Local Search in Two-Fold EMO Algorithm to Enhance Solution Similarity for Multi-objective Vehicle Routing Problems

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Abstract. In this paper, we propose a memetic EMO algorithm that enhances the similarity of two sets of non-dominated solutions. We employ our algorithm in vehicle routing problems (VRPs) where the demand of customers varies. We consider two periods of different demand in a problem that are Normal Demand Period (NDP) and High Demand Period (HDP). In each period, we can find a set of non-dominated solutions with respect to several objectives such as minimizing total cost for delivery, minimizing maximum cost, minimizing the number of vehicles, minimizing total delay to the date of delivery and so on. Although a set of non-dominated solutions can be searched independently in each period, drivers of vehicles prefer to have similar routes in NDP and HDP in order to reduce their fatigue to drive on a different route. In this paper, we propose a local search that enhance the similarity of routes in NDP and HDP. Simulation results show that the proposed memetic EMO algorithm can find a similar set of non-dominated solutions in HDP to the one in NDP.

Keywords: memetic algorithm, local search, solution similarity, vehicle routing problem.

1 Introduction

Although we have various approaches in EMO (Evolutionary Multi-criterion Optimization) community [1-3], there are few research works that investigate the similarity among obtained sets of non-dominated solutions. Deb considered topologies of several non-dominated solutions in Chapter 9 of his book [4]. 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 single 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. In this paper, we propose a memetic EMO algorithm that enhances the similarity of solutions in different sets of non-dominated solutions.

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We employ Vehicle Routing Problems (VRPs) to consider the similarity in different sets of solutions. The VRP is a complex combinatorial optimization problem that can be seen as a merge of two well-known problems: Traveling Salesman Problems (TSP) and Bin Packing Problems (BRPs). 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. As for objective functions considered in VRPs, many research works [5-9] on the VRP try to minimize the total route cost that is calculated using the distance or the duration between customers. Among them the research works in [7-9] are related to multi-objective optimization. Tan *et al.* [7] and Saadah *et al.* [8] employed the travel distance and the number of vehicles to be minimized. Chitty and Hernandez [9] tried to minimize the total mean transit time and the total variance in transit time.

In this paper, we employ three objectives. One is to minimize maximum routing time and another is to minimize the number of vehicles in VRPs. 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. Even if the total routing time is minimized, the central depot should be opened until the last vehicle comes back to the depot. In order to minimize the active duration of the central depot, the maximum routing time should be minimized.

As for the third objective, we consider the similarity of solutions. In this paper, we suppose two periods with different demands. One period has a normal demand of customers. The other has a higher demand. We refer the former period and the latter period as Normal Demand Period (NDP) and High Demand Period (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 big changes of each route from the depot, a solution (i.e., a set of route) in HDP should be similar to a solution in 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 [10] 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. In order to enhance the similarity between sets of non-dominated solutions in NDP and HDP, we showed the effectiveness of utilization of a solution set in NDP for population initialization in HDP [10]. In this paper, we propose a local search method in a memetic EMO algorithm to enhance the solution similarity in HDP to a solution set in NDP.

We organize this paper as follows: Section 2 gives the problem model for multi-objective VRPs. We define a measure of the similarity between solutions in Section 3. The outline of our two-fold EMO algorithm is described in Section 4. In section 5, we propose a local search algorithm that enhances the solution similarity introduced in the second phase of the two-fold memetic EMO algorithm. Section 6 describes simulation results that show the effectiveness of the proposed local search algorithm. Conclusions are drawn in Section 7.