Discrete PSO for VRPTW with quality objective

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1 Introduction

Vehicle Routing Problems (VRPs), used for planning logistics distribution systems, are a well-known class of problems consisting in finding the best set of routes for the vehicles have to serve the demand of a set of geographically scattered customers [1]. The standard objective is to determine the feasible set of routes for the available vehicles which minimizes the total fleet operating cost, usually measured in terms of distance and time.

Here we consider a specific VRP with Time Windows (VRPTW) with the objective of minimizing the service times for customers as a measure of the quality of service provided. The VRPTW is a VRP in which each client fixes a time window where the service has to be completed [3]. In the real world applications, motivated by market requirements or the type of services provided, some companies consider reducing waiting time of customer a priority to increase the quality of service. Several VRP models can be found in the literature with similar purpose. The cumulative capacitated vehicle routing problem (CCVRP) minimizes the sum of arrival times at customers and it is mainly applied to emergency or disaster relief logistics [2, 4]. The Multiple Travelling Repairmen Problem (M-TVRP) minimizes the total time delay [5] and the Bus School Routing Problem minimizes the average time used by students in arriving to their school [6]. These problems do not consider time windows constraints and therefore, this is the first model with these constraints and a quality of service objective.

We use an adaptation of Particle Swarm Optimization (PSO) metaheuristic for discrete problems named Jumping Frog Optimization (JFO). PSO is a promising relatively recent metaheuristic introduced by James Kennedy and Russel Eberhat [7]. It is a evolutionary method inspired by the social behaviour of individuals within swarms in nature, like flocks of birds or banks of fish. The JFO approach proposed in [8, 9] is based on the particles point of view instead of the solutions or particle's position.

2 VRPTW with quality objective

A realistic requirement on service quality is that the vehicles must arrive to the n customers as soon as possible. We consider a VRPTW which explicitly includes this objective, that is, to arrive to each customer i as soon as possible within the corresponding time window $[e_i, l_i]$. This objective that measure the quality service is formulated in two ways, in addition to the cumulative objective, the sum of arrive or service times of vehicle k at customer i, s_{ik}. One objective minimizes the average proportion on the time windows that customers have to wait for service, and another one maximizes the total time that vehicles arrive before closing time window of each customers. Thus the cost function applied to the corresponding models are:

$$\min \sum \sum s_{ik} \tag{1}$$

$$\min \frac{1}{n} \sum \sum \frac{s_{ik} - e_i}{l_i - e_i} \tag{2}$$

$$\max \sum \sum (l_i - s_i^k) \tag{3}$$

3 Discrete PSO proposed

Several adaptations of PSO deal with discrete and multi-objective problems. The proposed JFO is similar to PSO, however we do not use the velocity concept but it keeps the notion of attraction of the leaders. The metaphor of JFO is that of a group of frogs looking around for food while jumping from lilypad to lilypad. This group of frogs competes for food by jumping to the best locations so that if a frog is well-placed, then other frogs tend to move towards it. The JFO approach uses an interesting scheme without the need of velocity to update the particles position. Instead, the position is updated using a follower-attractor system. When a particle want to jump to better positions, the particle uses the best positioned particles as references. For this particular case, a particle (a follower) that wants to move towards the a better positioned particle in the swarm (an attractor), it tries to be similar to the attractor, i.e. the follower will analyze the components of the attractors position to somehow copy them, and eventually jump to a new better position.

JFO considers a swarm S containing n particles ($S = 1, 2, \ldots, n$) whose positions x_i evolve in the solution space, jumping from one solution to another. The number of particles selected in the swarm is fixed. The position of a particle is encoded as a feasible solution to the problem. At each iteration, each particle has a random behaviour, or jumps to another solution in a manner guided by the effect of some attractors. JFO considers three attractors for the movement of each particle i: its own best position to date (b_i), the best position of its social neighbourhood (g_i), interpreted as the best position obtained within the social neighbourhood of the particle, and the best position to date obtained by all the particles, which is called the global best position (g^*). A jump approaching an attractor consists of changing the current solution by including some feature of the attractor. Each particle is further allowed to behave randomly and perform random jumps. A random jump consists of performing a random move on the position.

4 Experimental results

In the experiments the proposed JFO is evaluated using an current instance of a distribution company. The data provides the location of customers to be served in a day, exactly 72 customers with their respective time windows. The geographical location allowed us to obtain the matrices of distances and times. For the experimentation, the proposed JFO procedure used a swarm of 50 particles and neighbourhoods of 5 particles. We generate a initial swarm by constructing feasible solutions using GRASP metaheuristics. The results show behaviour of the JFO procedure for 70 iterations. The JFO metaheuristic was implemented using the following combination of probabilities for the four types of movements in each iteration: random 0.20, cognitive 0.20, social 0.30 and global 0.30. The experiment testes and compares the results of applying JFO procedure to the cumulative model and to the two models with new quality service objectives.

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