ARTICLE IN PRESS

Information Sciences xxx (2014) xxx–xxx

Contents lists available at ScienceDirect

Information Sciences

journal homepage: www.elsevier.com/locate/ins

A multi-population cooperative coevolutionary algorithm for multi-objective capacitated arc routing problem

Ronghua Shang [a,*], Yuying Wang [a], Jia Wang [a], Licheng Jiao [a], Shuo Wang [b], Liping Qi [a]

[a] *Key Laboratory of Intelligent Perception and Image Understanding of Ministry of Education of China, Xidian University, Xi'an 710071, China*
[b] *Cercia, School of Computer Science, The University of Birmingham Edgbaston, Birmingham B15 2TT, UK*

ARTICLE INFO

Article history:
Received 9 March 2013
Received in revised form 5 February 2014
Accepted 3 March 2014
Available online xxxx

Keywords:
Capacitated arc routing problem
Coevolution
Multi-objective optimization
Evolutionary algorithm

ABSTRACT

Capacitated Arc Routing Problem (CARP) has drawn much attention during the last few years. In addition to the goal of minimizing the total cost of all the routes, many real-world applications of CARP also need to balance these routes. The Multi-objective CARP (MO-CARP) commonly exists in practical applications. In order to solve MO-CARP efficiently and accurately, this paper presents a Multi-population Cooperative Coevolutionary Algorithm (MPCCA) for MO-CARP. Firstly, MPCCA applies the divide-and-conquer method to decompose the whole population into multiple subpopulations according to their different direction vectors. These subpopulations evolve separately in each generation and the adjacent subpopulations can share their individuals in the form of cooperative subpopulations. Secondly, multiple subpopulations are used to search different objective subregions simultaneously, so individuals in each subpopulation have a different fitness function, which can be modeled as a Single Objective CARP (SO-CARP). The advanced MAENS approach for single-objective CARP can be used to search each objective subregion. Thirdly, the internal elitism archive is used to construct evolutionary pool for each subregion, which greatly speeds up the convergence. Lastly, the fast nondominated ranking and crowding distance of NSGA-II are used for selecting the offspring and keeping the diversity. MPCCA is tested on 91 CARP benchmarks. The experimental results show that MPCCA obtains better generalization performance over the compared algorithms.

1. Introduction

Capacitated Arc Routing Problem (CARP) focuses on servicing task edges of an undirected and connected network graph under certain conditions, which is a classic combinatorial optimization problem [5]. Many applications in real-word can be modeled as CARP, such as school bus scheduling [4], sprinkler path planning [13] and garbage cleaning [31,42]. Since CARP is NP-hard, many classical heuristic and meta-heuristic algorithms were proposed to solve this problem in the past few years. The heuristics include Path-Scanning [21], Augment-Merge [14] and Ulusoy's tour splitting technique [56]. The meta-heuristics include the tabu search algorithms [24], the tabu scatter search algorithm [22], the variable neighborhood search algorithm [25], the guided local search algorithm [6], memetic algorithms (MA) [33,54], and the global repair operator [36]. With the goal of minimizing the total cost, CARP has been formulated as a single-objective optimization problem (SOP) traditionally. However, more than one objective needs to be considered in practical applications. For example, in actual

* Corresponding author. Tel.: +86 02988202279.
E-mail address: rhshang@mail.xidian.edu.cn (R. Shang).

http://dx.doi.org/10.1016/j.ins.2014.03.008
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applications, the relevant departments not only want to get the vehicle arrangement with the minimum route consumption but also need to consider *makespan* (the cost of the longest route) [32]. The two objectives are conflicting with each other. No unique global optimal solution exists in this case. Thus, the algorithm should return a set of solutions which produce good "tradeoffs" between the two goals. Among all existing solutions for multi-objective optimization problems (MOPs), the majority focused on numerical optimization [38–50]. Very few discussed MO-CARP. MO-CARP combines MOP with the combinatorial optimization problem, which makes it a very challenging problem. Lacomme first proposed to use the genetic algorithm (GA) for MO-CARP, named LMOGA [32]. Inspired by the nondominated sorted GA (NSGA-II) [12], the procedure of LMOGA was improved by using good constructive heuristics to seed the initial population and by including a local search strategy. Lacomme made a comparative experiment between NSGA-II and LMOGA for MO-CARP and SO-CARP in terms of solution quality and computational efficiency. After Lacomme's work, decomposition-based MA with extended neighborhood search (D-MAENS) was proposed to solve MO-CARP by Mei et al. [35]. D-MAENS combines the advantages of multi-objective evolutionary algorithms based on decomposition (MOEA/D) [62] and the MAENS approaches [54] for SO-CARP. With the same evolution strategy as in NSGA-II, D-MAENS shows a superior performance over LMOGA on 81 CARP instances. However, D-MAENS is still inadequate because it uses the framework of MOEA/D to solve MO-CARP. MOEA/D makes the assumption that each Pareto optimal solution of original MOPs is the global optimal solution to a scalar optimization subproblem [15]. However, for most multi-objective combinatorial optimization problems including MO-CARP, this assumption is no longer valid. There exist solutions which are not optimal for any weighted sum of the objectives in MO-CARP. Furthermore, due to the high discreteness of the Pareto front (*PF*) in MO-CARP, one Pareto optimal solution may corresponds to the optimal solution of multiple decomposed subproblems. The search process can be greatly hindered, and many computing resources can be wasted. Therefore, the optimization strategy based on problem decomposition is not suitable for MO-CARP [35].

Coevolutionary Algorithm (CA) is a new class of evolutionary algorithm (EA). Based on the theory of coevolution over the past decade, it shows great advantages over traditional EAs [58]. The main differences between CA and EA are: 1. in traditional EAs, the fitness function is predefined and immutable during the evolutionary process. However, the real fitness should be local. Representing the struggle between individual and environment, it is susceptible to the changes of environment. CAs pay more attention on the coordination between the population and the environment, and between the populations. 2. EAs only consider the competition between populations, without considers the possibility of collaboration between populations. On the contrary, both competition mechanism and collaboration mechanism exist in CAs, which is the so-called coevolution. In a broad sense, most CAs fall into three categories depending on interaction ways: the cooperative CA based on symbiotic mechanism, the competitive CA based on population competition and the CA based on predator–prey mechanism [19,60]. The representatives of cooperative CAs include the cooperative coevolutionary GA (CCGA) proposed by Potter and De Jong [43,44], the cooperative particle swarm optimizer (CPSO-S_K) [57] proposed by Van den Bergh and Engelbrecht, and the distributed cooperative CA (DCCEA) [53] proposed by Tan et al. Their main idea is to utilize "divide and conquer" to solve high-dimensional numerical optimization problems by dividing the n-dimensional decision vector into the n components and using n subpopulations to optimize each of these n components [61]. The fitness of a particular individual in a specific subpopulation depends on its ability of cooperating with other individuals to generate good solutions. The representatives of competitive CAs include Coevolutionary augmented Lagrangian methods for constrained optimization proposed by Tahk and Sun [52] and the GA based on multi-population competitive coevolution (GAMCC) proposed by Li et al. [34]. The main idea of competitive CAs is to reserve two populations: one population representing the solutions of the problem and the other population putting the violation degree to a condition of the first population as the fitness [47]. The stringent requirements will promote the evolution of the first population. There are also some works about the CAs based on predator–prey mechanism. For example, Hillis was the first to build the model of predator–prey coevolution and then propose the coevolutionary GA (CGA) [26]; Paredis proposed a life-time fitness evaluation CGA [41].

In our recent work, we proposed a Coevolutionary Multi-Objective Optimization Algorithm based on Direction Vectors (DVCMOA) [28]. Our simulation results showed that it outperforms other MOEAs in the field of numerical optimization. Although DVCMOA can get good performance on numerical optimization filed, it cannot be used to solve MO-CARP directly. To overcome this issue, a Multi-population Cooperative CA (MPCCA) for MO-CARP is proposed in this paper. The proposed algorithm divides the whole objective space into a plurality of subareas by a set of uniformly distributed direction vectors. The individuals located in different areas constitute different subpopulations. These subpopulations evolve independently. At the beginning of each iteration, all the individuals are combined together and reassigned to different subpopulations according to the size of each direction vector. Using this strategy, it can make better use of the information of the current population during the search process and can assign a more appropriate individual to each subpopulation. More importantly, during the evolution of each subpopulation, its adjacent subpopulations can provide useful information through neighborhood sharing. Incorporated with various features like multi-elite archiving mechanism, neighborhood sharing, the fast non-dominated sorting and the crowding distance approach of NSGA-II, the MPCCA is capable of maintaining archive diversity and a fast convergence in the evolution. Compared with the state-of-art algorithms, our experiments show that MPCCA are superior in convergence speed and the closeness to the *PF*.

The remainder of this paper is organized as follows: the related works are given in Section 2, including the detailed introduction of MO-CARP model, the definitions of evolutionary multi-objective optimization and the description of direction vector. In Section 3, our new method MPCCA is proposed, followed by the experimental study in Section 4. Finally, the conclusions and future work are included in Section 5.

Please cite this article in press as: R. Shang et al., A multi-population cooperative coevolutionary algorithm for multi-objective capacitated arc routing problem, Inform. Sci. (2014), http://dx.doi.org/10.1016/j.ins.2014.03.008