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A multi-objective memetic algorithm based on locality-sensitive hashing for one-to-many-to-one dynamic pickup-and-delivery problem

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ABSTRACT

This paper presents an early attempt to solve one-to-many-to-one dynamic pickup-and-delivery problem (DPDP) by proposing a multi-objective memetic algorithm called LSH-MOMA, which is a synergy of multi-objective evolutionary algorithm and locality-sensitive hashing (LSH) based local search. Three objectives namely route length, response time, and workload are optimized simultaneously in an evolutionary framework. In each generation of LSH-MOMA, LSH-based rectification and local search are imposed to repair and improve the individual solutions. LSH-MOMA is evaluated on four benchmark DPDPs and the experimental results show that LSH-MOMA is efficient in obtaining optimal tradeoff solutions of the three objectives.

1. Introduction

Pickup-and-delivery problems (PDPs) [3,5,47] constitute a subset of vehicle routing problems (VRPs) [13] wherein objects or people have to be transported from an origin to a destination. They are fundamental problems of transportation and logistic distribution aiming to find an optimal vehicle route to serve customers associated with pickup and/or delivery requests under transportation capacity constraints. The route optimization in PDPs can lead to significant economic savings, e.g., the reduction of operating cost, traffic congestion, and pollution emission, and thus increase the sustainability of city development.

The majority of PDPs are optimized using a static model, i.e., all input data of the problems are known in advance and fixed during the route planning, however the increasing competitive pressures and expectations of high customer satisfaction have forced the logistic service providers to respond to dynamic requests over time. The development of communication technologies, geographic information systems and computer technologies also have greatly motivated the study of dynamic PDPs (DPDPs). In DPDPs, vehicle routes can be re-planned according to actual travel times, new requests, and unexpected events [6,8,45,51]. This kind of problem is also called online or real-time routing problem in other work [28]. PDPs have been proved to be NP-hard [5] and DPDPs represent the harder cases.

Evolutionary computation techniques such as Genetic Algorithm (GA) [26], Ant Colony Optimization (ACO) [17], and Particle Swarm Optimization (PSO) [30] have been widely used to solve DPDPs due to their ability to obtain satisfactory results in tractable

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time cost [40]. For instance, Cheung et al. [10] studied a mathematical model for dynamic fleet management taking into account the real-time vehicle locations, travel time, and incoming pickup and delivery requests. A GA based solution was proposed to determine a route plan through solving a static vehicle routing problem before daily operation, and then the route is re-optimized as dynamic information arrives. Haghani and Jung [25] presented a GA to solve DPDP with soft time windows where multiple vehicles with different capacities, real-time service requests, and time-dependent travel times are considered. Benyahia and Potvin [4] proposed a genetic programming to model the decision process of a human vehicle dispatcher in DPDP. In [43], a GA embedded in a rolling horizon framework was put forward to solve DPDP with time windows for long-distance freight forwarding with newly arriving requests. Cortés et al. [12] proposed a PSO-based approach to solve a DPDP formulated under a hybrid predictive control (HPC) scheme. Sáez et al. [46] extended [12] by developing more efficient solution algorithms based on GA and fuzzy clustering for the multi-vehicle DPDP. The same group in [38] further generalized their approaches based on generic evolutionary algorithms and HPC scheme to support the dispatcher of a real-time dial-a-ride service. Euchi et al. [19] presented an artificial ACO with 2-opt local search to solve dynamic VRP with pickup and delivery.

Most of the aforementioned approaches were proposed for single-objective problems, where the main objective namely traveling cost (in terms of time/distance) is optimized. However, the dynamic nature of DPDP introduces new conflicting objectives such as response time (or latency) and service workload. Multi-objective optimization methods such as multi-objective evolutionary algorithms (MOEAs) [11,15,23,34,44,49,53] are greatly desirable because of their capability of obtaining multiple trade-off solutions. Many MOEAs have been proposed for static VRPs/PDPs [18,20,21,24,29,52,66] and a few for general dynamic VRPs [22,55]. Yet, there is very limited work on multi-objective DPDP. The work of Núnez et al. [41] represents one of the very few attempts to use multi-objective optimization model for DPDP. In [41], the authors proposed a multiobjective-model-based predictive control framework implemented with GA to solve the dial-a-ride problem, i.e., a one-to-one DPDP, considering two opposing goals namely user and operator costs.

This paper proposes a multi-objective memetic algorithm [9,31,37,39,42] namely LSH-MOMA to solve DPDP by optimizing the route length, response time, and service workload, simultaneously. We focus on the single-vehicle one-to-many-to-one (1-M-1) DPDP, one of the most typical routing problems in city courier. In 1-M-1 DPDP, some commodities are initially available at the depot and delivered to the customers in the course of operation. At the same time, some other commodities either requested in advance or dynamically are collected from the customers and destined to the same depot. New customer pickup requests are received through a call center and forward to the vehicle during the operation. The vehicle route is dynamically changed in response to new requests. Many other types of DPDPs, especially one-to-one DPDPs, have been extensively studied and overviews can be found in [6] and [45]. However, efficient solutions for 1-M-1 DPDP are still lacking to provide practical trade-off decisions that can satisfy the multiple conflicting objectives in real-world express courier service.

This work presents an early attempt to solve the 1-M-1 DPDP by proposing LSH-MOMA as a synergy of MOEA and locality-sensitive hashing (LSH) [1] based local search. Memetic algorithms, taking advantage of both population-based global search and local search, have been shown to obtain better performance than their conventional counterparts in various complex real-world problems [2,7,27,32,33,50,57,59,60,62–64] including VRPs [35,56] and PDPs [58]. In LSH-MOMA, a vehicle is arranged to start from a depot and follow an initially scheduled Hamiltonian route to serve static requests. Afterward, the route is re-planned in response to new requests, so that the three objectives are optimized subject to transportation capacity constraint. The static requests must be served in the solution route whereas the dynamic requests could be selectively responded. A population of candidate routes is evolved using a MOEA framework where LSH-based rectification and local search are introduced to repair and improve the candidate solutions respectively in each generation. LSH-MOMA is tested on four benchmark 1-M-1 DPDPs with different scales of customer nodes. The experimental results demonstrate the superiority of LSH-MOMA to the other counterpart algorithms in identifying reasonable tradeoff solutions.

The main contributions of this study are threefold: (1) a three-objective 1-M-1 DPDP is formulated and benchmark problems based on both Euclidean plane and real map are studied; (2) an LSH-based method is proposed for fast identification of geometrically nearest neighbors, which enables route planning algorithms to handle problems in large environments; (3) a new memetic algorithm namely LSH-MOMA is put forward to solve the formulated 1-M-1 DPDP, which is expected to inspire the design of new MOEA-based approaches for DPDPs.

The rest of this paper is organized as follows. Section 2 provides the formulation of the three-objective 1-M-1 DPDP. Section 3 introduces the LSH-based nearest neighbors identification method. Section 4 presents the details of the proposed LSH-MOMA. Section 5 provides the experimental design and results on benchmark problems. Finally, Section 6 concludes this study.

2. Problem formulation

This section formulates the single-vehicle 1-M-1 DPDP. As shown in Fig. 1, to solve a 1-M-1 DPDP is to find an optimal closed-loop vehicle route that starts from a depot, then accesses the customer nodes in the course and finally ends up at the same depot. The vehicle carries delivery commodities on off-line requests away from the depot, and then serves delivery and pickup requests following a planned route. Once new dynamic requests arrive, the vehicle could choose to respond the requests by re-planning the route or just ignore them. The optimality of the route is defined in terms of three objectives namely route length, response time, and service workload in this study.

Without loss of generality, we confine the routing of a 1-M-1 DPDP in a rectangle $R = R_x \times R_y$. The definitions of customer node, depot, service route, vehicle capacity constraint, real-time load, route length, response time and workload are provided as follows: