Multi-objective Vehicle Routing Problems Using Two-Fold EMO Algorithms to Enhance Solution Similarity on Non-dominated Solutions

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Abstract. In this paper, we focus on the importance of examining characteristics of non-dominated solutions especially when a user should select only one solution from non-dominated solutions at a time, and select another solution due to the change of problem conditions. Although he can select any solution from non-dominated solutions, the similarity of selected solutions should be considered in practical cases. We show simulation results on vehicle routing problems that have two demands of customers: Normal Demand Problem (NDP) and High Demand Problem (HDP). In our definition the HDP is an extended problem of NDP. We examined two ways of applying an EMO algorithm. One is to apply it to each problem independently. The other is to apply it to the HDP with initial solutions generated from non-dominated solutions for the NDP. We show that the similarity of the obtained sets of non-dominated solutions is enhanced by the latter approach.

1 Introduction

Although we have many approaches in EMO (Evolutionary Multi-criterion Optimization) community [1, 2] recently, there are few research works that investigate the similarity of obtained non-dominated solutions. Deb considered topologies of several non-dominated solutions in Chapter 9 of his book [3]. He examined the topologies or structures of three-bar and ten-bar truss. He showed that neighboring non-dominated solutions on the obtained front are under the same topology, and NSGA-II can find the gap between the different topologies. While he considered the similarity of solutions in a set of non-dominated solutions from a topological point of view, there is no research work relating to EMO that considers the similarity of solutions in different sets of non-dominated solutions from that point of view.

We employ the Vehicle Routing Problem (VRP) to consider the similarity in different sets of solutions. The VRP is a complex combinatorial optimization problem, which can be seen as a merge of two well-known problems: the Traveling Salesman Problem (TSP) and the Bin Packing Problem (BRP). This problem can be described as follows: Given a fleet of vehicles, a common depot, and several customers scattered geographically. Find the sets of routes for the fleet of vehicles. Many research works [4, 5, 6, 7, 8] on the VRP try to minimize the total route cost

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that is calculated using the distance or the duration between customers. Several hybrid algorithms have been proposed to improve the search ability of genetic algorithms [4, 5]. The research works in [6, 7, 8] are related to multi-objective optimization. Tan *et al.* [6] and Saadah *et al.* [7] employed the travel distance and the number of vehicles to be minimized. Chitty and Hernandez [8] tried to minimize the total mean transit time and the total variance in transit time.

In this paper, we employ an EMO algorithm, NSGA-II [9], to our vehicle routing problems with minimizing the number of vehicles and the maximum routing time among the vehicles. It should be noted that we don't employ the total routing time of all the vehicles, but use the maximum routing time among the vehicles. We employed it in order to minimize the active duration of the central depot. We consider two problems with different demands. One problem has a normal demand of customers. The other has a high demand. We refer the former problem and the latter problem as NDP and HDP, respectively. We define the demand in the HDP as an extended demand of the NDP in this paper. For example, we assume that the demand in the HDP is a demand occurring in a high season such as Christmas season. In that season, the depot may have an extra demand as well as the demand in the normal season. In order to avoid a large change of each route from the depot, a solution (i.e., a set of route) in the HDP should be similar to a solution in the NDP. This situation requires us to consider the similarity of solutions on different non-dominated solutions in multi-objective VRPs.

In order to find a set of non-dominated solutions in the HDP that is similar to a set of non-dominated solutions in the NDP, we apply a two-fold EMO algorithm to the problem. In a two-fold EMO algorithm, first we find a set of non-dominated solutions for the NDP by an EMO algorithm. Then we generate a set of initial solutions for the HDP from the non-dominated solutions for the NDP. We apply an EMO algorithm to the HDP with initial solutions that are similar to those of the NDP problem.

We organize this paper as follows: Section 2 gives the problem model for multi-objective VRPs. The outline of our two-fold EMO algorithm is described in Section 3. We define a measure of the similarity between solutions in Section 4. A small example of our multi-objective VRP is also shown in Section 4. Section 5 presents the extensive simulations and compares results of the two-fold EMO algorithm and those obtained individually for the HDP and NDP. Conclusions are drawn in Section 6.

2 Multi-objective Vehicle Routing Problems

The domain of VRPs has large variety of problems such as capacitated VRP, multiple depot VRP, periodic VRP, split delivery VRP, stochastic VRP, VPR with backhauls, VRP with pick-up and delivering, VRP with satellite facilities, and VRP with time windows. These problems have the basic architecture of the VRP except their own constraints. Their constraints are arisen in practical cases. Please see for the detail of the VRP problem in [10].

The objective of the basic problem is to minimize a total cost is described as follows:

$$\text{Minimize } \sum_{m=1}^{M} c_m \,, \tag{1}$$