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Inventory management in a closed-loop supply chain with advance demand information

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ABSTRACT

We study inventory control for rental operations in a closed-loop supply chain. In such a system (e.g., Netflix), customers create online queues in a service provider's website to indicate the items that they would like to rent. Leveraging this advance demand information, we propose effective forecast models and formulate a multi-item inventory control problem. We prove that the (L, U) policy is optimal in our multi-item setting. We also consider an aggregate service level constraint across all items and propose heuristics.

1. Introduction

Closed-loop supply chains create additional value from the reuse of products through leasing (rentals), recycling, or remanufacturing. As of 2011, remanufacturing alone have generated more than $43B as revenue in the closed-loop supply chains in the US, supporting 180,000 full-time jobs [13]. Effectively managing closed-loop supply chains requires a set of non-trivial decisions at strategic (e.g., leasing versus selling), tactical (e.g., acquisition of used products), and operational (e.g., scheduling deliveries) levels [12]. In this paper, we study an operational problem, i.e., inventory management of a firm that rents out a set of non-identical products to its customers in a closed-loop supply chain. What is unique in our setting is the availability of advance demand information as we next explain through an example.

Consider the example of online DVD rental services (e.g., Netflix), which allow subscribers to rent movies or video games online and receive/return the DVD discs by mail. The service starts when a customer creates an online rental queue on the service provider's website. The customer can keep an item for as long as desired, but there is a limit on the number of items that can be checked out at any time. To rent a new item, the customer mails a currently checked out item back to the service provider, and upon the receipt of the item, the service provider sends out the next item according to the customer's online queue. Thus, by forecasting when a customer will return a currently checked out item, the service provider can immediately infer the following: (1) when a new demand for the customer will occur, (2) what the new demand will be from the customer's online queue, and (3) when the inventory of the returned item will increase by one unit. Clearly, the online queue serves as the link between the return and demand processes, and, moreover, it provides valuable future demand information.

In this paper, we leverage this advance demand information and ask the following questions. What is the optimal inventory management policy considering the link between the return and demand processes? How can practical considerations, such as an aggregate service level requirement across all items, be incorporated into the inventory management policy? Finally, what is the value of the advance demand information provided by a customer through his or her online queue? This rich information structure allows us to devise innovative forecast methods that are different from those proposed for brick-and-mortar rental firms (e.g., [1]). Furthermore, we focus on the *in-circulation* items which, for example, correspond to the DVDs with stable demand after the new release rental peak. Thus, our paper complements recent studies on determining initial order quantity for newly released items (e.g., [2]).

To determine the optimal inventory control policy, we first model the return and demand processes in the closed-loop supply chain. Then, building on these models, we formulate the inventory

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management problem as a multi-item, multi-period dynamic program with a finite planning horizon. The state variable is the currently held items of customers and their online queues. We find that a state-dependent (L, U) policy is optimal. That is, in each period, depending on the state, there exists two thresholds, L and U (with $L \le U$), for each item in the system. If the on-hand inventory for the item is smaller (greater, respectively) than L (U, respectively), it is optimal to bring the inventory level to L (U, respectively); if the on-hand inventory level is in between L and U, staying put is optimal. This result extends the optimality of the (L, U) policy from a single-item setting (e.g., [9]) to a multi-item setting. We further show that the problem is separable in items, so that computing the optimal policy reduces to solving multiple single-item problems.

In practice, an important consideration of a service provider is customer satisfaction, which is closely related to an aggregate service level (fill rate) across all items. To study this issue, we introduce an aggregate service level constraint into our model. This constraint complicates the problem considerably so that the separability result and thus the optimality of the (L, U) policy may no longer hold. To address this challenge, we consider a single-period multi-item problem instead, which is a simplification commonly employed in the literature (e.g., [5]). We observe that this formulation belongs to the class of classical knapsack problems, based on which we propose an inventory heuristic. Another challenge of the service constraint lies in its computation. In the literature, an approximate service level is considered (e.g., [6]), which may be too coarse in our setting. Thus, to tackle this challenge, we propose a three-step algorithm to exactly compute the service level (see [4]).

To examine the value of the advance demand information provided by the online customer queues, we conduct an extensive simulation study. We observe that our methods create cost savings of about 40% compared to a base case scenario. This suggests that our methods can potentially benefit other Netflix-like online rental businesses, such as Rent the Runway.

In the closed-loop supply chain management literature, several papers incorporated remanufacturing and product returns into classical inventory control problems in, for example, multi-echelon (e.g., [7]) and assembly (e.g., [8]) systems. In addition, inventory management for spare parts has received significant attention. Our problem differs from these problems in three dimensions. First, we consider a subscription-based rental service—it does not require remanufacturing operations, and, more importantly, the return and demand events from a subscriber are closely linked through the customer's online queue. Second, by leveraging this unique online queue information we build a dynamic forecast model that links the item-level return and demand processes, while simple static demand models, such as (compound) Bernoulli or (compound) Poisson, are typically used in the spare parts inventory problems (e.g., [5]). Finally, we propose a solution approach based on a dynamic program, which has not been well studied in the spare parts literature.

2. Main model and results

We consider the daily operations of a typical closed-loop rental supply chain, as exemplified by an online DVD rental system illustrated in Fig. 1. The supply chain consists of multiple regional shipping centers (RSCs) and a central warehouse (CWH). The RSCs fulfill demand from customers located within a geographical region, while the CWH fulfills orders from the RSCs and restocks excess inventory sent back from the RSCs.

Each RSC in the supply chain faces an identical inventory management problem with different parameters. Hence, the inventory problem of the entire supply chain can be decoupled into multiple problems, one for each RSC. In this paper, we focus on a representative RSC which operates according to a daily-reviewed inventory system. We assume that replenishment orders placed by the RSC in a day arrive from the CWH the next day morning via overnight shipping. Thus, the inventory replenishment lead time is effectively zero. Besides ordering inventory from the CWH, the RSC can also send excess inventory to the CWH via overnight shipping, so that the CWH can use them to replenish other RSCs at a later time.

The sequence of the item receiving and shipping events at the RSC can be described as follows: (1) items ordered from the CWH on the previous day are received, (2) items returned by customers are received and restocked at the RSC, (3) new rental demands from customer online queues are fulfilled with the on-hand inventory, (4) forecasts are generated for the next day customer returns and new demands, and (5) based on the updated forecasts, inventory decisions such as ordering or sending back extra copies to the CWH are determined for all items at the RSC. This five-step cycle repeats everyday.

Our main focus is on the inventory control of *in-circulation* items. For example, in an online DVD rental system, in-circulation items are the DVDs with stable demand following the peak demand of the new release period. For in-circulation items, there are usually surplus inventories in the system. Therefore, we shall assume that the CWH has ample inventory to fulfill orders from the RSCs. This is also a quite standard assumption in the inventory literature. For ease of exposition and without loss of generality, we shall also assume that each customer can rent at most *one* item at any given time. Finally, we note that if a new rental demand from a customer's online queue cannot be met by the RSC's on-hand inventory, the unmet demand is expedited directly from the CWH to the customer as depicted in Fig. 1. This top-choice fulfillment assumption enables us to develop a tractable demand forecast model as we explain below.

Formally, we assume that there are a total of I unique items in circulation and J customers that are served by the RSC. Let i ($i = 1, \dots, I$) denote the index of each item and j ($j = 1, \dots, J$) the index of each customer. Furthermore, $W(k, j)$ corresponds to the item in the kth position of customer j's online queue list, where $W(0, j)$ is the item currently held by customer j. Also, let p_{ij} represent the next-day return probability for item i from customer j. When customer j does not possess item i, i.e., when $i \neq W(0, j)$, we let $p_{ij} = 0$.

2.1. Item-level return and demand forecast models

2.1.1. Return forecast model

For a given item, the quantity of its returns on the next day can be calculated by considering all the possible returns from customers who possess that item. Formally, define X_{ij} as a Bernoulli random variable so that $X_{ij} = 1$ with probability p_{ij} and $X_{ij} = 0$ with probability $1 - p_{ij}$, where p_{ij} is the next-day return probability for item i from customer j. This probability can be estimated from the rental history of a customer. The total number of item i to be returned on the next day, denoted by R_i, can be written as

$$R_i = \sum_{j=1}^{J} X_{ij}. \tag{1}$$

2.1.2. Demand forecast model

Intuitively, the customer online queue provides future demand information to the service provider. We now study how to utilize this information to forecast the next-day demand for each item.

Consider customer j, who holds the item denoted by $W(0, j)$. If the item is returned, then it triggers a demand for the item $W(1, j)$,