9, 12]. The quantity of returns in product leasing systems can be predicted relatively easier. Denizel et al. [12] stated that the quantity of returns through a trade-in program can be correlated with the sales forecast of new products. For either case, consideration of both product returns and demand is important for remanufacturing [13].

A few previous studies forecasted the quantity and timing of product returns. Goh and Varaprasad [14] developed a Box-Jenkins transfer function model to forecast returns of used products. The model required past sales and return data to estimate the return probabilities in each period. Later on, Kelle and Silver [15] developed a model to forecast the returns of containers. The model required less parameter estimation than that proposed by Goh and Varaprasad [14]. Toktay et al. [16] established a queuing network model for the inventory management of returned and remanufactured products, in which perfect substitution between new and remanufactured products was considered. In their study, a geometrically distributed lag model (DLM) was used to forecast product returns. Clottey et al. [17] proposed an exponential DLM for product returns in continuous time. Krapp et al. [18] proposed a Bayesian-based forecasting approach to estimate the number of returned products. Krapp et al. [19] further extended their methodology by incorporating Kalman filter to enhance forecasting accuracy. Aydin et al. [20] established a multiobjective optimization model based on Stackelberg game theory to determine product line solutions for both new and remanufactured products, pricing decisions of supply chain partners, and product return rate for remanufacturing. Kwak and Kim [21] proposed a decision-support model to determine the optimal design of new and remanufactured products simultaneously and the number of returned products, in which the trade-off between total profit and environmental impact was examined. A mixed-integer programming model was developed to determine the optimal reverse logistics network design with different scenarios of product returns [22]. Sun et al. [23] studied a multi-period acquisition pricing and inventory problem for remanufacturing to determine the optimal take-back price and inventory level of product returns.

Some studies have considered the quality of product returns. Guide and Wassenhove [1] studied the importance of managing the quality and quantity of product returns to the profitability of remanufactured products. A few studies indicated that higher quality of returns would lead to higher profitability of remanufactured products because of cost savings in the recovery process. Aras et al. [9] investigated the effect of classifying returned products as low- and high-quality returns on cost savings in a hybrid manufacturing and remanufacturing system. Ferguson et al. [24] examined the grading of product returns into different quality levels in a product leasing system. They found that an average of 4% profit increase could be achieved through a grading system depending on the quantity of available returns and demand for remanufactured products. Denizel et al. [12] formulated a stochastic programming model to determine the quantity and quality of return cores under uncertain quality of returns. Srivastava and Srivastava [7] developed a system dynamics model to estimate product returns with consideration of product grading in a reverse logistic network. Zikopoulos and Tagaras [25] proposed a profit-maximization model to investigate the profitability of a single-period reverse supply chain network considering the uncertainty in the quality of product returns. Zeballos et al. [26] extended the aforementioned model to examine the uncertainty in the quality and quantity of returns with simultaneous consideration of forward and reverse supply chain networks. Galbreth and Blackburn [27] examined the optimal acquisition quantities for both uniformly distributed continuous and discrete quality conditions. A profit-maximization model was proposed by Guide et al. [28] to determine the quantity, quality, and acquisition prices of returns as well as the price of remanufactured products in a single period. In their study, demand of remanufactured products and product return rates were assumed to be known and product returns were independent of sales. Teunter and Flapper [29] examined the optimal acquisition price of returns with different quality levels and remanufacturing policies for both deterministic and uncertain demands. Liang et al. [30] adopted a convolution-based method to forecast the quantity and quality of electrical vehicle battery returns based on sales, product life expectancy, and customer return behavior information. Niknejad and Petrovic [31] established a fuzzy mixed-integer algorithm to optimize the reverse logistics network with consideration of uncertain demand and uncertainty in the quantity and quality levels of returned products. Most of the aforementioned studies ignored the effect of the quality of returns on the take-back and remanufacturing costs. However, both acquisition price and remanufacturing cost are highly dependent on the quality of returns.

Several previous studies considered the perfect substitution of new and remanufactured products in their hybrid manufacturing and remanufacturing models [32, 33]. Mukhopadhyay and Ma [34] developed a model to determine the optimal procurement and production quantities for a hybrid system considering the uncertainty associated with both quality of returns and demand. El Saadany and Jaber [35] proposed a hybrid inventory model to determine the product return rate considering acquisition price and quality of returns with constant demand. Wang et al. [10] and Macedo et al. [33] established models to determine an optimal policy on the manufacturing and remanufacturing of returned products in a hybrid system. However, perfect substitution may not be suitable, particularly for consumer products wherein demand is highly dependent on customer utilities.

From the above review, determining the optimal quantity and quality levels of used products to be collected for remanufacturing under uncertain quality and multiple periods of returns has not been properly addressed in previous studies. When the available number of returns is more than the demand for remanufactured products, companies need to determine the optimal quantity for each period with consideration of the supply of product returns, demand for remanufactured products, and take-back and inventory costs. Variations and uncertainty in the quality of product returns would also affect the remanufacturing cost. Furthermore, most of the previous studies modeled product returns and demands for remanufactured and new products separately and stochastic distribution theory was quite often used to model the returns and the demands. However, used product returns and the demands for remanufactured and new products may not follow a random distribution model, and product returns actually quite depend on new product sales. In this paper, a novel methodology for determining the optimal product returns for remanufacturing is proposed to address the uncertainty in the quantity and quality of returns. In the proposed methodology, the following issues are considered that were not addressed properly in the previous studies: (1) the effects of new product sales and demand for remanufactured products on product returns, (2) the effect of quality of returns on the take-back and remanufacturing costs, (3) the effect of quality of returns on the inventory cost of remanufactured products, and (4) incorporation of consumer preferences in the demand estimation of new and remanufactured products.

The rest of this paper is organized as follows. Section 2 describes the proposed methodology of determining the optimal quantity and quality levels of product returns for remanufacturing with consideration of uncertain quality and multi-period of returns. Section 3 presents a case study on the determination of optimal quantity and quality levels of returned tablet PCs based on the proposed methodology. Results of the post-optimality analyses under different quality scenarios and inventory cost considerations are also presented. Section 4 provides a discussion of the results. Section 5 provides the conclusion and future research direction.

2 Proposed methodology

Figure 1 shows the centralized closed-loop supply chain considered in this study. The straight-line and dashed-line arrows indicate the forward and reverse flows of the supply chain, respectively. The manufacturer produces new products and delivers them to chain retailers, who then sell the products to customers in the first market. The first market refers to a developed region where consumers are generally more interested in and willing to pay for brand-new products than remanufactured products. Used and defective products are collected by chain retailers through trade-in programs. The returned products are categorized into different quality levels based on their conditions. The manufacturer needs to determine the quantity and quality levels of the used products, which will be collected in a specific period based on the estimated demand of remanufactured products. Thereafter, the manufacturer refurbishes the returned products and sells them in the second market. The second market is normally a relatively less developed region where consumers are generally unable to afford brand-new products and may be interested in lower-priced remanufactured products. Remanufactured products are assumed to have like-new condition and have same warranty as new products do. In this research, multiple market segments are considered in both new product and remanufactured product development.

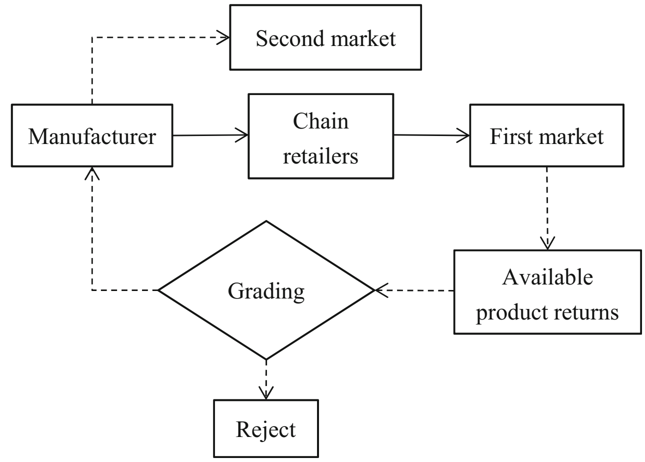


Fig. 1 Closed-loop supply chain

In the proposed methodology, an optimization model is formulated to determine the optimal quantity and quality levels of used products to be collected for remanufacturing with consideration of (1) the sales of new products, (2) demand for remanufactured products, (3) the uncertainty in the quality of returns, and (4) inventory costs. The objective of this model is to minimize the total cost of producing remanufactured products, that is, the sum of the take-back, remanufacturing, and inventory costs. The following two issues are also addressed in the proposed methodology:

1. The effect of new product sales on product returns, and
2. The effect of demand for remanufactured products on product returns.

Figure 2 shows a flowchart of the proposed methodology. First, the sales of new products are estimated based on a dynamic market demand model that was developed in our previous study [36]. Based on the sales estimates, the quantity of available product returns and the timing of collecting them are forecasted using a geometrical distributed lag model (DLM). Thereafter, the quality levels of the available product returns

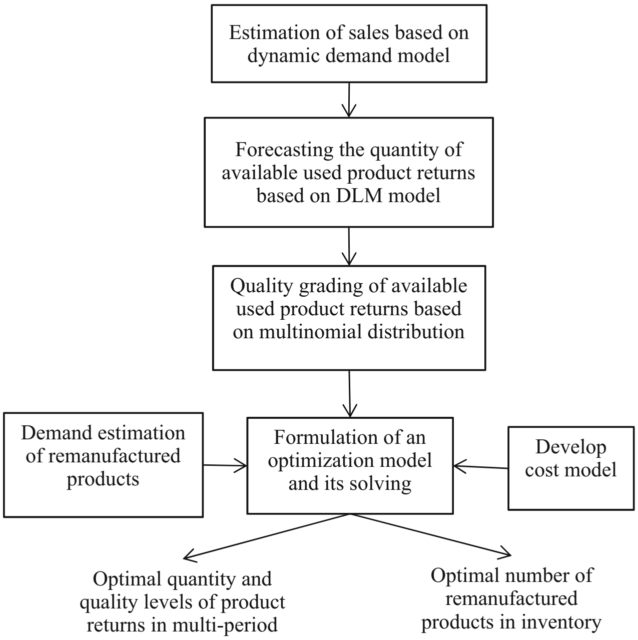


Fig. 2 Methodology for the determination of the optimal quantity and quality levels of returned products

are estimated using a multinomial distribution. The demand for remanufactured products is also estimated based on a dynamic market demand model. The cost model for producing remanufactured products mainly consists of take-back, remanufacturing, and inventory costs. Once the cost model is developed and the demand for remanufactured products is estimated, an optimization model can be formulated with the objective of minimizing the cost of producing remanufactured products. After solving the model, the optimal quantity and quality levels of used products to be collected for remanufacturing and inventory level of the remanufactured products for each period can be obtained. Details of the proposed methodology are described in the following subsections.

2.1 Forecasting the quantity of available used products to be collected under multi-period

Traditional statistical forecasting techniques, such as time-series method or exponential smoothing, cannot address the correlation between sales and product returns [17]. In this research, DLM is employed to capture the correlation [16–18], which can be expressed as follows:

$$m_t^{\mathrm{ret}} = \sum_{k=1}^{t-1} \beta_k n_{t-k} + \varepsilon_t; \quad \text{for } t = 2, 3, \ldots, T. \tag{1}$$

where n_t and m_t^{ret} denote the number of products sold and available returned products, respectively, at time t; and β_k is a geometric delay function for the returns which are sold at time $t-k$ [16, 18], which represents the return rate at a specific time.

Products, which are sold at time t, can be collected starting from time $t+1$ or later periods according to the delay function that can be expressed as follows:

$$\beta_k = pq(1-q)^{k-1} \tag{2}$$

where p is the probability that a sold product will ever be returned and q is the conditional probability that a product would be returned in the next period given that it will be returned. The condition of q is that the product will eventually be returned.

2.2 Quality grading of available used product returns

The quality of used product returns has significant effect on the remanufacturing cost [6]. As discussed in Section 1, grading returned products into different quality levels helps reduce the cost of producing remanufactured products. Zikopoulos and Tagaras [25] conducted a numerical analysis to investigate different quality levels of returns. Zeballos et al. [26] modeled the uncertain quality of returns considering five quality levels and three quality scenarios (i.e., good, medium, and bad). Multinomial distribution, a generalization of binomial distribution, has been utilized to determine the fraction of each quality level of returned products when more than two possible quality levels are present [28, 29].

Four quality levels are considered in the current study. Post-optimality analyses of various quality distributions of returned products are considered in this research to investigate the change of total cost of producing remanufactured products when the quantities and quality levels of returned products vary. Three quality scenarios, namely, good, average, and bad, are studied and the quality distribution function for different quality scenarios can be expressed as follows:

$$f\left(Q_{lt}^s \mid l_1^s \;\; l_2^s \;\; l_3^s \;\; l_4^s\right); \quad \text{for } s = 1, 2, 3 \text{ and } t = 2, 3, \ldots, T. \tag{3}$$

where Q_{lt}^s represents the quality distribution variable of returned products with quality level l at time t for scenario s given the fixed probability parameters based on multinomial distributions; and l_l^s is the fixed probability parameter of quality level l for the scenario s.

Quality distribution of returned products is estimated based on multinomial distribution where multinomial probability density function can be expressed as follows:

$$f(x|n, \pi) = \frac{n!}{x_1! \cdots x_k!} \pi_1^{x_1} \cdots \pi_k^{x_k} \tag{4}$$

where n is the total number of independent trials; k is the number of possible outcomes for each trial; x_k is the number of trials of outcome k and a nonnegative integer value and

$x_1 + \cdots + x_k = n$; and π_k is the fixed probability of outcome k and a nonnegative scalar value and $\pi_1 + \cdots + \pi_k = 1$.

2.3 Estimations of sales of new products and demand for remanufactured products

The sales of new products and demand for remanufactured products were estimated based on the dynamic market demand model developed in our previous study, wherein consumer preferences on both new and remanufactured products are obtained using conjoint analysis [36]. The model was developed by incorporating the dynamic choice models into a Bass diffusion model. The dynamic choice models were generated using the multinomial logit (MNL)-based discrete choice analysis (DCA) [37] and dynamic utility functions. The dynamic utility functions were generated with consideration of the change in product prices over time and expressed as follows:

$$U_{ij}^t = \sum_{k=1}^{M} \sum_{l=1}^{N_k} u_{ikl} x_{jkl} + f_{ijt}^{\mathrm{pr}} \tag{5}$$

where U_{ij}^t represents the utility of the jth product profile in the ith segment at time t; u_{ikl} is the part-worth utility of the lth level of the kth attribute in the ith segment; M and N_k denote the number of attributes and number of attribute levels in the kth attribute, respectively; x_{jkl} denotes a dummy variable equal to 1 if the lth level of the kth attribute is selected for the product profile j and 0 otherwise; and f_{ijt}^{pr} is the utility of price of the jth product in the ith segment at time t. Utility can be described as the total quality or value of a given product among a set of competitive products perceived by customers. Attributes are the design and/or product characteristics of a product profile which differentiate products from each other.

Individual utility functions are used in the development of the MNL choice models, which include two main parts in the utility function, namely, a deterministic part and a random disturbance. The deterministic utility function considers the observable independent variables of product profiles, and the random disturbance considers random error of product profiles. All model coefficients are assumed identical across all respondents and are linear within the observed (deterministic) part of the utility function. Random error is combined with the systematic part of the choice models by considering unobserved factors in choice decisions. Random error terms are assumed independent and identically distributed across respondent choices that reduce computation difficulty. Stochastic distribution is assigned to estimate the unmeasured or unobserved behavior of the sampled group according to assumptions made by decision makers [37]. The choice probabilities are developed independently from irrelevant alternatives that accommodate proportional substitution among alternatives and prevent the correlation among the alternatives. This feature provides a computational advantage in terms of adding or extracting alternatives in a choice set [38]. Hence, the dynamic choice models were generated by integrating the dynamic utility functions into the MNL model as follows:

$$\Pr_{ip}^t = \frac{e^{U_{ip}^t}}{\sum_{j=1}^{J} e^{U_{ij}^t} + \sum_{k=1}^{K} e^{U_{ik}^t} + e^{U_{ip}^t}} \tag{6}$$

where $\Pr_{ip}^t$ is the probability of selecting the pth product among the company's existing and competitive products in the ith segment at time t; U_{ip}^t is the utility of the pth product in segment i at time t; U_{ik}^t is the utility of the kth company's existing product in segment i at time t; and U_{ij}^t is the utility of the jth competitive product in segment i at time t.

The sales and demand of products are estimated by incorporating a choice model into a Bass diffusion model [40]. The advantage of adopting choice-based Bass diffusion models in the proposed methodology is that they can enable dynamic change and updating of product features and the competition among products [39]. In this study, the dynamic choice models shown in (6) are incorporated into Bass diffusion models to develop dynamic market demand models for estimating the sales of new products and demand for remanufactured products. A Bass diffusion model can be expressed as follows:

$$S(t) = [m - N(t)]\left[p + q\frac{N(t)}{m}\right] \tag{7}$$

where $S(t)$ is the estimated sales at time t, $N(t)$ is the cumulative sales until time t, p is the innovation coefficient, q is the imitation coefficient; and m is the market potential.

By incorporating dynamic choice models into Bass diffusion models, a dynamic market demand model for new products in the primary market can be formulated as follows:

$$n_{ip}^t = \left[\Pr_{ip}^t \mathrm{MP}_i - \sum_{i=1}^{I} \sum_{p=1}^{P} \sum_{t=0}^{Tn} n_{ip}^t\right]\left[p_1 + q_1 \frac{\sum_{i=1}^{I} \sum_{p=1}^{P} \sum_{t=0}^{Tn} n_{ip}^t}{\Pr_{ip}^t \mathrm{MP}_i}\right] \tag{8}$$

where n_{ip}^t is the market demand of the pth new product in segment i at time t; $\Pr_{ip}^t$ is the probability of choosing the pth new product among the new and existing products of a company, and the competitor's products in segment i at time t; p_1 and q_1 are the innovation and imitation coefficients of the new products, respectively; MP_i is the estimated market potential of segment i in the primary market; and I, P, and Tn are the numbers of segments in the primary market, new products, and time periods, respectively.

The dynamic market demand for remanufactured products in the second market can be developed similarly and expressed as follows:

$$n_{zr}^{t} = \left[\Pr_{zr}^{t}\mathrm{MP}_z - \sum_{z=1}^{Z}\sum_{r=1}^{R}\sum_{t=t_k}^{Tr} n_{zr}^{t}\right]\left[p_2 + q_2\frac{\sum_{z=1}^{Z}\sum_{r=1}^{R}\sum_{t=t_k}^{Tr} n_{zr}^{t}}{\Pr_{zr}(t)\mathrm{MP}_z}\right] \quad (9)$$

where n_{zr}^{t} is the market demand of the rth remanufactured product in segment z at time t; $\Pr_{zr}^{t}$ is the probability of choosing the rth remanufactured product at time t among the remanufactured product(s) of the company and the competitor's products in segment z; p_2 and q_2 are the innovation and imitation coefficients of the remanufactured products, respectively; MP_z is the estimated market potential of segment z in the second market; and Z, R, and Tr are the number of segments in the second market, remanufactured products, and time periods, respectively.

The market potentials, MP_i and MP_z, can be estimated by using various methods such as jury of expert opinion and Delphi methods. If historical data of the market potentials is available, they can also be estimated based on the historical data by using time-series methods.

2.4 Formulation of an optimization model

An optimization model is developed to determine the optimal quantity and quality levels of product returns for remanufacturing. The decision variables are the quantity of used products to be collected for each quality level in each period and the number of remanufactured products in inventory at the end of each period. The objective of this model is to minimize the total cost of producing remanufactured products, that is, the sum of the take-back, remanufacturing, and inventory costs. Thus, the objective function can be formulated as follows:

$$\sum_{t=2}^{T-1}\sum_{l=1}^{L} m_{lt}^{s}\left(c_l^{\mathrm{tb}} + c_l^{\mathrm{rem}}\right) + \left(\sum_{t=3}^{T-1} s_t^{s}\right)c^{\mathrm{inv}} \quad (10)$$

where m_{lt}^{s} denotes the number of returned products with quality level l at time t for scenario s; c_l^{tb} and c_l^{rem} are the take-back and remanufacturing costs of quality level l, respectively; c^{inv} is the inventory cost of a remanufactured product; and s_t^{s} is the number of remanufactured products in the inventory at the end of period t for scenario s, which can be calculated by subtracting the total demand for remanufactured products at time t (n_r^{t}) from the sum of remanufactured products in inventory at the end of previous time period and the number of returns. Thus, s_t^{s} can be calculated as follows:

$$s_t^{s} = s_{t-1}^{s} + \sum_{l=1}^{L} m_{lt}^{s} - n_r^{t}; \quad \text{for } t = 2, 3, 4, \ldots T. \quad (11)$$

$$s_1^{s} = 0 \quad (12)$$

Equation (12) means that no remanufactured products are produced in the first period, because product returns are only available starting from the second period. After collection, the returned products are shipped to the manufacturer and disassembled, repaired, cleaned, and assembled again. Any returned products which are sold in the same period after collection are not considered in the inventory. Otherwise, they are treated as inventory items at the end of the period. The following constraints are required in the formulation of the optimization model:

$$m_{lt}^{s} \le m_t^{\mathrm{ret}}.Q_{lt}^{s}; \qquad \text{r } t = 2, 3, 4, \ldots, T-1 \text{ and } l = 1, 2, 3, 4. \quad (13)$$

$$\sum_{t=2}^{T} n_r^{t} \le \sum_{t=2}^{T}\sum_{l=1}^{L} m_{lt}^{s} \quad (14)$$

Equation (13) ensures that the number of returned products for each quality level in each period is less than or equal to the available number of used products for the corresponding quality level and period. Equation (14) assures that the total number of used product returns is more than or equal to the total demand for remanufactured products. To study the effect of inventory cost on product returns and total cost, the inventory cost (\$/unit/year) is estimated as 15% of the take-back cost for electronic products [41]. The formulated optimization model is an integer programming one and can be solved by using some commercial software tools.

3 Case study

The proposed methodology was applied to determine the optimal quantity and quality levels of used tablet PCs to be collected for remanufacturing based on our previous case study of product line design involving both new and remanufactured tablet PC. Details of the case study can be found in our publication [36]. The product line solution for maximum profits obtained in our previous case study is adopted here to illustrate the proposed methodology which contains one 7-in. model and two 10-in. models of new tablet PCs, as well as one 10-in. remanufactured tablet PC. The time of launching the two new tablet PCs is the month zero and the best time of launching the 10-in. remanufactured tablet PC is the 13th month which was determined in our previous study. Specifications of the three new and one remanufactured tablet PCs can be found in Table 9. The dynamic utility functions generated in our previous case study based on conjoint analysis were also adopted here to estimate the demands of new and remanufactured tablet PCs in each period, which can be found in Table 10.

Time periods are specified quarterly. New tablet PCs are launched in the first market from periods 1 to 12, and used tablet PCs are collected starting from period 2. Remanufactured tablet PCs are launched in the second market starting from period 5 (i.e., approximately on the 13th month). Therefore, used tablet PCs can be collected starting from period 2 to period 16 because the market demands for remanufactured tablet PCs were forecasted during those periods. The sales of new tablet PCs and demand for remanufactured tablet PCs were estimated using Eqs. (8) and (9), respectively. The number of available returns for each period was estimated based on geometrical DLM. Table 1 shows the estimated sales of new products, demand for remanufactured products, and the number of available returned tablet PCs in each period.

Multinomial distribution was used to estimate the available quantities of the returned tablet PCs for individual quality levels. In the case study, the returned tablet PCs were categorized into four quality levels, namely, quality level 1 to quality level 4. Quality level 1 is the best, whereas quality level 4 is the worst. Post-optimality analyses under three quality scenarios, namely, good, average, and bad, as well as the effect of inventory cost on the cost of remanufactured tablet PCs were also examined in this case study. The following sub-sections present the implementation results under the three quality scenarios with or without inventory cost consideration.

3.1 Implementation results under average quality scenario

In the average quality scenario, the probabilities of the four quality levels of the returned tablet PCs were all set as 0.25. First, the quantities of available returned tablet PCs for individual quality levels in each period were calculated based on multinomial distribution with reference to the total number of available returned tablet PCs in the corresponding period. Then, the optimization model was solved using a Matlab integer linear programming solver and the optimal quantities of returned tablet PCs for individual quality levels in each period, demand for remanufactured products in each period, and costs of take-back, remanufacturing and inventory were determined. Table 2 shows the optimal quantity of returned tablet PCs for each quality level to be collected for remanufacturing and the number of remanufactured products in inventory when no inventory cost is considered based on the average quality scenario. The total cost of collecting and producing the remanufactured products is USD 1,002,370. The cost parameters were obtained from internet sources. The take-back costs for returned tablet PCs with quality levels 1, 2, 3, and 4 are 100, 90, 80, and 70 USD, respectively. The remanufacturing costs for returned tablet PCs with quality levels 1, 2, 3, and 4 are 40, 65, 90, and 115 USD, respectively. Overall, for this scenario without inventory cost consideration, around 96% of available returns in quality level 1, 85% of available returns in quality level 2, and 37% of available returns in quality level 3 need to be collected for remanufacturing in order to minimize the total cost of producing remanufactured products.

Table 1 Sales, demand, and number of available returned tablet PCs

Period	Sales	Demand	Available returned tablet PCs
1	1044	0	0
2	1704	0	80
3	2649	0	199
4	3742	0	375
5	4404	115	613
6	4283	276	868
7	3685	450	1080
8	2553	700	1219
9	1775	967	1255
10	983	1154	1230
11	754	1094	1149
12	376	851	1060
13	0	507	956
14	0	298	837
15	0	135	732
16	0	85	640
Total	27,952	6632	12,293

Table 3 shows the optimal quantity of returned tablet PCs for each quality level to be collected for remanufacturing and the number of remanufactured tablet PCs in inventory when the inventory cost ($/unit/year) is set to 15% of the take-back cost [40] based on the average quality scenario. The total cost of collecting and producing the remanufactured product is USD 1,017,196. Overall, for this scenario with inventory cost consideration, around 96% of available returns in quality level 1, 80% of available returns in quality level 2, 41% of available returns in quality level 3, and 2% of available returns in quality level 4 need to be collected for remanufacturing in order to minimize the total cost of producing remanufactured products.

3.2 Implementation results under good quality scenario

In the good quality scenario, the probabilities of the returned tablet PCs with the quality levels 1, 2, 3 and 4 are 0.40, 0.30, 0.20, and 0.10, respectively. Table 4 shows the optimal quantity of returned tablet PCs in each quality level to be collected for remanufacturing and the number of remanufactured tablet PCs in inventory when no inventory cost is considered based on the good quality scenario. The estimated total cost of collecting and producing remanufactured tablet PCs is USD

Table 2 Number and inventory levels of the returned tablet PCs with no inventory cost (average quality scenario)

Period	Returned tablet PCs					Inventory
	Quality level 1	Quality level 2	Quality level 3	Quality level 4	Total	
1	0	0	0	0	0	0
2	14	22	25	0	61	61
3	53	57	0	0	110	171
4	93	93	0	0	186	357
5	148	144	0	0	292	534
6	194	222	0	0	416	674
7	270	271	0	0	541	765
8	316	292	0	0	608	673
9	286	307	320	0	913	619
10	296	311	313	0	920	385
11	258	291	297	0	846	137
12	272	261	181	0	714	0
13	255	219	33	0	507	0
14	200	98	0	0	298	0
15	135	0	0	0	135	0
16	85	0	0	0	85	0
Total	2875	2588	1169	0	6632	4376

960,115. Overall, for this scenario without considering inventory cost, around 93% of available returns in quality level 1 and 56% of available returns in quality level 2 need to be collected for remanufacturing. However, none of available returns in quality levels 3 and 4 are required to be collected.

Table 5 shows the optimal quantity of returned tablet PCs in each quality level to be collected for remanufacturing and the number of remanufactured tablet PCs in the inventory when the inventory cost is involved based on the good quality scenario. The estimated total cost of collecting and producing remanufactured tablet PCs is USD 973,800. Overall, for this scenario with considering inventory cost, around 91% of available returns in quality level 1, 51% of available returns in quality level 2, and 11% of available returns in quality level

Table 3 Number and inventory levels of product returns involving inventory cost (Average quality scenario)

Period	Returned tablet PCs					Inventory
	Quality level 1	Quality level 2	Quality level 3	Quality level 4	Total	
1	0	0	0	0	0	0
2	14	0	0	0	14	14
3	53	0	0	0	53	67
4	93	0	0	0	93	160
5	148	144	0	0	292	337
6	194	222	0	0	416	477
7	270	271	0	0	541	568
8	316	292	60	0	668	536
9	286	307	320	0	913	482
10	296	311	313	0	920	248
11	258	291	297	0	846	0
12	272	261	272	46	851	0
13	255	219	33	0	507	0
14	200	98	0	0	298	0
15	135	0	0	0	135	0
16	85	0	0	0	85	0
Total	2875	2416	1295	46	6632	2889

Table 4 Number and inventory levels of the returned tablet PCs with no inventory cost (good quality scenario)

Period	Returned tablet PCs					Inventory
	Quality level 1	Quality level 2	Quality level 3	Quality level 4	Total	
1	0	0	0	0	0	0
2	30	0	0	0	30	30
3	78	69	0	0	147	177
4	141	121	0	0	262	439
5	231	0	0	0	231	555
6	345	252	0	0	597	876
7	426	0	0	0	426	852
8	468	380	0	0	848	1000
9	526	380	0	0	906	939
10	475	380	0	0	855	640
11	458	92	0	0	550	96
12	428	327	0	0	755	0
13	399	108	0	0	507	0
14	298	0	0	0	298	0
15	135	0	0	0	135	0
16	85	0	0	0	85	0
Total	4523	2109	0	0	6632	5604

3 need to be collected for remanufacturing. However, no available returns in quality level 4 are required to be collected.

3.3 Implementation results under bad quality scenario

In the bad quality scenario, the probabilities of the quality levels of the returned tablet PCs with the quality levels 1, 2, 3, and 4 are 0.10, 0.20, 0.30, and 0.40, respectively. Table 6 shows the optimal quantity of returned tablet PCs for each quality level to be collected for remanufacturing and the number of remanufactured tablet PCs in the inventory when no inventory cost is considered based on the bad quality scenario. The estimated total cost of collecting and producing remanufactured tablet PCs is USD 1,062,625. It can be noted in Table 6 that

Table 5 Number and inventory levels of the returned tablet PCs involving inventory cost (good quality scenario)

Period	Returned tablet PCs					Inventory
	Quality level 1	Quality level 2	Quality level 3	Quality level 4	Total	
1	0	0	0	0	0	0
2	0	0	0	0	0	0
3	0	0	0	0	0	0
4	141	0	0	0	141	141
5	231	0	0	0	231	257
6	345	0	0	0	345	326
7	426	0	0	0	426	302
8	468	380	0	0	848	450
9	526	380	0	0	906	389
10	475	380	0	0	855	90
11	458	359	187	0	1004	0
12	428	327	96	0	851	0
13	399	108	0	0	507	0
14	298	0	0	0	298	0
15	135	0	0	0	135	0
16	85	0	0	0	85	0
Total	4415	1934	283	0	6632	1955

Table 6 Number and inventory levels of returned tablet PCs with no inventory cost (bad quality scenario)

Period	Returned tablet PCs					Inventory
	Quality level 1	Quality level 2	Quality level 3	Quality level 4	Total	
1	0	0	0	0	0	0
2	9	13	31	0	53	53
3	15	42	0	0	57	110
4	31	89	27	0	147	257
5	55	120	171	0	346	488
6	77	180	280	0	537	749
7	120	220	304	0	644	943
8	118	243	396	0	757	1000
9	125	270	340	0	735	768
10	114	245	335	325	1019	633
11	115	205	373	0	693	232
12	104	200	315	0	619	0
13	79	211	217	0	507	0
14	83	159	56	0	298	0
15	75	60	0	0	135	0
16	64	21	0	0	85	0
Total	1184	2278	2845	325	6632	5233

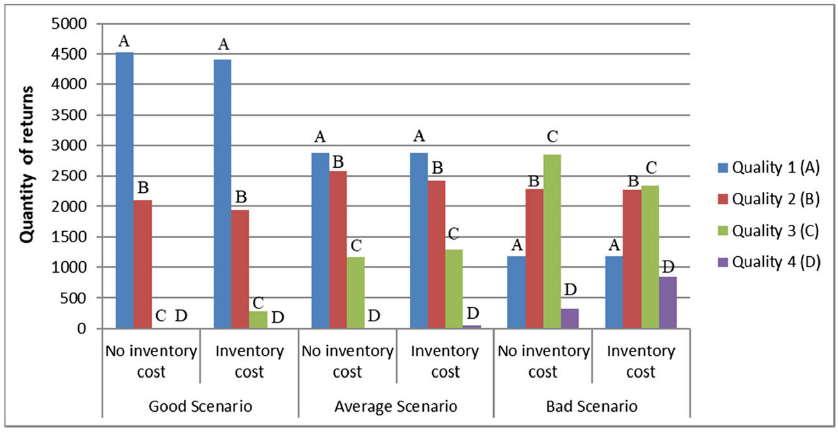
all of the available returns in quality level 1, 92% of the available returns in quality level 2, 78% of the available returns in quality level 3, and 6% of the available returns in quality level 4 need to be collected for remanufacturing.

Table 7 shows the optimal quantity of returned tablet PCs for each quality level to be collected for remanufacturing and the number of remanufactured tablet PCs in the inventory when the inventory cost is considered based on the bad quality scenario. The estimated total cost of collecting and producing remanufactured tablet PCs is USD 1,078,166. It can be noted in Table 7 that all of the available returns in quality level 1, 91% of the available returns in quality level 2, 64% of the available returns in quality level 3, and 17% of the available returns in quality level 4 need to be collected for remanufacturing.

Table 7 Number and inventory levels of the returned tablet PCs involving inventory cost (bad quality scenario)

Period	Returned tablet PCs					Inventory
	Quality level 1	Quality level 2	Quality level 3	Quality level 4	Total	
1	0	0	0	0	0	0
2	9	0	0	0	9	9
3	15	42	0	0	57	66
4	31	89	0	0	120	186
5	55	120	0	0	175	246
6	77	180	0	0	257	227
7	120	220	304	0	644	421
8	118	243	396	0	757	478
9	125	270	340	0	735	246
10	114	245	335	214	908	0
11	115	205	373	401	1094	0
12	104	200	315	232	851	0
13	79	211	217	0	507	0
14	83	159	56	0	298	0
15	75	60	0	0	135	0
16	64	21	0	0	85	0
Total	1184	2265	2336	847	6632	1879

Fig. 3 Summary of the optimal quantities of returns for the individual quality levels



4 Discussion of results

Based on the implementation results presented in sub-sections 3.1 to 3.3, Fig. 3 is generated to summarize the optimal quantities of used tablet PCs to be collected for individual quality levels under the three quality scenarios and inventory cost considerations. It can be noted that the number of used tablet PCs to be collected in quality levels 1 and 2 constitute a large percentage of the returns in the good and average scenarios. The number of used tablet PCs to be collected in quality levels 3 and 4 are relatively higher in the bad scenario than the ones in the good and average scenarios. This clearly shows that uncertainty in the quality of product returns would have considerable impact on the number of returns collected. On the other hand, it can be noted that the proportions of the returns with the quality levels 3 or 4 and inventory cost consideration are respectively higher that those without inventory cost consideration. When the inventory cost is not considered, the used products to be collected are mainly those with the quality levels 1 and 2. It is because higher cost savings can be achieved if the used products to be collected are with higher quality. When the inventory cost is considered, the number of returns with lower quality increases to compensate for the incurred inventory cost. Therefore, inventory cost would also affect the quality of product returns to be collected.

Figure 4 summarizes the number of stocks under the three quality scenarios with and without inventory costs. It can be noted that for all the quality scenarios, the number of stocks decreases when the inventory cost is considered. Without considering inventory cost, the number of stocks in the bad quality scenario is relatively higher than those in the average and good quality scenarios. However, the number of stocks in the bad quality scenario is considerably lower than those in the average and good quality scenarios when the inventory cost is considered. The figures clearly indicate how the number of available returns in different quality scenarios and inventory cost would affect the number of stocks. When the inventory cost is zero, the product returns with higher quality are collected and kept as inventory.

Table 8 illustrates the overall analysis of the total cost of collecting and producing remanufactured tablet PCs under different quality scenarios and inventory cost consideration. The total costs obtained based on the average quality scenario are used for the benchmark. The percentages shown in the brackets of Table 8 are the difference in percentages between the total costs obtained based on the average quality scenario and that

Fig. 4 Number of stocks under different quality scenarios and inventory cost considerations

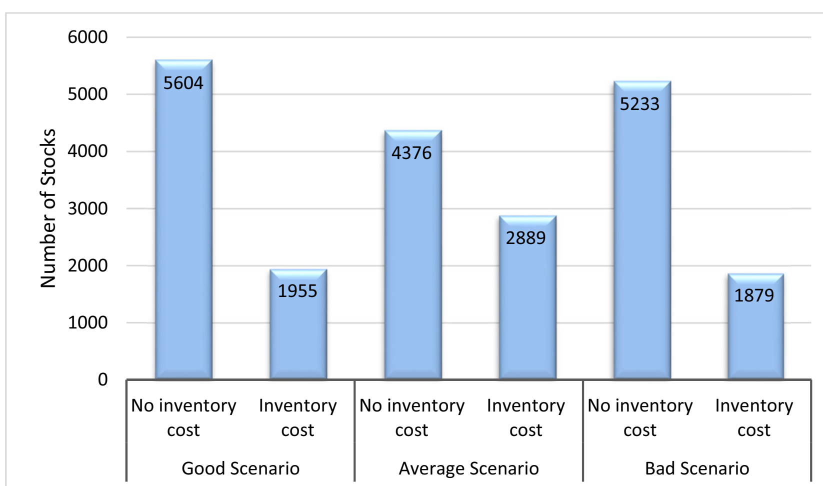


Table 8 Overall analysis of the total cost estimations

	Average scenario	Good scenario	Bad scenario
No inventory cost	USD 1,002,370	USD 960,115 (− 4.2%)	USD 1,062,625 (+ 6.0%)
Inventory cost (15% of the take-back cost)	USD 1,017,196	USD 973,800 (− 4.3%)	USD 1,078,166 (+ 6.0%)
Difference of the total costs (with and without inventory cost)	+ 1.5%	+ 1.4%	+ 1.5%

based on the corresponding scenario. Table 8 also shows that the total cost obtained based on the good quality scenario is approximately 4% lower than the one based on the average scenario. However, the total cost obtained based on the bad scenario is approximately 6% higher than the one based on the average scenario. The total cost increases approximately 0.5 to 1% when the inventory cost is considered. As seen from the results in Table 8, uncertainty in the quality of product returns and consideration of inventory cost would have considerable impact on the economic viability of remanufacturing projects.

The total costs obtained based on the bad scenario with or without inventory cost consideration are also approximately 11% higher than the corresponding ones based on the good quality scenario. This result indicates that the quality of product returns could significantly affect the cost of remanufactured products. The differences in percentages between the total costs with and without involving inventory costs for all the three scenarios are minimal. However, it can be noted that higher percentages of the difference are obtained when more used tablet PCs with good quality are collected.

5 Conclusions and future work

Managing product returns has been found to be essential in the production planning and control for remanufacturing and inventory control management of product returns. However, considerable uncertainties have been found in the quantity, timing, and quality of returned products. Most of the previous studies considered product returns and demands for remanufactured and new products separately and stochastic distribution theory was quite often used to model the returns and the demands. However, the demand for remanufactured and new products may not follow a random distribution model. On the other hand, the effects of demand for remanufactured products and sales of new products on product returns have not been addressed properly in previous studies. The effect of quality of returns on the take-back and remanufacturing costs were also not considered in previous studies. However, both acquisition price and remanufacturing cost are highly dependent on the quality of returns. In this paper, a novel methodology is proposed to determine the optimal quantity and quality levels of used products to be collected for remanufacturing with consideration of multi-period and uncertain quality of the returns. The effects of sales of new products and demand for remanufactured products on product returns are also addressed in the proposed methodology. Post-optimality analyses were performed on the different quality scenarios and inventory cost consideration. The implementation results of a case study of tablet PCs indicate that the inventory cost of returned tablet PCs would lead to 0.5 to 1.1% changes in the total cost of remanufactured tablet PCs, whereas the uncertainty in the quality of returns would result in 4 to 6% changes in the total cost.

This study can provide useful information to both managers and researchers in several aspects. From the research aspect, the optimal quantity and quality levels of used products to be collected in multi-period can be determined, particularly when numerous returns are available. From the industrial aspect, the results of this study can be used to assess the financial viability of remanufacturing projects, and support the production planning and control for remanufacturing, as well as the inventory control management for product returns and remanufactured products. Post-optimality analyses can help decision makers have a better understanding of the effects of different quality scenarios and inventory cost on the total cost of producing remanufactured products. It was found that returns with higher quality would help increase the profitability of remanufactured products and provide better cost savings than the returns with lower quality. Once the new and remanufactured products are launched in markets, their actual sales data can be utilized to predict their future sales based on the dynamic demand models. This would help to improve the prediction accuracy of their future sales.

This study could be extended in several aspects. First, capacity constraints for production and inventory could be incorporated into the methodology without any substantial changes. Second, the uncertainty in the demand for remanufactured products could be considered in future studies. Third, an industrial case study would be conducted in future to further validate the effectiveness of the proposed methodology. In this research, the stock-out cases are not considered in the proposed model. However, the model can be extended by taking backorder cases into account. The effect of consumer behavior on returning used products could also be investigated in future studies.

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Specifications of new and remanufactured tablet PCs

Table 9 Specifications of three new and one remanufactured tablet PCs

Product	Screen size (in)	Hard disk (GB)	Memory (GB)	Dual CPU (GHz)	Screen resolution	Connectivity	Price (USD)
New product 1	10	32	2	1.4	1024 × 768	Wi-Fi	473
New product 2	10	64	2	1.4	2048 × 1536	Wi-Fi + 4G	707
New product 3	7	64	2	1	1024 × 768	Wi-Fi + 3G	532
Remanufactured product 1	10	32	1	1.4	1024 × 768	Wi-Fi + 4G	403

Dynamic utility functions for the first and second markets

Table 10 Coefficients of utility functions for the first and second markets

Market	Segment	x_1	x_2	x_{31}	x_{32}	x_{41}	x_{42}	x_{51}	x_{52}	x_{61}	x_{62}	x_{71}	x_{72}	x_{81}	x_{82}	Regr. const.
First	1	0.67	0.17	− 0.30	− 0.09	− 0.48	− 0.09	− 0.10	− 0.04	− 0.39	− 0.40	− 0.58	− 0.17	0.99	0.66	3.07
	2	0.48	− 0.26	− 0.19	− 0.53	− 0.33	− 0.31	− 0.03	0.39	− 0.44	− 0.19	− 1.08	− 0.31	− 0.25	− 0.22	3.44
	3	0.48	0.07	− 0.43	− 0.14	− 0.62	− 0.13	− 0.44	0.01	− 0.29	− 0.18	− 0.14	− 0.07	2.13	1.01	2.21
Second	1	− 0.30	0.45	0	0.02	− 1.05	0	0.21	0.02	− 0.14	− 0.40	− 0.40	− 0.21	0.38	0.43	3.63
	2	− 0.35	0.10	− 0.11	0.13	− 0.21	− 0.32	− 0.08	− 0.11	− 0.13	0.01	− 0.64	− 0.10	1.33	0.64	3.08

To estimate the utility of continuous-value prices, a curve-fitting method was applied by using the estimated coefficients of x_{81} and x_{82} to generate the utility functions for the continuous-value prices for each segment of the corresponding market. The results are shown as follows:

$$f_{1pt}^{\mathrm{pr}} = 1.16 - 1.1 \times 10^{-4} p_p^t - 2.2 \times 10^{-6} \left(p_p^t\right)^2$$
$$f_{2pt}^{\mathrm{pr}} = -0.11 - 9.8 \times 10^{-4} p_p^t + 1.62 \times 10^{-6} \left(p_p^t\right)^2$$
$$f_{3pt}^{\mathrm{pr}} = 3.92 - 8 \times 10^{-3} p_p^t + 3.47 \times 10^{-6} \left(p_p^t\right)^2$$
$$f_{1rt}^{\mathrm{pr}} = -0.18 + 3.3 \times 10^{-3} p_r^t - 4.4 \times 10^{-6} \left(p_r^t\right)^2$$
$$f_{2rt}^{\mathrm{pr}} = 2.42 - 4.8 \times 10^{-3} p_r^t + 1.98 \times 10^{-6} \left(p_r^t\right)^2$$

where f_{mpt}^{pr} is the utility function of price for the pth new product in segment m at time t and m is equal to 1, 2, and 3. f_{nrt}^{price} is the utility function of price for the rth remanufactured product in segment n at time t and n is equal to 1 and 2.

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