An Improved GA for solving multiple depot VRP

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Abstract. Multi-depot vehicle routing problem is a NP-hard combinatorial optimization problem. In this paper, we proposed an improved genetic algorithm (GA), which combined GA with fitness-scaling and local search. The experiments compared the proposed approach with standard GA, simulated annealing, Tabu search, and particle swarm optimization. The results showed that the proposed method was superior to GA, SA, TS, and PSO, w.r.t. solution accuracy.

Introduction

The Vehicle Routing Problem (VRP) is a whole class of problems that optimize the cost of product delivery by vehicles from depots to customers under certain constraints [1, 2]. In this study, we focus on the Multiple Depot VRP (MDVRP).

The VRP falls within the NP-hard problem. At present, there are two schools of methods. One is the integer programming based methods, which can obtain global optimal solutions with exponentially increasing computation time. Therefore, those methods are infeasible. The other is heuristics-based methods, approximate solutions are found fast enough and sufficiently accurate. Recent reports show that Genetic Algorithm (GA) [3], Simulated Annealing (SA) [4], Tabu search (TS) [5], Particle Swarm Optimization (PSO) [6] can be used to solve VRP. However, the performance of pure SA is not satisfactory [7], the performance of pure TS is generally neither satisfactory nor competitive [8-10]. The discrete version of PSO performs far behind the basic ant colony algorithm [11, 12].

In this paper, we proposed an improved GA (IGA) method that combines the advantages of the fitness-scaling mechanism and 2-opt local search movement. The paper aims at improving the solution accuracy.

Problem Definition

Suppose S represents the number of depots, and $\mathbb{D}$ the index set of depots index

$$\mathbb{D} = \{1, 2, ..., S\} \tag{1}$$

and suppose U is the number of customers, and $\mathbb{C}$ the index set of customers

$$\mathbb{C} = \{1, 2, ..., U\} \tag{2}$$

The node index set $\mathbb{V}$ is the combination of the sets of depots and customers

$$\mathbb{V} = \mathbb{C} \cup \mathbb{D} = \{1, 2, ..., S + U\} \tag{3}$$

where a node is either a depot or a customer.

Each depot stores and supplies various products. Suppose T denotes the total number of types of products, and $\mathbb{P}$ the product index set

$$\mathbb{P} = \{1, 2, ..., T\} \tag{4}$$

Suppose Q_i is the total number of vehicles stationed in depot i, we can define $\mathbb{F}_i$ the index set of vehicles stationed in depot i

$$\mathbb{F}_i = \{1, 2, ..., Q_i\} \tag{5}$$

The mathematical formula of MDVRP is written as

$$f = \sum_{i \in \mathbb{D}} \sum_{k \in \mathbb{F}_i} \sum_{m \in \mathbb{V}} \sum_{n \in \mathbb{V}} c_{mn} x_{ikmn} \tag{6}$$

where x_{ikmn} is a binary variable with 1 representing vehicle k serving depot i visits node n after node m, and 0 otherwise. c_{mn} is the distance between node m and node n. In addition, MDVRP is subject to following 6 criteria:

$$\sum_{k \in \mathbb{F}_i} \sum_{m \in \mathbb{C}} \left(d_{jm} \sum_{n \in \mathbb{V}} x_{ikmn} \right) \le s_{ij}, \forall i \in \mathbb{D}, \forall j \in \mathbb{P} \tag{C.1}$$

where d_{jm} is the demand of product j for node m, and s_{ij} is the supply of product j from depot i. The supply of each type of product from the depot should not be less than the corresponding demand from customers served by all vehicles in the same depot.

$$\sum_{j \in \mathbb{P}} \sum_{m \in \mathbb{C}} \left(d_{jm} v_j \sum_{n \in \mathbb{V}} x_{ikmn} \right) \le e_{ik}, \forall i \in \mathbb{D}, \forall k \in \mathbb{F}_i \tag{C.2}$$

where e_{ik} denotes the capacity of vehicle k serving depot i. The total volume of different products requested by customers served by the same vehicle should not be more than the capacity of the same vehicle.

$$\sum_{i \in \mathbb{D}} \sum_{k \in \mathbb{F}_i} \sum_{m \in \mathbb{V}} x_{ikmn} = 1, \forall n \in \mathbb{C} \tag{C.3}$$

which requires each customer should be served once and only one vehicle.

$$\sum_{n \in \mathbb{V}} x_{iknm} = \sum_{n \in \mathbb{V}} x_{ikmn}, \forall i \in \mathbb{D}, \forall k \in \mathbb{F}_i, \forall m \in \mathbb{V} \tag{C.4}$$

which requires that any vehicle entered a customer should leave from the same customer.

$$\sum_{m \in \mathbb{V}} \sum_{n \in \mathbb{V}} x_{ikmn} \le |\mathbb{E}_k| - 1, \forall \mathbb{E}_k \subseteq \mathbb{C}, |\mathbb{E}_k| \ge 2, \forall i \in \mathbb{D}, \forall k \in \mathbb{F}_i \tag{C.5}$$

where $\mathbb{E}_k$ denotes the set of customers visited by vehicle k.

$$x_{ikmn} \in \{0,1\}, \forall i \in \mathbb{D}, \forall k \in \mathbb{F}_i, \forall m \in \mathbb{V}, \forall n \in \mathbb{V} \tag{C.6}$$

which requires the value of the decision variable should be binary.

Methodology

Fitness scaling converts the raw fitness values to a range suitable for better selection. Power-rank fitness scaling strategy [13, 14] is selected. Afterwards, 2-opt is an intra-route movement to improve the solutions. It consists of replacing two non-adjacent arcs belonging to the route by two other arcs not belonging to it, by which the connectivity of the route is re-established [15].

Based on aforementioned description, we proposed the IGA, which combined standard GA with fitness-scaling and local search.

Experiments and Results

The Cordeau dataset contains 33 benchmark problems. We compared the proposed IGA with standard GA, SA, TS, and PSO. For each problem, each algorithm was conducted 50 times. The best results among 50 runs were recorded. The parameters are obtained by trial-and-error method. The results are evaluated by the best (minimum) objective value f_{best}, and the percentage deviation (P_D) defined as

$$P_D = \frac{f_{best} - f_{KB}}{f_{KB}} \times 100\% \tag{13}$$

where f_{KB} represents the known-best objective value, which can be downloaded from the homepage of the Cordeau dataset. Table 1 reports the best (minimum) results and its deviation in terms of percentage by all algorithms for all benchmark problems.

Table 1 Algorithm comparison among 50 runs

Instance	GA	SA	TS	PSO	IGA
p01	0.0000	0.0000	0.0093	0.0000	0.0000
p02	0.0000	0.0000	0.0000	0.0000	0.0000
p03	0.0000	0.0000	0.0264	0.0000	0.0000
p04	0.0000	0.0000	0.0000	0.0000	0.0000
p05	0.0000	0.0000	0.0000	0.0000	0.0000
p06	0.0000	0.0000	0.0000	0.0000	0.0000
p07	0.0000	0.0000	0.0000	0.0000	0.0000
p08	0.0000	0.0000	0.0000	0.0000	0.0000
p09	0.0136	0.0000	0.0202	0.0000	0.0000
p10	0.0000	0.0000	0.0000	0.0265	0.0000
p11	0.0600	0.0000	0.0000	0.0290	0.0000
p12	0.0000	0.0000	0.0000	0.0000	0.0000
p13	0.0000	0.0000	0.0000	0.0000	0.0000
p14	0.0000	0.0000	0.0000	0.0000	0.0000
p15	0.0102	0.0127	0.0000	0.0000	0.0000
p16	0.0124	0.0000	0.0315	0.0127	0.0050
p17	0.0098	0.0265	0.0282	0.0176	0.0000
p18	0.0000	0.0292	0.0100	0.0229	0.0000
p19	0.0491	0.0000	0.0000	0.0000	0.0401
p20	0.0356	0.0073	0.0000	0.0433	0.0273
p21	0.0271	0.0211	0.1493	0.0293	0.0227
p22	0.0698	0.0651	0.0686	0.0483	0.1034
p23	0.0045	0.1136	0.0208	0.1363	0.0142
pr01	0.0020	0.0000	0.0000	0.0000	0.0000
pr02	0.0000	0.0000	0.0000	0.0000	0.0000
pr03	0.0000	0.0000	0.0000	0.0000	0.0000
pr04	0.0000	0.0000	0.0000	0.0000	0.0000
pr05	0.0000	0.0220	0.0410	0.0303	0.0000
pr06	0.0503	0.0413	0.0000	0.0000	0.0283
pr07	0.0000	0.0152	0.0165	0.0000	0.0071
pr08	0.0593	0.0357	0.0000	0.0000	0.0000
pr09	0.0000	0.0450	0.0000	0.0311	0.0000
pr10	0.0000	0.0000	0.0698	0.0554	0.0219

Results indicated that the proposed IGA method performed the best. It reached the known-best solutions in 24 instances and failed in only 9 instances. In addition, standard GA performed the worst and it won only 20 instances and failed in 13 instances. SA, TS, and PSO won 21 instances and failed in 12 instances.

Conclusions

In this paper, we proposed an improved GA algorithm in order to solve MDVRP. Thirty-three benchmark problems were used to test the performance of the proposed algorithm. The results showed the superiority of the proposed IGA algorithm to other methods.

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