A two-individual evolutionary algorithm for cumulative capacitated vehicle routing problem

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1 Introduction

The cumulative vehicle routing problem (CCVRP) is a variant of the well-known vehicle routing problem, initially investigated by Ngueveu *et al.* [5]. The CCVRP can be defined on a complete undirected graph $G = (V, E)$ with $V = D \cup C$ and $E = \{(i, j) : i, j \in V\}$, where D is the set of depots ($|D| \geq 1$) and $C = \{C_1, C_2, ...C_m\}$ is the set of customers. Moreover, a symmetric non-negative matrix $Y = (d_{ij})$ for the edges (i, j) is associated with E, where d_{ij} represents the travel time (or equivalently the distance) between two vertices. There is a fleet R of K vehicles with a given capacity. Each customer $i \in C$ has a demand q_i that is served when a vehicle visits the customer. A candidate solution to the CCVRP with single depot is a set of k ($k \leq K$) disjoint Hamiltonian tours starting and ending at the depot such that each customer is served exactly once by a vehicle, and the sum of customer demands served by a vehicle does not exceed its capacity. The goal of the CCVRP is to minimizes the sum of the waiting times of all customers. As a customer-centric model, the CCVRP naturally occurs in various contexts, including post-disaster relief activities and the school bus routing problem.

2 Two-individual evolutionary algorithm for CCVRP

This paper presents a two-individual evolutionary algorithm (TIEA) following the MA framework to solve the CCVRP, inspired by recent successful study with a very small population [3]. The TIEA combines population-based genetic search with neighborhood-based local search. The basic idea behind the algorithm is that population-based search provides more opportunities for exploration, while neighborhood search provides more opportunities for exploitation [1]. When combined in an appropriate way the resulting hybrid method can provide a good balance between exploitation and exploration, thus ensuring high search performance.

TIEA uses a small population with only two individuals, which overcomes the disadvantage of a large population whose management induces high computational costs. TIEA employs a special crossover called dEAX that is inspired by the edge assembly crossover [4] to generate high-quality offspring. The dEAX method is based on the insight that high-quality solutions share common edges, which are likely to be part of the optimal solution. The resulting offspring inherits the majority of edges from the parents, with only a few extra edges introduced to eliminate sub-tours. This characteristic enables efficient search, saving expensive computational effort for local search to improve the offspring solution. Following the crossover, IEA uses a feasible and infeasible variable neighborhood descent to improve the solution, utilizing seven neighborhood operators to adaptively explore both feasible and infeasible search spaces, which helps to find high-quality solutions lying on the feasible-infeasible boundary.

3 Computational results

Table 1 shows the summarized results of TIEA compared to three reference algorithms UHGS [7], AVNS [6], BSO [2] and the Best-Known Solutions (BKS) ever reported in the literature on three commonly used benchmark instance sets CMT, GWKC, and L in terms of the best (f_{best}) and average f_{avg} results over 20 independent runs (a maximum of one hour per run). Columns "#Wins", "#Ties" and "#Losses" indicate the number of instances where our algorithm obtain better, equal and worse results compared to each reference algorithm, respectively.

We observe that TIEA outperforms the reference algorithms for most instances. Generally, TIEA improves on the best-known solutions for 12 instances (new upper bounds) out of the 39 benchmark instances. For the CMT instances, TIEA achieves all of the best-known results. For the medium GWKC instances, TIEA achieves 4 new best results and matches 9 best-known results. For the large L instances, TIEA reports 8 new record-breaking results and matches 3 best-known results. When TIEA was run for a longer time (two hours), it can further improve its results for several medium instances (see TIEA_EX).

TAB. 1 – Summary of the comparative results of TIEA with the reference algorithms.

Instance	Pair algorithms	f_{best}			f_{avg}		
		#Wins	#Ties	#Losses	#Wins	#Ties	#Losses
CMT(7)	TIEA vs. BKS	0	7	0	-	-	-
	TIEA vs. AVNS [6]	0	7	0	5	0	2
	TIEA vs. BSO [2]	0	7	0	5	0	2
	TIEA vs. UHGS [7]	0	7	0	1	1	5
GWKC(20)	TIEA_EX vs. BKS	5	13	2	-	-	-
	TIEA vs. BKS	4	9	7	-	-	-
	TIEA vs. AVNS [6]	12	8	0	18	0	2
	TIEA vs. BSO [2]	13	5	2	16	0	4
	TIEA vs. UHGS [7]	7	8	5	3	0	17
L(12)	TIEA vs. BKS	8	3	1	-	-	-
	TIEA vs. AVNS [6]	9	2	1	12	0	0
	TIEA vs. BSO [2]	10	2	0	11	0	1

Références

[1] Jin-Kao Hao. Memetic algorithms in discrete optimization. In Ferrante Neri, Cotta Carlos, and Moscato Pablo, editors, *Handbook of Memetic Algorithms*, volume 379, chapter 6, pages 73–94. Springer, Heidelberg, Germany, 2012.

[2] Liangjun Ke. A brain storm optimization approach for the cumulative capacitated vehicle routing problem. *Memetic Computing*, 10 :411–421, 2018.

[3] Laurent Moalic and Alexandre Gondran. Variations on memetic algorithms for graph coloring problems. *Journal of Heuristics*, 24 :1–24, 2018.

[4] Yuichi Nagata and Shigenobu Kobayashi. A powerful genetic algorithm using edge assembly crossover for the traveling salesman problem. *INFORMS Journal on Computing*, 25(2) :346–363, 2013.

[5] Sandra Ulrich Ngueveu, Christian Prins, and Roberto Wolfler Calvo. An effective memetic algorithm for the cumulative capacitated vehicle routing problem. *Computers & Operations Research*, 37(11) :1877–1885, 2010.

[6] Jeeu Fong Sze, Said Salhi, and Niaz Wassan. The cumulative capacitated vehicle routing problem with min-sum and min-max objectives : An effective hybridisation of adaptive variable neighbourhood search and large neighbourhood search. *Transportation Research Part B : Methodological*, 101 :162–184, 2017.

[7] Thibaut Vidal, Teodor Gabriel Crainic, Michel Gendreau, and Christian Prins. A unified solution framework for multi-attribute vehicle routing problems. *European Journal of Operational Research*, 234(3) :658–673, 2014.