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Robustness of inventory replenishment and customer selection policies for the dynamic and stochastic inventory-routing problem

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ABSTRACT

When inventory management, distribution and routing decisions are determined simultaneously, implementing a vendor-managed inventory strategy, a difficult combinatorial optimization problem must be solved to determine which customers to visit, how much to replenish, and how to route the vehicles around them. This is known as the inventory-routing problem. We analyze a distribution system with one depot, one vehicle and many customers under the most commonly used inventory policy, namely the (s,S), for different values of s. In this paper we propose three different customer selection methods: big orders first, lowest storage first, and equal quantity discount. Each of these policies will select a different subset of customers to be replenished in each period. The selected customers must then be visited by a vehicle in order to deliver a commodity to satisfy the customers' demands. The system was analyzed using public benchmark instances of different sizes regarding the number of customers involved. We compare the quality and the robustness of our algorithms and detailed computational experiments show that our methods can significantly improve upon existing solutions from the literature.

1. Introduction

Supply chain performance, coordination and integration are some key success factors in obtaining competitive advantages [17]. Inventory and distribution management are two main activities towards that integration, and are said to account for more than 60% of the total logistics costs [12]. The integration of inventory and distribution decisions gives rise to the inventory-routing problem (IRP), which has been studied for the past few decades and has received much attention lately [9]. However, most of these studies focus on optimizing a problem for which all information is known a priori, which is often not the case in practice.

The demand information in an IRP can be static when customers demand is known before the planning, or dynamic, which means it is gradually revealed over time [5,10]. The dynamic and stochastic IRP (DSIRP) aims not at providing a static output, but rather a solution strategy that uses the revealed information, specifying which actions must be taken as time goes by [4]. Recently, Bertazzi et al. [5], Solyalı et al. [23] and Coelho et al. [10] have solved DSIRPs with the goal of minimizing the total inventory, distribution and shortage cost. They considered at least one of the classical inventory policies, i.e., maximum level or order-up-to-level (OU). They tested their algorithms on instances containing several customers and periods.

In what follows, we review some relevant papers that solve problems similar to the one addressed in this paper. Moin et al. [18] consider a deterministic scenario and develop a hybrid genetic algorithm for the multi-product multi-period IRP. The algorithm is designed to work in two steps: the first to pickup commodities from a supplier, and the second to plan visits and deliveries to the customers. Salhi et al. [21] solved a multi-depot IRP using a giant tour for each depot which was later improved by local search. This algorithm was compared to a truncated execution of CPLEX which provided bounds for the solution. Bertazzi et al. [5] have formulated the SIRP as a dynamic program and have solved it by means of a heuristic rollout algorithm, sampling unknown demands and solving a series of deterministic instances. Finally, Coelho et al. [10] proposed a rolling horizon algorithm to solve the DSIRP. Demand was forecasted based on historical data, an adaptive large neighborhood search algorithm selected customers for replenishments, and a network flow model was solved to

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determine optimal delivery quantities. These authors allowed the use of transshipments and direct deliveries to avoid stockouts after the realization of the demand. The setting of our problem description follows that of this paper.

The choice of which inventory policy to apply largely influences the cost of the optimized function. Typically, an inventory policy uses three key parameters: when replenish, how much to replenish, and how often the inventory level is reviewed. For the periodic review inventory system, Wensing [24] describes three policies. One is the OU which refers to a (t, S) system. Here, in each period t, the quantity delivered is that to fill the inventory capacity up to S. Other policies are the (t, s, S) and the (t, s, q). In the former, the customer is served if the inventory level is less than s. In the latter, the replenishment level q is flexible but bounded by the storage capacity. The policies should be articulated with strategies for clients selection, because sometimes it is not possible to serve all clients due to vehicle capacities, and in such cases, it is necessary to prioritize some of them.

Several other exact and metaheuristic methods have been used to find feasible solutions for this problem and its variants. Simic and Simic [22] argue that for complex optimization problems such as the IRP, hybrid methods with techniques such as artificial neural networks, genetic algorithms, tabu search, simulated annealing and evolutionary algorithms can be successfully applied. Some of the techniques used to solve IRPs are summarized next. Genetic algorithms have been employed by Christiansen et al. [6] and Liu and Lee [15], who clustered customers in geographical areas to serve them together. Local search operators were explored by Javid and Azad [13] and Qin et al. [19], who changed the delivery schedule for customers and adjusted the quantities delivered accordingly. Li et al. [14], Liu and Lin [16] and Sajjadi and Cheraghi [20] used simulated annealing to integrate location decisions into the IRP. Adaptive large neighborhood search [8] and a hybrid of mathematical programming and local search [3] have also been used. Finally, exact methods relying on branch-and-cut [2,7] and branch-cut-and-price [11] have also been developed.

In this paper we study a DSIRP in which decisions must be made without future information about the demand, which is gradually revealed over time. In this situation, we developed adaptive policies in order to select customers to be replenished in each period. We propose a new three-step solution algorithm, which is flexible enough to consider several different inventory replenishment policies. We are then able to evaluate and compare the performance of our policies on demand satisfaction, average inventory kept at the customers' site, transportation cost, and total cost. Moreover, we show the effect of integrating tactical and operational decisions into the same solution algorithm. We compare the performance of our algorithm on benchmark instances available in the literature, and our results show that the right combination of inventory replenishment policies and customer selection can yield significant savings over the best-known solutions from a competing algorithm.

The remainder of this paper is organized as follows. In Section 2 we formally describe the problem. In Section 3 we present our solution procedure which includes customer selection, quantities determination, and vehicle routing. In Section 4, we present the results of extensive computational experiments and we analyze the trade-off between inventory and transportation costs. We describe how we can identify dominated solutions under a multi-objective optimization approach, and we compare our solutions against the ones from the literature. In Section 5 we present our findings and conclusions.

2. Problem description

The IRP under study consists of one supplier and several retailers as depicted in Fig. 1. We assume that the supplier has enough inventory to satisfy the demand of its customers. Customers demand is gradually revealed over time, thus it is said to be dynamic and unknown to the decision maker at the time all decisions are made. The problem is defined over several periods, typically days, and without loss of generality we assume that the demand becomes known at the end of the period. This demand can encompass a set of products organized in a pallet, and we will then treat a single commodity as it is done in other IRPs. The supplier has a single capacitated vehicle to distribute the products and to satisfy the final demand of the customers.

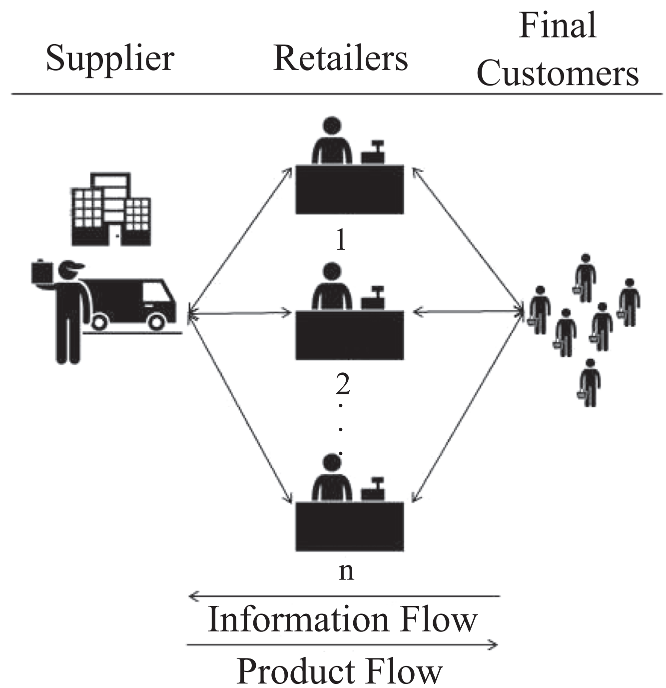

Fig. 1. A typical IRP instance with one supplier, n retailers, and a set of final customers representing the demand of the retailers.

The IRP is defined on a graph $\mathcal{G} = (\mathcal{V}, \mathcal{A})$, where $\mathcal{V} = \{0, \ldots, n\}$ is the vertex set and $\mathcal{A} = \{(i, j): i, j \in \mathcal{V}, i \neq j\}$ is the arc set. Vertex 0 represents the supplier and the remainder vertices of $\mathcal{V}'$ represent n retailers. The problem is defined over a finite time horizon $\mathcal{H} = \{1, \ldots, p\}$.

The costs incurred is the total of inventory and transportation costs. Inventory costs include the inventory holding and shortage penalties. A transportation cost is paid for each arc traversed by the vehicle. The transportation cost is based on a symmetric distance matrix.

Let n represent the number of customers, each with an initial inventory I_i^0, and let the demand of customer i in period t be d_i^t. Each customer has a maximum inventory capacity C_i, and incurs a unit holding cost h_i per period. Shortages are penalized with z per unit per period.

A single vehicle with capacity Q is available at the depot. The depot has an initial inventory I_0^0, and inventories incur a unit holding cost h_0. A symmetric transportation cost c_{ij} is known. We denote by I_0^t the inventory level at the depot in period t, I_i^t the inventory level at customer i at the end of period t, and l_i^t its lost demand. Let q_i^t be the quantity of products delivered to customer i in period t. At the end of each period t, the inventory level I_i^t for each customer i is updated based on its demand d_i^t, its lost sales l_i^t, the inventory level at previous period I_i^{t-1}, and the quantity q_i^t delivered to it.

A solution to the problem determines the periods in which