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An ant colony algorithm for the multi-compartment vehicle routing problem

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ABSTRACT

We demonstrate the use of Ant Colony System (ACS) to solve the capacitated vehicle routing problem associated with collection of recycling waste from households, treated as nodes in a spatial network. For networks where the nodes are concentrated in separate clusters, the use of *k*-means clustering can greatly improve the efficiency of the solution. The ACS algorithm is extended to model the use of multi-compartment vehicles with kerbside sorting of waste into separate compartments for glass, paper, etc. The algorithm produces high-quality solutions for two-compartment test problems.

1. Introduction

1.1. Vehicle routing problems

Vehicle routing problems (VRPs) are an extension of the classic travelling salesman problem (TSP), in which one or more vehicles travel around a network, leaving from and returning to a depot node. Customers are located on the network and each customer must be visited by exactly one vehicle. Customers are usually located at network nodes (although in arc routing problems they are distributed along arcs of the network). The object is to find the vehicle routing(s) of minimum cost, e.g. to minimise the total route length.

An important type of VRP for practical application is the capacitated vehicle routing problem (CVRP). In this, there is a demand associated with each customer, representing an amount of goods which must be collected (or delivered). Each vehicle has a capacity which cannot be exceeded, and when the vehicle is full (or empty) it returns to the depot. There are many variants of CVRP with additional constraints, for example CVRPTW in which each customer may have a time window during which a visit must be scheduled. A survey of such variants is given in [1]. The study of CVRPs has become of increasing practical importance as distribution networks become more complex, and with the growth of online shopping, leading to a recent resurgence of research interest [2].

1.2. Waste collection

In this paper we consider a basic CVRP applied to the collection of domestic waste for recycling. Waste collection is becoming an increasingly complicated task for municipal authorities, and growing environmental concerns are gradually changing the orientation of solid waste management. In the UK, recyclable waste generated by households is organised by local authorities (LAs, for example District Councils), either with their own vehicles or contracted to private companies. Each LA decides on the nature and level of service it will provide, taking into account social and economic factors under the headings of collection, transportation and disposal [3,4]. Reports have shown that logistics costs represent up to 95% of the total cost of recycling [5], so the importance of devising the most cost-efficient routes using the minimum number of vehicles is crucial. A new factor motivating research in this area is the imposition of large fines for missing government-set recycling targets.

1.3. Multi-compartment vehicles

Once a waste collection vehicle is full to capacity, it must move to a waste disposal site (commonly referred to as a tip) to unload. Frequently the tip is at the same location as the vehicle depot, but it may be located at a different node in the network. At the tip, the waste is sorted into its constituent types (paper, glass, etc.) which are disposed of or recycled in different processes.

A recent development is the introduction of multi-compartment stillage trucks for domestic waste collection. These vehicles typically have four separate compartments, so that glass can be stored

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separately from paper, for example. The vehicle crew must perform kerbside sorting of the waste in customers' recycling boxes, and this slows up the collection process. This disadvantage is hopefully outweighed by the improvement in quantity and quality of the recyclable material produced. The pros and cons of kerbside sorting as against commingled collection in single-compartment vehicles, are discussed in [5–7].

2. Previous work

2.1. Solving the CVRP

Standard OR techniques of dynamic programming, or branch and cut, can be used to produce exact solutions for only small CVRP problems; as of 2007, the largest problem to be solved exactly had 135 nodes [8]. Starting with the algorithm of Clarke and Wright in 1964, several heuristics have been proposed, which construct tours and/or improve existing tours [9]. In particular we mention the improvement of a completed sub-tour (from the depot through some or all nodes and returning to the depot) by r-optimal methods [10]; the 2-opt algorithm tests whether a tour length can be shortened by crossing two of its non-adjacent arcs, i.e. by replacing arcs (a, b) and (c, d) by (a, c) and (b, d). Constructive heuristic methods are tailored for specific problems, which restricts their use in wider applications. This has led to the development of more versatile metaheuristics, which offer global search strategies for exploring the solution space. Metaheuristics which have been applied to the VRP include tabu search [11,12] and simulated annealing [13]. More recently, soft computing techniques have proved successful in solving CVRP instances. Thangiah [14] used genetic algorithms in conjunction with these two metaheuristics in 1999, and since 2003 several papers [15–20] have extended the use of genetic algorithms for the VRP, including with time windows. Khouadjia et al. [21] have used particle swarm optimisation and variable neighbourhood search for a dynamic VRP. Adaptive Large Neighbourhood Search [8] uses a variety of heuristic algorithms (chosen by roulette wheel selection) to destroy and then repair solutions, and has been shown to solve a range of VRP variants, including CVRP, CVRPTW and multi-depot CVRP.

Perhaps the most successful soft computing approach for the TSP and related problems such as job shop scheduling and quadratic assignment, is ant colony optimization (ACO). The details are given in the next section, but essentially the algorithm as applied to the VRP is as follows. At the start of each iteration, ants (autonomous agents) are placed at random nodes of the network, ready to construct tours; their initial tour length is the distance from the depot to their starting node. They maintain a tabu list to avoid returning to already-visited nodes, and decide their next move stochastically, with probabilities based on the amount of pheromone present on the possible arcs. Once all ants have completed their tours they return to the depot node. They then update the pheromone levels on the arcs they visited (local updating), and the levels on the arcs in the tour with the shortest total length are further increased (global updating). Over a large number of iterations, the pheromone levels encourage ants to use high-quality paths through the network, resulting in shorter-length tours being discovered. The original algorithm is known as Ant System (AS), and a later, more successful variant is called Ant Colony System (ACS); both are described in Dorigo and Stützle's book [22].

Mazzeo and Loiseau [23] used the ACS to solve some benchmark CVRP problems, and report good performance in comparison with some of the methods described above. Karadimas et al. [24,25] applied an ACO algorithm to the problem of urban solid waste collection, although they avoided the need to include capacity constraints in the ACO by first breaking the network into a set of sub-areas, each of which could be serviced by a single vehicle without unloading, an approach also followed in [26]. ACO was also applied to urban waste collection in [27], although they model the problem as a capacitated arc routing problem (CARP) extended to comply with traffic rules. They apply two versions of the ACO: the Ant System, and a populational AS in which only a subset of elite solutions update the pheromone trails. They highlight the benefits of integrating these methods with decision support systems to aid planners in their decisions. Rizzoli et al. [28] describe a commercial ACO package and its performance on a number of real-world freight distribution problems, including dynamic handling of orders. ACO algorithms for the VRP have been hybridized with scatter search [29], with genetic algorithms [32], and with savings algorithms and problem decomposition [30,31].

2.2. Solving the CVRP with multiple compartments

The multi-compartment VRP (MCVRP) was identified already in 1979 as a variant of VRP which had practical significance; Christofides et al. [9] give as examples a delivery vehicle which has refrigerated and non-refrigerated compartments for foodstuffs, and a tanker which distributes different types of petroleum products. The problem has not however attracted the attention of researchers until recently. There have been heuristic approaches to the petroleum distribution problem in [33,34], and the food distribution problem in [35], the latter using Lagrangean relaxation. In 2008 El Fallahi et al. [36] tackled a distribution problem in which a depot stocks m different products which must be delivered to customers by a fleet of identical vehicles, each with m compartments of limited capacities. Unlike in the multi-compartment waste collection problem, it is permitted for different vehicles to deliver different products to the same customer. The paper demonstrates a memetic algorithm (a genetic algorithm hybridised with a local search procedure) and a tabu search procedure for the MCVRP. Most recently, in 2010 Muyldermans and Pang [38] addressed the MCVRP applied to distribution. Their heuristic started by constructing the Clarke and Wright solution, and used 2-opt for improvement, coupled with guided local search. They used this algorithm to compare the costs of MC-collection against commingled collection.

3. The ACS algorithm

The two main phases of the ACO algorithm are the ants' route construction and the pheromone update. In the tour construction phase, M ants concurrently build tours beginning from starting nodes randomly chosen in the network of N customer nodes (plus the depot node). At each construction step, ant k currently at node i applies a probabilistic random proportional rule to decide which node to go to next. It selects the move to expand its tour by taking into account the following two values:

- The heuristic function η_{ij} which represents the attractiveness of the move, usually calculated as the inverse of the distance/cost on the arc from node i to node j.
- The level of pheromone on the arc (i, j), denoted τ_{ij}, which indicates how useful it has been in the past to traverse this particular arc.

Given these parameters, the probability with which the ant chooses to go to node n next is

$$p_{in}^k = \frac{(\tau_{in})^\alpha (\eta_{in})^\beta}{\sum_{l \in \mathcal{N}_i^k} (\tau_{il})^\alpha (\eta_{il})^\beta} \quad (1)$$

if node $n \in \mathcal{N}_i^k$, and $p_{in}^k = 0$ otherwise. Here, $\mathcal{N}_i^k$ is the feasible neighbourhood (i.e. the nodes which are directly accessible from node i