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A decomposition based memetic algorithm for multi-objective vehicle routing problem with time windows

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ABSTRACT

Multi-objective evolutionary algorithm based on decomposition (MOEA/D) provides an excellent algorithmic framework for solving multi-objective optimization problems. It decomposes a target problem into a set of scalar sub-problems and optimizes them simultaneously. Due to its simplicity and outstanding performance, MOEA/D has been widely studied and applied. However, for solving the multi-objective vehicle routing problem with time windows (MO-VRPTW), MOEA/D faces a difficulty that many sub-problems have duplicated best solutions. It is well-known that MO-VRPTW is a challenging problem and has very few Pareto optimal solutions. To address this problem, a novel selection operator is designed in this work to enhance the original MOEA/D for dealing with MO-VRPTW. Moreover, three local search methods are introduced into the enhanced algorithm. Experimental results indicate that the proposed algorithm can obtain highly competitive results on Solomon's benchmark problems. Especially for instances with long time windows, the proposed algorithm can obtain more diverse set of non-dominated solutions than the other algorithms. The effectiveness of the proposed selection operator is also demonstrated by further analysis.

1. Introduction

Vehicle routing problem with time windows (VRPTW) is an important variant of vehicle routing problem (VRP) which is an extensively studied combinational optimization problem and has been used in many real applications. The VRPTW can be defined as designing routes for a fleet of vehicles with limited capacity to serve a set of customers with known demands and predefined time window. Each route starts from and ends at the central depot. Each customer is visited once and only once by exactly one vehicle [1]. Due to its complexities and usefulness, VRPTW has been attracting much research effort. Many exact methods [2], heuristic and meta-heuristic methods [3] have been developed. However, most of the existing works focus on VRPTW with single optimization objective. In real-life, there are several optimization objectives related to the tours of VRPTW, such as the number of used vehicles, total traveled distance, makespan or traveling time of the longest route, total waiting time, and total delay time [4]. Therefore, it is necessary to develop optimization techniques for multi-objective VRPTW (MO-VRPTW) to provide the decision makers with more comprehensive information about the target problems.

At present, many research efforts have been devoted to solving MO-VRPTW by using multi-objective optimization techniques. Hong and Park [5] constructed a linear goal programming model for the bi-objective VRPTW and developed a heuristic algorithm to reduce the computational burden inherent to the application of the model. Gehring et al. and Alvarenga et al. developed two-phase approaches for the MO-VRPTW, the first phase minimizes the number of vehicles and the second phase minimizes the total distance [6] or the total traveling time [7]. Rahoual et al. [8] solved the VRPTW by using the non-dominated sorting genetic algorithm (NSGA) with elitist and sharing strategy, which was the first work that employed the multi-objective evolutionary algorithm (MOEA) to solve MO-VRPTW. Ombuki et al. [9] investigated the effectiveness of solving VRPTW by using a multi-objective optimization model and a multi-objective genetic algorithm. Tan et al. [10] introduced the heuristics methods into MOEA to perform local exploitation and proposed a hybrid multi-objective evolutionary algorithm for MO-VRPTW. Geiger et al. [11] proposed an interactive multi-objective approach with variable neighborhood search to solve various components of general vehicle routing problems including MO-VRPTW. Xu et al. [12] introduced a hybrid algorithm to solve tri-objective VRPTW. Garcia-Najera et al. [13] first considered the similarity of solutions in solving MO-VRPTW. They designed a similarity measure between solutions and introduced it into multi-objective optimization approach to obtain better diversity [14]. Gong et al. [15] developed multi-objective particle

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swarm optimization (PSO) algorithms for solving MO-VRPTW. Ghoseiri and Ghannadpour [16] investigated a bi-objective VRPTW and developed a multi-objective genetic algorithm for solving it. Chiang et al. [17] incorporated problem-specific knowledge into the genetic operators and developed an evolutionary algorithm for MO-VRPTW. Melian-Batista et al. [18] considered both the total traveled distance and traveling time balance, and developed a solution approach based on the scatter search metaheuristic for real-world MO-VRPTW. Banos et al. [19] combined evolutionary computation with simulated annealing and developed a hybrid algorithm for MO-VRPTW that considers both the traveled distance and the workload balance. The abovementioned works have illustrated the superiority of solving VRPTW by using multi-objective optimization models.

By evolving a population of solutions, multi-objective evolutionary algorithms (MOEAs) are able to approximate the Pareto optimal set in a single run. MOEAs have been very successful in solving multi-objective optimization problems, and a lot of research efforts have been made in this area [20]. More recently, Zhang and Li [21] combined decomposition methods and the evolutionary computation together, and proposed a multi-objective evolutionary algorithm based on decomposition (MOEA/D). MOEA/D provides an excellent general evolutionary algorithmic framework for multi-objective optimization. It has attracted increasing research interests. MOEA/D decomposes the multi-objective optimization problem into a set of scalar optimization problems, while evolutionary algorithm is applied to optimize the scalar subproblems simultaneously.

Due to its simplicity and outstanding performance, MOEA/D has been investigated widely and applied successfully on various continuous and discrete MOPs. MO-VRPTW is a special type of MOP which has one discrete target like the number of used vehicles, and some continuous targets like total traveled distance, total cost of routings, makespan or traveling time of the longest route. Because of this, MO-VRPTW has a discrete Pareto front which is composed of very few Pareto optimal solutions. The above features of MO-VRPTW imply that MOEA/D will have many subproblems with duplicated best solutions when solving MO-VRPTW. In this work, in order to obtain a good diversity of solutions, a novel selection operator is designed to enhance MOEA/D for dealing with MO-VRPTW.

On the other hand, it is a major advantage of MOEA/D that single objective local search methods can be used in the optimization of each subproblem in a natural way [20]. Although there are many suggested meta-heuristic methods for VRPTW, three effective methods are selected to form a memetic MOEA/D (M-MOEA/D) in this work. Memetic algorithm (MA) is a type of population based meta-heuristics algorithm. It is composed of an evolutionary framework and a set of local search methods that are activated within the generation cycle of the external framework [22]. It has been applied to solve a wide variety of optimization problems, including the classical combinatorial optimization problem VRPTW [23]. However, few efforts have been devoted to Memetic algorithm for MO-VRPTW [10,12].

The goal of this paper is to enhance MOEA/D for dealing with MO-VRPTW. We propose a memetic MOEA/D with a novel selection operator (M-MOEA/D) for MO-VRPTW. M-MOEA/D enhances the original MOEA/D in the following two aspects:

1. A specially designed selection operation for updating the current best solution of each subproblem is developed according to the characteristics of the MO-VRPTW.
2. Three types of local search methods which have different searching behaviors are employed periodically to form a memetic algorithm.

The rest of this paper is organized as follows. Section 2 describes the mathematical model of the MO-VRPTW. Section 3 presents the framework of the proposed M-MOEA/D. Based on the benchmarks of Solomon's 56 data sets, Section 4 verifies the effectiveness of the proposed M-MOEA/D and presents further analysis on it. Finally, conclusion is given in Section 5.

2. A multi-objective optimization model for the VRPTW

The VRPTW can be defined as follows: n customers are waiting to be served, each of which requires a quantity of goods. The central depot has a fleet of vehicles to deliver the goods. Each vehicle has the same capacity, which must be greater than or equal to the total of all demands on the route traveled by one vehicle. Besides, each customer must be visited once and only once by exactly one vehicle. The time window constraint is denoted by a predefined time interval which can be described by the earliest arrival time and the latest arrival time. The vehicles have to arrive at the customers before the latest arrival time, while arriving earlier than the earliest arrival time, waiting occurs. Each customer imposes an additional service time to the route, taking into consideration the loading or unloading time of goods. Each vehicle is supposed to complete its individual route within the time window of the depot. A solution of the VRPTW is a collection of routes in which a vehicle starts from the depot, visits customer nodes and then returns to depot under capacity and time window constraints. The number of routes in the network is equal to the number of vehicles used, one vehicle is dedicated to one route.

The objective of the MO-VRPTW is to obtain the minimum distance traveled by the vehicles and the minimum total number of vehicles used to serve the customers while the total customers have been served. The mathematical representation of the MO-VRPTW can be described as follows. Define $G=(V,A)$ as a directed complete graph, where $V=\{c_0,c_1,\ldots,c_n\}$ is the node set, and $A=\{\langle c_i,c_j\rangle \mid c_i,c_j\in V, i\neq j\}$ is the arc set. c_0 represents the depot, and $c_i(i=1,2,\ldots n)$ represents the customer. Each vehicle has the same capacity Q. Each node is associated with a demand quantity q_i among which node c_0 is associated with $q_0=0$. Each arc in the network represents a connection between two nodes and also indicates the direction it travels. Each arc is associated with a traveling time t_{ij}, which is proportional to the Euclidean distance d_{ij} between nodes c_i and c_j. A time window $[e_i,l_i]$ during the time when the service has to be started is considered. If the vehicle arrives at the node c_i before e_i, it will wait at the node until e_i, and then, a service time s_i is considered. For depot c_0, the time window is defined as that e_0 is the earliest start time, and l_0 is the latest return time of all the vehicles. When the vehicle arrives at customer c_i within the time windows, it has to stay at the location of customer c_i for a time interval at least s_i for service. Let K represents the number of the total used vehicles.

The optimization model for the MO-VRPTW can be mathematically defined as follows:

$$\begin{cases} \min F(x)=(f_1,f_2) \\ f_1=K \\ f_2=\sum_{i=1}^{N}\sum_{j=0,j\neq i}^{N}\sum_{k=1}^{K} d_{ij}x_{ijk} \end{cases} \tag{1}$$

Subject to

$$x_{ijk}=\begin{cases} 1 & \text{if arc}\langle c_i,c_j\rangle \text{ is traversed by vehicle } k \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

$$\sum_{j=1}^{N} x_{0jk}=\sum_{i=1}^{N} x_{i0k}=1, \quad k\in\{1,2,\ldots,K\} \tag{3}$$

$$\sum_{j=0,j\neq i}^{N} x_{ijk}=\sum_{j=0,j\neq i}^{N} x_{jik}\le 1, \quad i\in\{1,2,\ldots,N\}, \quad k\in\{1,2,\ldots,K\} \tag{4}$$