고객의 서비스 수준을 고려한 차량경로문제의 발견적 해법

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A Heuristic Algorithm for Vehicle Routing Problem with Customer's Service Level

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요 약

본 연구는 지리학적으로 산재해 있는 다양한 수요지점을 서비스할 수 있는 차량경로모델을 개발한다. 즉 다양한 수요지점을 구역으로 분할하여 각 수요지점의 수요량과 서비스 레벨을 고려하여 최적차량 운송계획 모형을 개발하는 데 있다. 본 연구 방법에서 사용된 접근 방법으로 먼저 단일 출발점에서 각 수요지점의 수요조건을 만족하는 범위 내에서 최소의 운반 거리 및 수요 조건을 만족하도록 각 서비스 지역을 할당하는 Clustering Algorithm을 개발하여 단일 구역별 최적의 이동 경로를 개발하였다. 그리고 각 수요지점별 수요량의 평균과 표준편차를 고려하여 새로운 Saving Algorithm을 기반으로 하여 운송 가능한 차량별 수요지점을 할당하였다.

또한 각 차량경로 구역별 서비스 레벨을 고려한 개선된 알고리즘을 사용하여 차량경로 문제의 근본적인 목적인 이동 거리(비용, 시간)의 최소화와 고객서비스 극대화를 동시에 달성하기 위한 최적 차량 운송 계획 모델을 개발하였다. 마지막으로 수치적 예제를 통해 본 연구에서 사용된 모델들과 기존 모델들과의 비교를 수행하였다.

1. Introduction

The vehicle routing problem (VRP) is the problem of designing optimal deliver or collection routes from one or several depots to a number of geographically scattered customers. The VRP and all its variations play a central role in the fields of physical distribution and logistics. In the Vehicle Routing Problem, a set of customers require some kind of service, which is offered by a fleet of vehicles. The goal is to find routes for the vehicles, each starting from a given depot to which they must return, such that every customer is visited exactly once. Usually there is also an objective that needs to be optimized, e.g. minimizing the travel cost or the number of vehicles needed (Gendreau, Laporte & Seguin 1996).

The most important characteristics of the vehicle routing problem under stochastic demand is that it is no longer possible to assume that routes can be followed as planned. Due to the uncertainty of demands, a route failure may occur at some point along the route where the vehicle load has been exhausted before all customer demands are met. In that case, some resources or corrective action has to be taken. There are various recourse strategies that can be used depending on the company's routing policy and the amount of available information on customer demands.

2. The Stochastic Vehicle Routing Problem

The first needs for solving practical transportation problems were satisfied with deterministic parameters like cost, customer demands or vehicle travel times. The dispatcher has to choose between different strategies of restocking. In the case when the new unexpected demand is greater then the capacity left on the vehicle the route should be broken and the vehicle directly returned to the depot. Because of these stochastic parameters new class of VRP problem was defined the stochastic vehicle routing Problem (SVRP) denotes that at least one of vehicle routing problem parameters is stochastic. If the set of customers visited in time is stochastic we have VRP with stochastic customers (VRPSC). VRP with stochastic travel times (VRPSTT) means that travel time is not deterministic. VRP with stochastic demands (VRPSD) means that each or some of customers have stochastic demands.

The VRPSD is defined on a complete graph G = (V, A, D), where $V = \{ v_0, v_1, \ldots, v_n \}$ is a set of nodes (customers) with node v_0 denoting the depot, $A = \{ (v_i, v_j) : i,j \in \{0, \ldots, n\}, v_i, v_j \in V, v_i \neq v_j \}$ is the set of arcs joining the nodes, and $D = \{d_{ij} : v_i, v_j \in V, v_i \neq v_j\}$ are the travel costs (distances) between nodes. One vehicle with capacity Q has to deliver goods to the customers according to their demands. The objective is to minimize the total expected distance traveled with satisfying the following assumptions.

Customers' demands are stochastic variables ξ_i, $i = 1, \ldots, n$ independently distributed with known distributions. The actual demand of each customer is only known when the vehicle arrives at the customer location. It is also assumed that ξ_i does not exceed the vehicle's capacity Q, and follows a discrete probability distribution $p_{ik}=Prob(\xi_i = k)$, $k = 0, 1, 2, \ldots , K \leq Q$. A feasible solution to the VRPSD is a permutation of the customers $V = \{ v_0, v_1, \ldots, v_n \}$ starting at the depot (that is v_0), and it is called a priori tour. The vehicle visits the customers in the order given by the a priori tour, and has to choose, according to the actual customer's demand, whether to proceed to the next customer or to go to depot for restocking.

A stochastic vehicle routing problem arises when some of the elements of the problem are stochastic. This could be relevant for many of the components that may be included in a standard VRP, for instance travel times, demands. Stochastic vehicle routing problems are usually formulated as two-stage stochastic programming problems. Then probabilistic information is used to construct an a priori plan, and recourse actions are defined to handle the situations that occur when the random variables are realized (Hvattum, Lokketangen & Laporte, 2003). In this problem customer demands are random and usually (but not always) independent.

Laporte, Louveaux and Mercure (1989) proposed a two-index chance constrained model for the VRPSC as well as an associated branch-and-cut algorithm capable of solving instances involving up to 30 vertices. They also introduced a bounded penalty model in which the cost of recourse associated with a given route cannot exceed a preset proportion of the first stage route cost. The best exact solution approach for the VRPSD is again the integer L-shaped algorithm. Séguin (1994) and Gendreau, Laporte and Séguin (1995) proposed the first implementation of this method for the solution of the VRPSD and were able to solve instances of up to 70 vertices. Laporte, Louveaux and Vanhamme (2002) imposed an additional restriction, namely that the expected demand of a route does not exceed the vehicle capacity, and they also exploited properties of the demand under known distributions (Poisson and normal) in the generation of lower bounding functionals on the cost of recourse.

3. Problem Description and Solution

This paper deals with a variation where customers' demands are uncertain and are assumed to follow given discrete probability distributions. This situation arises in practice whenever a distribution company faces the problem of deliveries to a set of customers, whose demands are uncertain. This paper focuses on deliveries, but all the discussion carries through in case of collections especially. The problem of finding a tour through the customers that minimizes expected distance traveled is known as the vehicle routing problem with stochastic demands.

I described a class of vehicle routing problems under demand uncertainty as follows: Let the set of nodes of a given complete network be (*0, 1, 2, ..., m*). Node 0 denotes the depot and each number (*1, 2, ..., m*) represents the set of customers' locations. Distances $d(x, y)$ between nodes are assumed to be known. Q denotes vehicle capacity. The multi-vehicle is assumed. This is equivalent to assuming that a set of customers has been assigned to receive service by a given vehicle. Let ξ_i ($i = 1, 2, \ldots m$) be the random variable that describes the demand of customer i. The probability distribution of ξ_i is discrete and known, and is denoted by $p_{ik}=Prob(\xi_i = k)$, $k = 0, 1, \ldots K = Q$. Customers' demands are assumed to be stochastically independent, and their realizations become known upon the first arrival of the vehicle at each customer location. The vehicle is initially located at the depot. During service, when capacity is reached or exceeded, a return trip to the depot is performed in order to restore capacity up to Q. When all demands have been satisfied, the vehicle returns to the depot. The problem is to find a set of a priori routes, each to be served by a vehicle, such that customer demands on the route are fully satisfied and the total expected cost (distance) is minimized. Actual demand is revealed only upon visiting the customer. If there is a route failure at any node, the resource action is for the truck to travel back to depot for restocking and then to resume its journey as planned at the point where failure occurred. To reduce the likelihood of route failure, upon a service completion at a node, the vehicle can choose to (1) go directly to the next node and risk a shortage along the route, or (2) go back to the depot, restock to a full truck load, and then continue the journey with a cost for the restocking trip. (Yang, Mathur & Ballou, 2000)

Steps of solution are as follows:

❑ Step 1 (Seed selection)

: Choose seed points j_k in V to initialize each cluster k, based on the Pareto law.

❑ Step 2 (Allocation of customers to seeds)

: Compute the traveling cost (distance) d_{ik} of allocating each customer i to each cluster k as

$$d_{ij_k} = \min\{c_{0i} + c_{ij_k} + c_{j_k 0}, c_{0 j_k} + c_{j_k i} + c_{i0}\} - (c_{j_k 0} + c_{0 j_k}) \ .$$

The truck is loaded with full capacity and starting from the depot, it goes to each customer (node) i. And then first route sequence is determined.

❑ Step 3 (Route Construction)

: Demand of customer (node) i is satisfied. After that, if remaining amount on the truck is greater than full capacity at node i, the truck goes directly to the next customer of route sequence. If remaining amount on the truck is less than full capacity at node i, the truck goes back to the depot for preventive restocking and then continues the trip with a full capacity. And compute the service level of each cluster k.

❑ Step 4 (Route Optimization)

: If the demand of node i is greater than remaining amount on the truck, this is the situation of route failure. A mandatory restocking trip going to the depot and back to node i is then conducted. After satisfying all of the demand at node i, the truck return to the depot with remaining load.

are initially formed by rotating a ray centered at the depot. The number of vehicle route m is fixed a priori, proposing a geometric method based on the partition of the plane into m cones according to the customer weights. The seed points are dummy customer located along the rays bisecting the cones. Once the clusters have been determined, the TSPs are solved optimally using a constraint relaxation based approach. Vehicle routes are then constructed by inserting at each step the customer assigned to that route seed having the least insertion cost. For this problem, the optimal a first route sequence is 6→8→7→5→4→3→2, second route is 10→9→11→14→13→12 and third route is 21→16→15→18→17→19→20 with the optimal restocking policy of returning to the depot if the remaining amount on the truck after serving customer i is less than truck capacity.

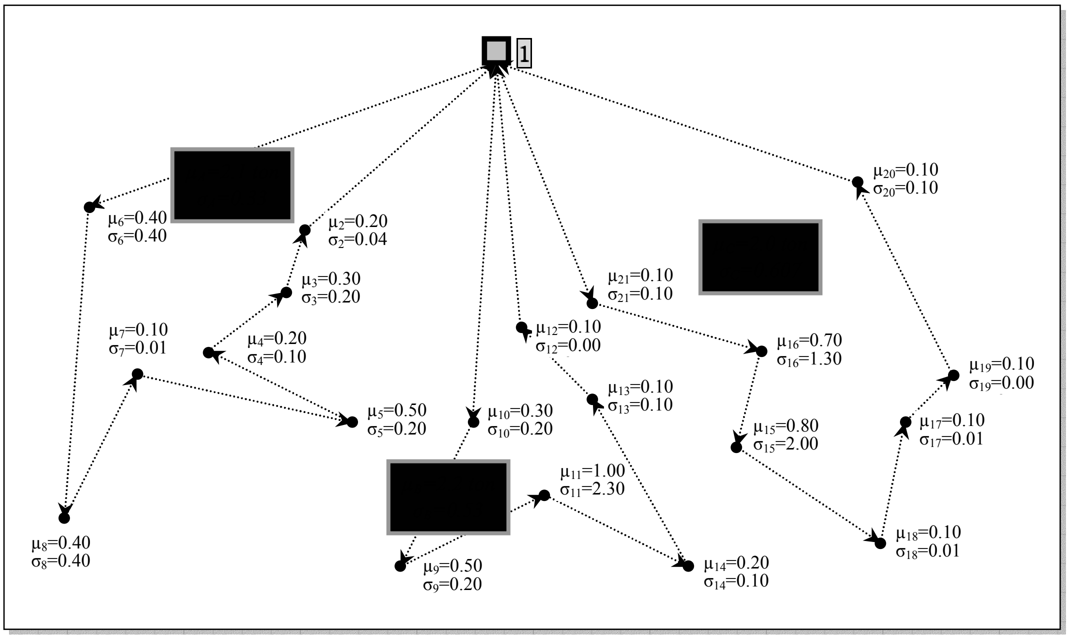

Figure 1. Step 3 : Route construction by corresponding TSP

Starting from the top of the demands list, based on the Pareto law for choosing seed points in the number of vehicle route m to initialize each cluster, feasible clusters

The algorithms described in the preceding section have been applied to several problems with stochastic demands. These problems are extension of the 21-

customers. The problems were constructed by adding a customer demand standard deviation at each delivery (or pickup) location. The customer demand quantity is used as the mean demand at each location. The standard deviations in customer demand were generated using a variation of demands.

Table 1. The computational result after first route construction

After Optimization	Route A	Route B	Route C
traveling course	6→8→ 7→5→ 4→3→ 2	10→9→ 11→14→ 13→12	21→16→ 15→18→ 17→19→ 20
total distance traveled	2,590 m	2,617 m	2,480 m
total customer demand	2.1 ton	2.2 ton	2.0 m
average demand standard deviation	0.33	0.53	0.607
customer service level	88 %	71 %	79 %

optimization considering customer service level, the route starts with same initial depot, but the route sequencing is different Figure 1. The re-optimization route calls for a new sequence of Route A (12→11→10→4→3→2), Route B (9→13→14→15→18→17→19→20), and Route C (6→7→8→5→16→21). With the new route sequence, no more route failure occurs at each route.

Table 2. The computational optimal after the resequencing

After Optimization	Route A	Route B	Route C
traveling course	12→11→ 10→4→ 3→2	9→13→ 14→15→ 18→17→ 19→20	6→7→ 8→5→ 16→21
total customer demand	2.1 ton	2.1 ton	2.1 ton
average demand standard deviation	0.54	0.52	0.52

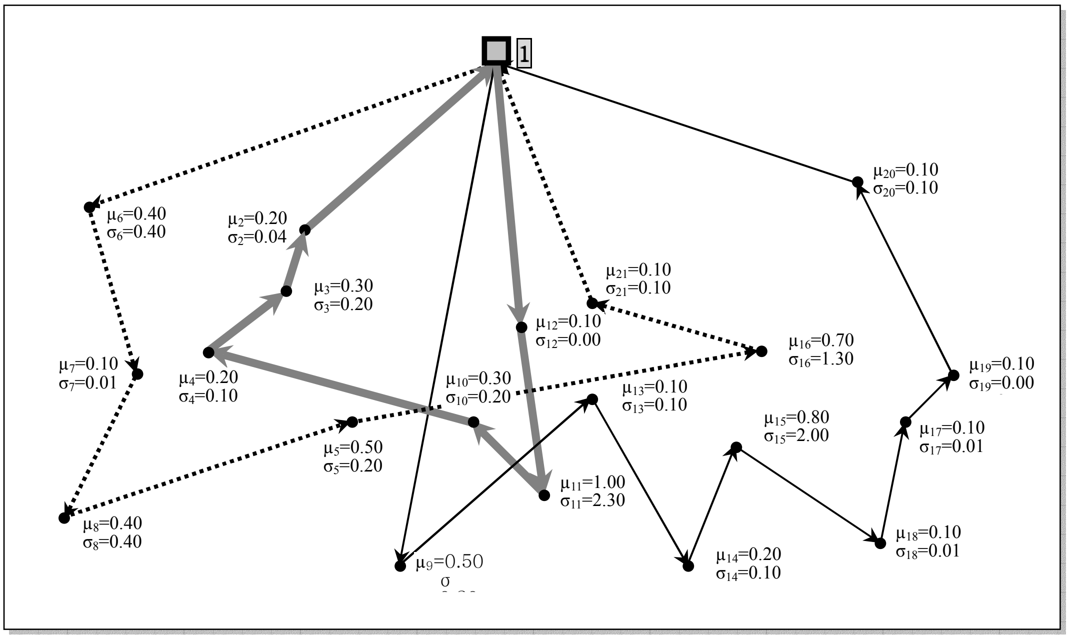

Figure 2. Step 3 : Route Optimization considering each customer service level

In each of the problems tested, the demands are assumed to be independent of each other and normally distributed. From considering of customer demand standard deviation, the new route sequencing is revealed. With re-

The total distance traveled is 7,891 m. The path followed by the vehicle with this re-optimization is shown on Figure 2. Table 2 tabulates the execution of the policy after the resequencing.

5. Findings and Conclusion

The standard VRP model usually needs to be extended in order to solve real world vehicle routing problems. This work has studied a unique approach to the SVRPs. Instead of adopting a simple recourse action usually suggested in the literature, optimal restocking policy of the vehicle has been incorporated in the route design considering customer service level. That is the restocking points are deliberately planned along the route, such that probability of the route failure and the accompanying recourse cost (including any possible penalty) is reduced and the total customer service level of the routes is enhanced. On the algorithmic side, Customer service level has probably come to concentrate on the development of faster, simpler (with fewer parameters) and more robust algorithms, even if this causes a small loss in solution quality.

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