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Application of a fuzzy ant colony system to solve the dynamic vehicle routing problem with uncertain service time

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ABSTRACT

Service management has been an important issue for many companies, especially for service-based companies. This paper studies a routing problem that is usually faced by on-site service companies. This type of company continuously receives orders during its working hours. In order to maximize the number of customers served and minimize the customer waiting time, the service team is responsible for determining which orders should be served during the ongoing working period and which orders should be served in the following working period. This paper represents this problem as a dynamic vehicle routing problem (DVRP). The proposed DVRP model also considers the uncertain service time using fuzzy theory. Furthermore, an algorithm using an improved fuzzy ant colony system (ACS) is proposed in order to solve the proposed model. The proposed algorithm embeds a cluster insertion algorithm into the ACS algorithm. The proposed algorithm is validated using some benchmark datasets. The results show that the proposed algorithm performs better than the previous fuzzy-ACS algorithm without cluster insertion algorithm. In addition, further sensitivity analysis is also presented to derive more information about the model and the proposed algorithm for application to real-world problems.

1. Introduction

The vehicle routing problem (VRP) is a well-known classical NP-hard problem and one of the most challenging combinatorial optimization tasks introduced by Dantzig and Ramser [1]. It aims to design an optimal route for a number of vehicles in serving a set of customers, subject to several constraints. The constraints might cover the available vehicles' capacity, number of vehicles, maximum working hours of the drivers, the customers' available time, etc. [2–4]. Possessing sufficient information regarding the constraints is very important. However, in many real applications, accurate and sufficient information might not be available. For instance, the travel time from one location to another location is not always exactly the same every time, due to a number of other factors, such as traffic jams, accidents, weather, or even wrong addresses. Therefore, many previous studies have used some assumptions. For example, the travel time and the number and customer locations have been known a priori. Unfortunately, these assumptions cannot meet practical applications. In current business applications, many scheduling problems are actually dynamic. New requests may appear over time and must be incorporated into an ongoing schedule [5]. In this case, the decision maker faces a dynamic decision-making problem in continuously

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changing the vehicle route based on the latest information, including customer location and resource availability. Theoretically, this problem can be modeled as a dynamic vehicle routing problem (DVRP) [5] .

The applications of DVRP can be found in various real-world applications, especially for on-site service companies for repair and maintenance, such as HP hardware on-site service, Sodexo on-site service, Supermicro hardware maintenance service, etc. The on-site service company works on repairing or maintaining its products used by customers. The company has limited resources, including technicians, vehicles and working time. In addition, when an order arrives, the company does not have accurate information regarding the service time needed for each order. The decision maker must decide whether or not the newly arrived customers can be inserted into the ongoing services. The decisions made must consider the estimated service time and available resources, including working hours and number of vehicles. In general, this system aims to maximize the number of customers served and minimize customer waiting time. This paper solves a DVRP with uncertain service time by applying fuzzy change-constraint programming and an ACS algorithm. The fuzzy-based method is chosen because it can deal with uncertain factors in a DVRP such as service time and travel time. The application of a fuzzy-based method in VRP can be found on some previous research [6–10].

DVRP can be solved either by exact methods or heuristic approaches. An exact method guarantees that its solution is the optimal one. Unfortunately, this requires complex computation. Thus, it only can solve relatively simple VRP problems with a small number of customers. Therefore, the meta-heuristic method is preferred to solve the DVRP. Recently, various meta-heuristic methods, i.e. tabu search [11], ant colony system (ACS) [12] and genetic algorithm (GA) [13–16], have been proposed to solve DVRP. Ant colony system (ACS) is an improvement on ACO which has been applied widely in routing problem [17, 18]. The solution of ACS is iteratively constructed by the collective behavior of ants. The ants choose their route according to the pheromone and attractiveness level of each path. The pheromone laid on the road is the indirect communication media between ants in order to find the shortest route to the food source [19]. Ants tend to choose the route which has a higher pheromone level. In solving DVRP, Montemanni et al. divide the working day into time slices. The ACS is applied to obtain the best route for each time slice [12]. Their results reveal that ACS is a promising algorithm for solving routing problems. Application of ACS in solving VRP or other transportation problem can also be found in [12,20–22]. This paper proposes to solve the DVRP using a heuristic-based method instead of the exact method since it has easier computation; thus, it can be applied to big-size problems. The improvement covers both the initialization part and the solution construction part. ACS is an algorithm inspired by ant behavior in finding food sources. Herein, the pheromone is the important factor in finding the shortest distance. In basic ACS, the initial pheromone is generated randomly. This paper applies a cluster insertion algorithm to reduce the risk caused by poor initial pheromone distribution. In addition, the solution construction rule is modified so that it is suitable for the fuzzy service time.

Furthermore, an improved ACS algorithm is applied to solve the abovementioned problem. The remainder of this paper is organized as follows. Section 2 briefly reviews the necessary background as it applies in this study. It covers both the DVRP model and ACS algorithm. Section 3 presents the proposed DVRP with uncertain service time and the proposed fuzzy-ACS. The experiments and evaluation are discussed in Section 4. Finally, the concluding remarks are offered in Section 5.

2. Background

This section briefly reviews DVRP, fuzzy approximation as an approach employed for dealing with uncertain service time, and ACS as the basic algorithm of the proposed method.

2.1. DVRP

DVRP divides customers into two categories: early customers and late customers [5]. Early customers are the known customers in the early working period while late customers appear randomly over time. Service time for each customer is unknown at the planning stage. At the beginning, the decision maker or dispatcher should arrange an optimal route for visiting all early customers. Within the working hours, new late customers may appear. The dispatcher must decide whether or not the new customers will be served. The decision is made by estimating the required total service time and the remaining available time. Once a vehicle is committed to serve a customer, it cannot be canceled. Afterwards, the current route is updated based on this decision. Since new customers may appear within the working hours, a vehicle which has completed its task before the end of working hours must wait at its last customer until its task is updated or the working hours are ended. The dispatcher updates the ongoing route every fixed period of time. In updating the current route, the dispatcher treats all known and not yet served customers as a static VRP. The idea of modeling DVRP as a sequence of static VRP-like instances was proposed by Kilby et al. [5].

2.2. Fuzzy set

Fuzzy set is a set dealing with a class of objects without crisp boundaries [23]. Each element has a membership degree defined as a real number within 0 and 1. A higher membership degree indicates higher confidence that this element belongs to that set. The fuzzy membership degree can be defined via several functions: Triangular, trapezoidal, Gaussian, generalized bell, sigmoidal, and Z-shape [24]. For computation simplification, this paper employs a triangular fuzzy function to represent

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