Computers & Industrial Engineering 86 (2015) 60–68

Contents lists available at ScienceDirect

Computers & Industrial Engineering

journal homepage: www.elsevier.com/locate/caie

An advanced hybrid meta-heuristic algorithm for the vehicle routing problem with backhauls and time windows

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ARTICLE INFO

Article history:
Available online 29 October 2014

Keywords:
Vehicle routing problem
Hybrid meta-heuristic algorithm
Simulated annealing
Tabu search

ABSTRACT

This paper presents an advanced hybrid meta-heuristic algorithm (HMA) to solve the vehicle routing problem with backhauls and time windows (VRPBTW). The VRPBTW is an extension of the vehicle routing problem with time windows (VRPTW) and the vehicle routing problem with backhauls (VRPB) that includes capacity, backhaul and time window constraints. In this problem, the customers are divided into two subsets consisting of linehaul and backhaul customers. Each vehicle starts from the depot, and goods are delivered from the depot to the linehaul customers. Goods are subsequently returned to the depot from the backhaul customers. The objective is to minimize the total distance that satisfies all of the constraints. The proposed meta-heuristic method is tested on a problem data set obtained from Solomon's VRPTW benchmark problems which includes 25, 50 and 100 demand nodes. The results of the computational studies show that the HMA outperforms the existing studies and provides better solutions than the best known solutions in practical computational times.

1. Introduction

Vehicle routing is an important activity in both the public and private sectors. For example, in the United States, transportation costs account for approximately 10% of the gross domestic product (Bowersox & Calantone, 1998). Consequently, even small improvements in routing efficiency can result in large cost reductions. Improved routing efficiency becomes even more important as fuel prices increase.

The vehicle routing problem involves the design of a set of minimum-cost vehicle routes, originating and terminating at a central depot, for a fleet of vehicles that services a set of customers with known demands. Each customer is serviced exactly once, and all customers must be assigned to the vehicles without exceeding the vehicle capacities (Canen & Pizzolato, 1994). The efficient routing and scheduling of vehicles can provide considerable cost reductions for industries and the governments (Tan, Lee, & Ou, 2001). The route cost of a vehicle is related with the total distance it travels, and the objective is to minimize the total cost of all routes using the minimum number of vehicles without violating any constraints. Although the primary objective is minimizing the total distance for the problem, there have been various objectives existing in the literature such as minimizing the total traveling time, maximizing the service quality, minimizing the total fuel consumption or multiple of them. On the other hand the physical characteristics of the problem diversify the problem with additional constraints. For instance, uncertain customer demand, fuzzy traveling times or time windows, multiple depot, heterogeneous fleet type, two or three dimensional truck loading plans, load splitting, time dependent routing etc. are the most commons (Lahyani, Khemakhem, & Semet, 2014).

The VRPBTW is a variant of the classical vehicle routing problem (VRP). The VRPBTW contains two subsets of customers, known as linehauls and backhauls. Each linehaul customer requires a given quantity of goods from a central depot, and a given quantity of goods is collected from each backhaul customer and returned to the depot. The backhauls must be visited after the linehauls in each route. Fleet type can be homogeneous as well as heterogeneous fleet of vehicles with different capacities (Repoussis & Tarantilis, 2010). Each customer must be serviced within a specified time window, and a vehicle is not allowed to begin service at a customer location after the time window's upper bound. A waiting time is incurred if a vehicle reaches a customer before the lower bound. VRP with limited capacitated vehicles is demonstrated as a NP-hard problem type (Archetti, Feillet, Gendreau, & Speranza, 2011). In addition to VRP, adding time windows and backhauls constraints generally do not simplify the problem and the VRPBTW is also known to be NP-hard (Thangiah, Potvin, & Sun, 1996).

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http://dx.doi.org/10.1016/j.cie.2014.10.014
0360-8352/

Much progress has been accomplished in the field of vehicle routing until now. Laporte (2009) presented the developments of the solution approaches on VRP in the last 50 years. Likewise, Eksioglu, Vural, and Reisman (2009) presents a taxonomic review of the vehicle routing problems. Although many heuristic and exact algorithms have been presented in the literature for the VRP and its variations (e.g., the capacitated vehicle routing problem, the vehicle routing problem with backhauls and the vehicle routing problem with time windows), only a few recent studies have been devoted to the VRPBTW. Gelinas, Desrochers, Desrosiers, and Solomon (1995) propose a new branching strategy for branch-and-bound approaches based on column generation. This algorithm finds optimal solutions to test problems with up to 100 customers. Thangiah et al. (1996) present an insertion algorithm to improve the initial solution and tested their algorithm by using Solomon's test problems. Duhamel, Potvin, and Rousseau (1997) design a tabu search heuristic for the VRPBTW with customer precedence. Reimann, Doerner, and Hartl (2002) improve the insertion algorithm by using an ant system. Cheung and Hang (2003) develop label-matching algorithms for solving the VRPBTW. Their heuristic approach can handle the addition of complex real-world constraints, such as vehicles of different capacities and penalties for vehicles that arrive early. Zhong and Cole (2005) use a guided local search heuristic to find an initial solution for the VRPBTW, and an adapted sweep algorithm is used to improve the solution. Cho and Wang (2005) adapt the nearest neighbor heuristic to the threshold accepting algorithm. Ropke and Pisinger (2006) use a neighbor search algorithm in which the VRPBTW is transformed to the VRPB and the routes are ordered according to time window constraints. Aghdaghi and Jolai (2008) develop a two-phase heuristic using a goal programming approach. A similar problem to the VRPBTW, which is time dependent vehicle routing problem with backhauls, is studied by Wang and Wang (2009). This problem also considers the traveling time between the nodes according to the time of day. The authors develop a two-phase heuristic algorithm to solve the problem, where an initial solution is generated in the first phase and this solution is improved by reactive tabu search. Recently an extension form of the VRPBTW is considered by Liu, Xie, Augusto, and Rodriguez (2013) which is called as vehicle routing problem with mixed backhauls and time windows (VRPMBTW). As distinct from the VRPBTW in this problem vehicles can serve to the linehaul and backhaul customers in a mixed order. The authors present two mixed integer mathematical model for the problem and proposes a genetic algorithm and a tabu search method. Both of the algorithms are tested on a benchmark dataset and compared with best known solutions. Belmecheri, Prins, Yalaoui, and Amodeo (2013) consider the VRPMBTW with heterogeneous fleet and propose a particle swarm optimization algorithm with a local search. Another type of the VRPBTW is studied by Pradenas, Oportus, and Parada (2013) which considers the environmental impact of the vehicles and aims to minimize greenhouse gases emissions. A scatter search is used to solve problem and analyzed with problems from the literature. Their results indicate that the proposed approach provides a decrease on greenhouse gases though in some cases the total traveled distance has increase.

According to the best of our knowledge, various heuristic and meta-heuristic algorithms are proposed to solve the VRPBTW. Most of them are integrated with a local search or route construction heuristics. However, a hybrid algorithm has not been proposed to solve the VRPBTW until now. It is known that although meta-heuristic algorithms have effectively tackled a wide variety of combinatorial problems, hybrid frameworks combining the strengths of different meta-heuristic approaches can lead to more powerful and efficient search methods. This paper presents an advanced hybrid meta-heuristic algorithm that integrates simulated annealing (SA) and tabu search (TS) to obtain more effective solutions for the VRPBTW which is the main contribution of the study. The hybrid structure of the SA and TS is proposed for some of the VRP problems except the VRPBTW, e.g., for the VRP proposed by Osman (1993), for the capacitated vehicle routing problem proposed by Lin, Lee, Ying, and Lee (2009), for the vehicle routing problem with cross-docking proposed by Mousavi and Moghaddam (2013). But, distinctly from the existing studies, HMA uses an improved route construction algorithm for initial solution and local search method to get effective solutions. In order to demonstrate the efficiency of the proposed framework, the HMA is tested on a problem data set obtained from Solomon's VRPTW benchmark problems which includes 25, 50 and 100 demand nodes. The computational studies are carried out for VRPTW, VRPBTW and VRPMBTW. The test results show that the solutions produced by the HMA perform better than the best known solutions. Section 2 of this paper describes the mathematical formulation of the VRPBTW. Section 3 describes the HMA proposed for the VRPBTW in detail. The computational results are reported in Section 4, and finally the conclusion is presented in Section 5.

2. Mathematical formulation

The problem is formulated based on the existing mathematical formulation for VRPB, with each vertex representing a customer (Toth & Vigo, 2002). Let $G(V, A)$ be an undirected graph with a vertex set $V = \{0\}\ L \cup B$, where the subsets L and B correspond to the linehaul and backhaul customers, respectively. The arc set A denotes all possible connections between the nodes. $\overline{G}(\overline{V}, \overline{A})$ is a directed graph obtained from G by defining $\overline{V} = V$ and $\overline{A} = A_1 \cup A_2 \cup A_3$, where

$$A_1 = \{(i,j) \in A : i \in L \cup \{0\}, j \in L\},$$
$$A_2 = \{(i,j) \in A : i \in L, j \in B \cup \{0\}\},$$
$$A_3 = \{(i,j) \in A : i \in B, j \in B \cup \{0\}\}.$$

In other words, the arc set $\overline{A}$ can be partitioned into three disjoint subsets. A_1 contains all of the arcs from the depot to linehaul vertices and from linehaul vertices to other linehaul vertices. A_2 contains all of the arcs from linehaul vertices to backhaul vertices and to the depot. A_3 contains all of the arcs from backhaul vertices to other backhaul vertices and to the depot. Consequently, $\overline{A}$ does not contain any arcs that result in an infeasible solution. Additionally, for each $i \in V$, $\Delta_i^+ = \{j : (i,j) \in \overline{A}\}$ and $\Delta_i^- = \{j : (j,i) \in \overline{A}\}$, define the forward and backward star of i, respectively. Forward star of i defines the set of vertices j which are directly reachable from node i. Analogously, backward star of i defines the set of vertices j which have direct path to node i. Using these definitions, the VRPBTW can be formulated into the following mixed-integer programming model:

Notation
K : Set of vehicles
d_i : Demand/supply for customer $i : \forall i \in \overline{V} \setminus \{0\}$
c_{ij} : Distance from node i to node j: $(i,j) \in \overline{A}$
t_{ij} : Travel time between node i and node j: $(i,j) \in \overline{A}$
a_i : Earliest arrival time at customer $i : \forall i \in \overline{V} \setminus \{0\}$
b_i : Latest arrival time at customer $i : \forall i \in \overline{V} \setminus \{0\}$
s_i : Service time for customer $i : \forall i \in \overline{V} \setminus \{0\}$
u_k : Capacity of vehicle k:$\forall k \in K$
T_{max} : Maximum route time allowed for vehicles
M : Penalty value

Decision variables
x_{ijk} : 1 if vehicle k travels from customer i to j, and 0 otherwise
w_{ik} : Service start time of vehicle k for customer i