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Application specific instance generator and a memetic algorithm for capacitated arc routing problems

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A B S T R A C T

Capacitated arc routing problem (CARP) is a well known combinatorial problem that requires identifying minimum total distance traveled by a fleet of vehicles in order to serve a set of roads without violating the vehicles' capacity constraints. A number of optimization algorithms have been proposed over the years to solve basic CARPs and their performance have been analyzed using selected benchmark suites available in literature. From an application point of view, there is a need to assess the performance of algorithms on specific class of instances that resemble realistic applications, e.g., inspection of electric power lines, garbage collection, winter gritting etc. In this paper we introduce a benchmark generator that controls the size and complexity of the underlying road network resembling a target application. It allows generation of road networks with multiple lanes, one-way/two-way roads and varying degree of connectedness. Furthermore, an algorithm capable of solving real life CARP instances efficiently within a fixed computational budget of evaluations is introduced. The proposed algorithm, referred to as MA-CARP, is a memetic algorithm embedded with a similarity based parent selection scheme inspired by multiple sequence alignment, hybrid crossovers and a modified neighborhood search to improve its rate of convergence. The mechanism of test instance generation is presented for three typical scenarios, namely, inspection of electric power lines, garbage collection and winter gritting. The code for the generator is available from http://seit.unsw.adfa.edu.au/research/sites/mdo/Research-Data/InstanceGenerator.rar. The performance of the algorithm is compared with a state-of-the-art algorithm for three generated benchmarks. The results obtained using the proposed algorithm are better for all the above instances clearly highlighting its potential for solving CARP problems.

1. Introduction

Capacitated arc routing problem (CARP) is a challenging combinatorial optimization problem, where the aim is to service a set of tasks with a fleet of homogeneous vehicles without exceeding their capacity, while minimizing the total distance traveled. During the last two decades, several optimization algorithms have been proposed to solve CARPs. The performance of such algorithms have been evaluated using traditional benchmarks such as *gdb* (DeArmon, 1981), *kshs* (Kiuchi et al., 1995), *val* (Benavent et al., 1992) and *egl* (Eglese, 1994; Eglese and Li, 1996; Li and Eglese, 1996), the set of Beullens et al. (2003), and the set of Brandão and Eglese (2008). The *gdb* set contains 23 instances while the *kshs* set contains 6 instances. The *val* set

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contains 34 instances based on ten different graphs. The *egl* set was introduced based on winter gritting data of Lancashire UK (Eglese, 1994; Eglese and Li, 1996; Li and Eglese, 1996). It contains 24 instances based on two graphs, each with a distinct set of required edges and capacity constraints. The test set generated by Beullens et al. (2003) is based on the inter-city road network in Flanders, Belgium. The set contains four subsets, namely, the sets C, D, E, and F, each of which contain 25 instances. The instances of sets D and F share the same networks with the instance sets C and E, but use vehicles of larger capacity. The set introduced by Brandão and Eglese (2008) contains ten large instances defined on a road network with 255 vertices and 375 edges of Lancashire road network. Different instances in the set were created by changing the set of edges required for service and the capacity of the vehicles. The characteristics of these data sets are summarized in Table 1.

It is theoretically possible to obtain road network details for specific region (e.g., from Google Maps). The existing instances are all generated from real life networks of various sizes. However, they may be of limited use for comprehensively evaluating algorithms' performance as they may represent isolated specific instances. Instead, to thoroughly test the performance of various CARP algorithms, the user should be able to manipulate the properties of graphs to create customized instances. For example, in a garbage collection problem, the waste pick-up sites must be distributed according to the distribution of waste amount (demand), which in turn is dependent on the density of population. The streets in the residential area may include one-way, two-way and multiple-lane roads. There could be one or more depots for dumping wastes. In the context of winter gritting, the service priority or demand distribution is closely dependent on the road distance or road surface temperatures (Handa et al., 2006) or current weather conditions (Tagmouti et al., 2007, 2010, 2011). For modeling such problems, the benchmark generator must be able to allow control of these characteristics (demand, directed-ness, task distribution etc.).

Research towards development of efficient algorithms to solve CARPs has grown rapidly over the years as they resemble a large number of practical applications such as mail delivery (Aráoz et al., 2006), garbage collection (Dijkgraaf and Gradus, 2007; Maniezzo, 2004; Bautista et al., 2008; De Rosa et al., 2002; Mourao and Amado, 2005; Laporte and Roberto Musmanno, 2010; Chu et al., 2006; Lacomme et al., 2005; Amponsah and Salhi, 2004; Gelders and Cattrysse, 1991), winter gritting (Handa et al., 2006; Tagmouti et al., 2007; Ghiani et al., 2001, 2004; Amberg and Domschke, 2000), inspection of gas pipelines (Han et al., 2004) and electric power lines (Stern and Dror, 1979), and snow removal (Polacek et al., 2008). CARP is known to be NP-hard and thus application of exact optimization methods is still limited to small problems (20–30 edges) (Golden and Wong, 1981). Although exact methods can solve some large instances of CARP, the computational cost is exorbitantly large, e.g., the branch-and-cut-price algorithm requires around 20,000 s (Martinelli et al., 2011) to solve a problem with 190 edges. In most real-world applications, it is necessary to obtain a solution within a given time budget. Different heuristic approaches have been proposed over the years to deal with CARP problems, which include augment-merge (Golden and Wong, 1981), path-scanning (Golden et al., 1983; Santos et al., 2009), construct-and-strike (Pearn, 1989), Ulusoy's tour splitting (Ulusoy, 1985), augment-insert (Pearn, 1991), etc. Metaheuristic approaches have also been used, such as Simulated Annealing (Eglese, 1994), Tabu Search (Mei et al., 2009), Variable Neighborhood Search (Tang et al., 2009), Guided Local Search (Beullens et al., 2003), Genetic Algorithm (Morgan and Mumford, 2009), Evolutionary Algorithm (EA) (Xing et al., 2010), Ant Colony Optimization (Bautista et al., 2008) and more recently Memetic Algorithm (MA) (Lacomme et al., 2004; Tang et al., 2009; Mei et al., 2009) which is an intelligent combination of a global and a local search. Recently, large scale CARP has also increasingly gained attention for which an algorithm RDG-MAENS (Route Distance Grouping-Memetic algorithm with extended neighborhood search) based on cooperative co-evolution algorithm was introduced by Mei et al. (2013a,b) and the improved lower bound and upper bound for large scale CARP was presented by Martinelli et al. (2013). Heuristic/metaheuristic methods have also been used recently in the context of vehicle routing problems (Şahin et al., 2013; Qu and Bard, 2013; Prins et al., 2014; Cong et al., 2013), where the objective is to cover all required nodes rather than arcs.

Table 1
Characteristics of existing benchmarks in literature.

Data set	Characteristics
gdb (DeArmon, 1981)	Small networks: Undirected graphs with 7–27 nodes and 11–55 edges. Homogeneous fleets. Flexible distance and demand. All the edges are tasks
kshs (Kiuchi et al., 1995)	Small networks: Undirected graphs with 6–10 nodes and 15 edges. Homogeneous fleets. Flexible distance and demand. All the edges are tasks
val (Benavent et al., 1992)	Medium networks: Undirected graphs with 24–50 nodes and 34–97 edges. Homogeneous fleets. Flexible distance and demand. All the edges are tasks
egl (Eglese, 1994; Eglese and Li, 1996; Li and Eglese, 1996)	Large networks: Undirected graphs with 77–140 nodes and 98–190 edges. Homogeneous fleets. Distance of edges equal to its demand. Some of the edges are tasks
C of Beullens et al. (2003)	Medium networks: Undirected graphs with 32–97 nodes and 42–140 edges. Homogeneous fleets. Flexible distance and demand. Some of the edges are tasks
E of Beullens et al. (2003)	Medium networks: Undirected graphs with 26–97 nodes and 35–142 edges. Homogeneous fleets. Distance of edges equal to its demand. Some of the edges are tasks
Set of Brandão and Eglese (2008)	Large networks: Undirected graphs with 255 nodes and 375 edges. Homogeneous fleets. Distance of edges equal to its demand. Some of the edges are tasks