Inventory Management for Items under Product Classification

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Abstract. This research studies inventory management problems under collaborative consumption. Collaborative consumption is widely referred to as sharing economy in recent years. In production or supply chain systems, collaborative consumption is achieved by common components in different product lines. While several products share the same components, factory managers can pool together demand uncertainty risks and reduce the need for excess inventory. However, collaborative consumption of items links inventory problems with multiple demand sources and makes the inventory problem difficult to solve.

This research uses dynamic programming to propose a flexible heuristic dynamic inventory management and capacity allocation method. The proposed model is able to approach simple and complex customers inventory and capacity allocation problem such that resource utilization is high, and resource idleness and overtime is reduced. It considers customer demand, cancellation, no-show, and service time uncertainties. We also construct a utility function to evaluate performance, which comprise of revenue, overtime cost and the potential loss on service quality. And the objective is to maximize the expected utility.

Keywords: dynamic programming, inventory management, sharing economy, time series

1. INTRODUCTION

This research studies inventory management problems under collaborative consumption. Collaborative consumption is widely referred to as sharing economy in recent years. In production or supply chain systems, collaborative consumption is achieved by common components in different product lines. While several products share the same components, factory managers can pool together demand uncertainty risks and reduce the need for excess inventory. However, collaborative consumption of items links inventory problems with multiple demand sources and makes the inventory problem difficult to solve.

In Figure 1., the concept of collaborative consumption of three items between three types of customers are shown. Some of the key components, such as *Item a*, are shared by multiple types of customers. In this example, the demand uncertainty risks of *Item a* are polled together between three demand sources.

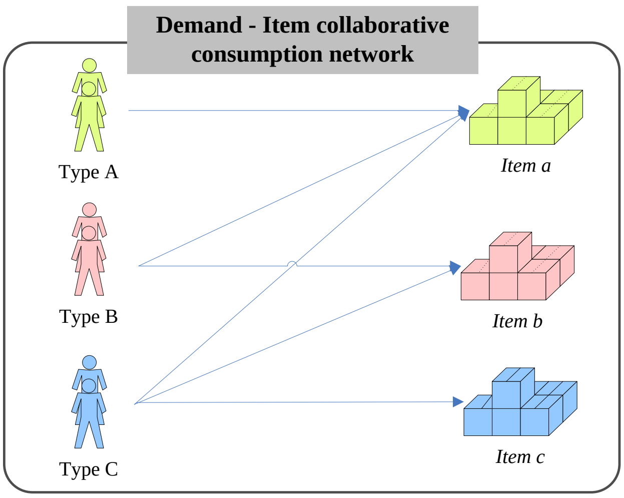

Figure 1. Collaborative Consumption of Items

2. LITERATURE REVIEW

This research uses dynamic programming to propose a flexible inventory management and capacity allocation method for items under collaborative consumption. The objective is to improve resource utilization and reduce resource idleness. The proposed model considers customer demand, cancellation, no-show, and service time uncertainties. We also construct a utility function to evaluate performance, which comprise of revenue, overtime cost and the potential loss on service quality.

Many researches combine the topic of capacity allocation and inventory management for items under collaborative consumption. Nevertheless, developed models change with the design of resource management and inventory management in every study. In the following, we summarize relevant research in literature in two different categories: single-resource capacity control and network capacity control.

2.1 Single-resource Inventory Control

Patrick et al. (2008) present a method to dynamically schedule patients with different priorities to a diagnostic facility. They model the scheduling process as a Markov decision process. Rather than maximizing revenue, the challenge facing the resource manager is to dynamically allocate available capacity to incoming demand to achieve wait-time targets in a cost-effective manner.

Kolisch and Sickinger (2008) consider two parallel CT-scanners providing medical service to three patient groups with different arrival patterns and cost-structures: scheduled outpatients, non-scheduled inpatients, and emergency patients. The problem is to allocate the available resources dynamically to the patients of the groups such that the expected total reward consisting of revenues, waiting costs, and penalty costs is maximized.

Ayvaz and Huh (2010) study the problem of dynamically allocating a fixed capacity of a single resource to demand arising from several patient types, elective surgery and emergency patients, who display different reactions to the delays in service. The elective surgery patients require a surgical operation that is not urgent and they are willing to wait in the system until the necessary resources become available for their treatment. By contrast, emergency patients arrive at the hospital in a critical condition, and they should either be admitted immediately; otherwise system will incur a rejecting cost. Since the optimal policy may be difficult to find, Ayvaz and Huh use dynamic programming to propose a simple threshold heuristic policy, in order to decide how much capacity to reserve for the emergency patients.

Liu et al. (2010) formulate the problem as Markov decision process. This paper proposes heuristic dynamic policy for scheduling patient appointments, taking into account the fact that patients may cancel or not show up for their appointments. And the results of the study clearly indicate that this booking policy has superior performance than other policies, especially when the patient load is high.

Ratcliffe et al. (2011) present a joint capacity control and overbooking model where a clinic maximizes profits by controlling bookings from two sequential patient classes with different no-show rates. They formulate the problem as a two stage dynamic programming model. In the first stage, we wish to determine the optimal booking number of urgent patients given that non urgent patients have already been booked. At the start of stage 2, the clinic must determine the optimal number of non urgent patients to book considering the urgent patients will be booked in the following period.

Schütz and Kolisch (2012) consider a problem where different classes of patients can book different types of service in advance and the service company has to respond immediately to the booking request confirming or rejecting it. The latter is only possible if there is enough free capacity. In this model, the service period of MRI scanner is broken down into a number of same length slots, and allowing examinations to use several contiguous slots. To reduce the negative impact of no-show patients, this study adopts double-booking in conjunction with fixed-interval rule.

2.2 Network Capacity and Inventory Control

Different from Single resource inventory model, inventory and capacity management becomes network type problems when multiple items are considered simultaneously.

Adan et al. (2002) classify patients into three types in accordance with the degree of urgency. The model they proposed considers the uncertainties of length of stay in hospital, and the resource consumption difference of beds, personnel and etc. Mix integer linear programming is used to solve for the surgery schedule such that resource utilization is high.

Gupta and Wang (2008) develop a Markov decision process model for the appointment-booking problem. In this model, resources are multiple doctors. Patients have different perceptions of choice in choosing the doctors, and the appointment can either be same-day or scheduled future. Hence, the clinic manager must balance the needs of those who book in advance and those who require a same-day appointment, in order to maximize revenue.

Through the previous reviews, most of the current publications focus on the problem of single-resource capacity control. On the other hand, analytical models which study multiple resources have seen little development. Nevertheless, patients nowadays need multiple resources treatment. Moreover, it is common that

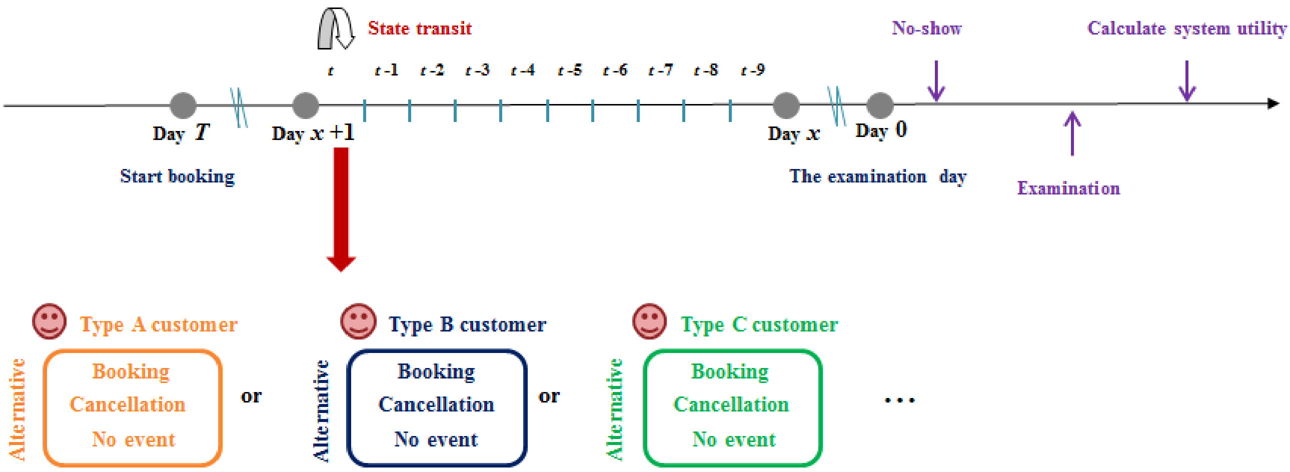

Figure 2. Planning Horizon

different types of patients share the same resource. Thus, our study presents a flexible heuristic dynamic inventory management and capacity allocation model for multi-resources and multi-demand types system. And we provide the inventory and capacity allocation policy at various states.

The rest of this paper is organized as follows. We begin in Section 3 with Problem Description. In Section 4 contains our numerical example and result. Then, in Section 5, we make a conclusion and suggestion for future research.

3. PROBLEM AND MODEL DESCRIPTION

While collaborative consumption exists, different demands share the same inventory items. Therefore, service level is restricted by the capacity and inventory of those items. In the following, we introduce a general dynamic programming model, which considers customer demand, cancellation, no-show, and service time uncertainties. Besides, there are some assumptions listed below, which are:

1. Demand, cancellation, and no-show are all discrete event.
2. Customer demand, cancellation, no-show, and service time are all uncertain, but with known probability distribution.
3. Customer demand, cancellation, no-show, and service time uncertainties are mutually independent.
4. To maintain the revenue of organization and avoid working overtime, utility function (revenue deduct overtime cost) is used to describe the system performance.
5. Single-block rule (Cayirli and Veral, 2003) is applied in this study, which assigns all customers to arrive as a block at the beginning of the clinic session.
6. The model we proposed is suitable for the environment that resources are limited and same day demand is not permitted.

This research considers both inventory allocation and optimal inventory level decisions for each decision epochs within the planning horizon. In this research, a dynamic programming model is proposed. Let T denote the length of planning horizon as shown in Figure 2. A dynamic programming model is constructed to solve the optimal inventory management problems within the finite planning horizon. The proposed dynamic programming algorithm utilizes backward induction as shown in Figure 2. In this study, the state variable of the dynamic programming model is the real time inventory level at the beginning of each day. The state variables y_t^k denotesthe total demand from type k customers at the end of period t, and γ_j^k is the demand of resource j with type k customer in certain day, which j∈{1,2,⋯,j}.

$$(Y_t^k;\gamma_1^k,\gamma_2^k,\ldots,\gamma_j^k),\ k\in\{1,2,\ldots,k\},\ t\in\{T,T\text{-}1,\ldots,1,0\} \quad (1)$$

The action variables are ordering decisions and inventory allocation decisions. In different states of each decision epochs, the binary variable a_t^k represents whether to accept the ordering with type k customer at time t. If a_t^k=1, accepted; a_t^k=0, do not accepted.

$$a_t^k\in\{0,1\},\ k\in\{1,2,\ldots,k\},\ t\in\{T,T\text{-}1,\ldots,1\} \quad (2)$$

Random demand arrivals makes initial inventory levels at the beginning of the next period uncertain. Between the two epochs, the related states of transition are shown as follows.

$$y_{t-1}^k=\begin{cases} y_t^k & \text{no event at time t} \\ y_t^k+1 & \text{accept a type k customer into system} \\ & \text{at time t} \\ y_t^k-1 & \text{type k customer cancell a order at time t}\end{cases} \quad (3)$$

The whole problem is modelled by a standard optimality equation of stochastic dynamic programming. The objective of the optimality equation is to maximize expected service level (order fulfillment rate) and to minimize expected inventory costs over a finite planning horizon T.

$$U_t(y_t^1, y_t^2, \ldots, y_t^K) = \underset{\gamma_j^k}{Max}\left\{\sum_{k=1}^{K} V_t\left(y_t^k; \gamma_1^k, \gamma_2^k, \ldots, \gamma_J^k\right)\right\} \quad (4)$$

$$\sum_{k=1}^{K} \gamma_j^k = H_j$$

$$\gamma_j^k \in Z_0^+$$

$$k \in \{1, 2, \ldots, K\}$$

$$j \in \{1, 2, \ldots, J\}$$

$$t \in \{T, T-1, \ldots, 0\}$$

4. CASE STUDY

To illustrate the robustness of the proposed model under collaborative consumption of resources, numerical results of our simulation study are presented in this section. In this example, we consider three items that are collaboratively consumed by demands from three different sources as shown in Figure 1. The arrival processes are assumed to follow Poisson processes with different arrival rates.

The proposed dynamic inventory management and capacity allocation method (DC) is compared to optimal inventory policy of dynamic programming method (OP). This comparison is for the validation of model feasibility. Furthermore, to verify the robustness of DC method, fixed capacity allocation and inventory (FC) method, and constant upper-limit inventory (Con) method is also compared in our numerical example.

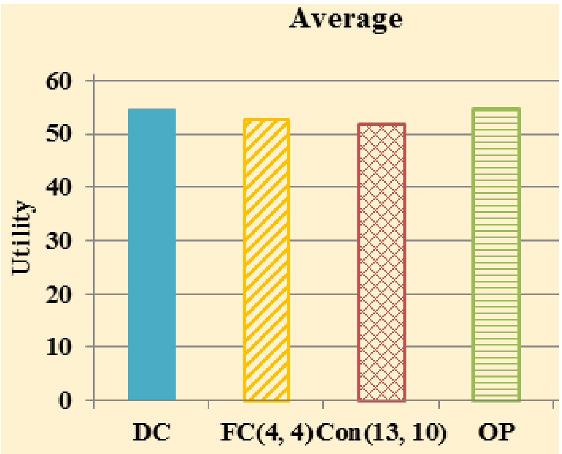

Figure 3. Expected Utility of 4 Inventory Method

The expected overall utility under different inventory control policies are shown in Figure 3. In Figure 3, there is only little difference between expected utility of DC method and OP method. Besides, the resource utilization and the number of booked customers of DC method and OP method are similar. FC will not change according to the number of booked customers. Therefore, its expected utility is lower than DC method.

In conclusion, while DC is computationally efficient, DC method has the near optimal expected utility to OP method and better performance than FC method and Con method.

5. CONCLUSION

This research presents a dynamic inventory management and capacity allocation (DC) method, which is based on dynamic programming. Our DC method can deal with simple and complex inventory and capacity allocation problems. The inventory policy for every state at all the decision times takes customer demand, cancellation, no-show, and service time uncertainties into consideration. And this policy is easy to introduce to inventory system in practice.

The DC method introduced in this paper could be an initial step toward future research. Each type of customer can further be classified into several tiers in accordance with the customer behavior, such as age, social status, physical health, etc. These factors may affect the demand, cancellation, no-show rate, and the examination duration of customers. Including these factors into the model, the policy we get will be more effective to the system performance.

5. ACKNOWLEDGEMENT

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