Expert Systems With Applications 61 (2016) 28–38

Contents lists available at ScienceDirect

Expert Systems With Applications

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

Hybrid large neighbourhood search algorithm for capacitated vehicle routing problem

Sener Akpinar*

Dokuz Eylul University, Faculty of Engineering, Department of Industrial Engineering, 35397 Izmir, Turkey

ARTICLE INFO

Article history:
Received 12 March 2016
Revised 12 May 2016
Accepted 13 May 2016
Available online 13 May 2016

Keywords:
Capacitated vehicle routing problem
Hybrid meta-heuristic
Large neighbourhood search
Ant colony optimization

ABSTRACT

This paper presents a new hybrid algorithm that executes large neighbourhood search algorithm in combination with the solution construction mechanism of the ant colony optimization algorithm (LNS–ACO) for the capacitated vehicle routing problem (CVRP). The proposed hybrid LNS–ACO algorithm aims at enhancing the performance of the large neighbourhood search algorithm by providing a satisfactory level of diversification via the solution construction mechanism of the ant colony optimization algorithm. Therefore, LNS–ACO algorithm combines its solution improvement mechanism with a solution construction mechanism. The performance of the proposed algorithm is tested on a set of CVRP instances. The hybrid LNS–ACO algorithm is compared against two other LNS variants and some of the formerly developed methods in terms of solution quality. Computational results indicate that the proposed hybrid LNS–ACO algorithm has a satisfactory performance in solving CVRP instances.

1. Introduction

Optimization is the processes of systematically making a design, system, or decision as effective as possible through a set of logically connected rules, generally referring to an optimization algorithm. Developing efficient optimization algorithms is an exploratory research field, since numerous real world problems could be modelled as an optimization problem and they need to be solved to optimality or near-optimality in reasonable time limits. In this respect, algorithmic design literature has been growing continuously within two directions: developing new search strategies and improving the performance of the existing search procedures by some modifications or hybridization one search procedure with other search procedures.

Optimization algorithms can be classified into two groups as exact and approximation methods. Exact solution procedures depend on full enumeration and guarantee the optimal solution of the problem on hand; however, they require excessive amount of time to identify the optimal solution as the problem size gets larger. Therefore, approximation algorithms are used widely than the exact solution procedures. From the optimization point of view, the key point is to select the appropriate optimization method for the problem on hand. Approximation algorithms generally start with a single solution or a pre-defined number of solutions while trying to identify the optimal solution for an optimization problem. They usually use some specific rules with the aim of guiding the algorithm towards the promising regions of solution space of the problem. These rules, namely heuristics, often provide some neighbourhood moves that change the current solution in order to explore the solution space of the problem. Specifying the heuristics to be used and connecting them within a logical manner are the key issues while developing efficient approximation algorithms.

The approximation algorithms are generally called as meta-heuristics, and they have the capability to provide satisfactory results for different types of optimization problems in reasonable time limits. However, meta-heuristic algorithms could also have some limitations as the premature convergence, which may cause the algorithm to trap in local optima or to stagnate and therefore it is a challenging problem for the meta-heuristics approaches. The best way to improve the effectiveness of a meta-heuristic algorithm and thus to overcome such limitations is to develop hybrid approaches, which generally combine superiorities of different search procedures. The reader can be suggested to see the review papers of Blum, Puchinger, Raidl, and Roli (2011), Crainic and Toulouse (2003), Preux and Talbi (1999), Raidl (2006), Talbi (2002) and Ting, Yang, Cheng, and Huang (2015) for detailed discussions about the hybrid meta-heuristics.

In this present paper, we propose a hybrid large neighbourhood search algorithm for the capacitated vehicle routing problem (CVRP). The proposed hybrid algorithm is a combination of large neighbourhood search (LNS) algorithm (Shaw, 1998) and ant colony optimization (ACO) algorithm (Dorigo, Maniezzo, Colorni, & Maniezzo, 1991). To the best of our knowledge, Elhassania, Jaouad,

* Corresponding author. Fax: +90 232 301 76 08.
E-mail address: sener.akpinar@deu.edu.tr

http://dx.doi.org/10.1016/j.eswa.2016.05.023
0957-4174/

and Ahmed (2013) firstly introduced the concept of hybridizing the LNS and ACO algorithms for a similar vehicle routing problem discussed in this paper, however search characteristics of their hybrid ACOLNS algorithm differ from our hybrid LNS-ACO algorithm. The similarities and differences between these two hybrid algorithms will be discussed in Section 4. The LNS algorithm uses two basic operators, destruction of a solution by a removal heuristic and reparation of the destroyed solution by an insertion heuristic. A removal heuristic generates an infeasible solution from the current solution and then the insertion heuristic rebuilds this solution to generate another feasible solution (Pisinger & Ropke, 2010). After that, LNS algorithm decides whether to accept or not this newly generated feasible solution as the new current solution via the guidance of an acceptance criterion (Shaw, 1998), (Schrimpf, Schneider, Stamm-Wilbrandt, & Dueck, 2000), (Ropke & Pisinger, 2006). In this paper, the proposed hybrid algorithm accepts only the improving solutions; otherwise, the algorithm generates a new solution via the solution construction mechanism of ACO with the guidance of the information derived from the incumbent solution. By doing so, the proposed algorithm achieves a solution construction characteristic besides the improvement characteristic of LNS algorithm, and therefore, the algorithm gains the ability to utilize the positive feedback mechanism of ACO. For detailed information about the variants and extensions of the LNS algorithm, the reader can be suggested to see the paper of Pisinger and Ropke (2010).

The remainder of the paper is organized as follows. The definition of the capacitated vehicle routing problem is given in Section 2. Basic steps of the LNS algorithm are given in Section 3. The proposed hybrid LNS–ACO algorithm is presented in Section 4. Computational study is presented in Section 5. Conclusions are given in Section 6.

2. Capacitated vehicle routing problem

The capacitated vehicle routing problem (CVRP) is the classical version of the routing problems. This problem consists of a single depot and a set of customers to be served from the depot via a set of K homogeneous capacitated vehicles. The objective of this problem is to determine the routes that minimize the total cost, that is, the problem is about the assignment of customers to vehicles and determining customer visit sequences for each route with the aim of minimizing the total travelled distance by the vehicles. Given a set of N customers and a single depot, the CVRP can be defined via a graph as $G = (N,\ E)$, where $N = \{0, \ldots, n\}$ is the node set and $E = \{(i,\ j) :\ i,\ j \in N\}$ is the edge set. Node 0 represents the depot that is the start and end node of the vehicles for their trips. The other nodes represent the customers having a known demand d_i and each customer must be served by exactly one vehicle. The travel distance from node i to node j is defined by $d_{ij} > 0$ and each vehicle has a unique capacity of Q_k. The total demand of the customers assigned to a route must not exceed the unique vehicle's capacity of Q_k. In accordance with these explanations, CVRP can be formulated as given below, where X_{ij}^k equals to 1 if vehicle k travels from node i to node j and 0 otherwise (Lin, Lee, Ying, & Lee, 2009).

$$Min \ \sum_{i=0}^{N}\sum_{j=0}^{N}\sum_{k=1}^{K} d_{ij}X_{ij}^{k} \tag{1}$$

Subject to

$$\sum_{k=1}^{K}\sum_{i=0}^{N} X_{ij}^{k} = 1 \quad j \in \{1, \ldots, N\} : i \neq j \tag{2}$$

$$\sum_{k=1}^{K}\sum_{j=0}^{N} X_{ij}^{k} = 1 \quad i \in \{1, \ldots, N\} : i \neq j \tag{3}$$

$$\sum_{i=0}^{N}\sum_{j=0}^{N} X_{ij}^{k} d_i \leq Q_k \quad k \in \{1, \ldots, K\} \tag{4}$$

$$\sum_{j=1}^{N} X_{ij}^{k} = \sum_{j=1}^{N} X_{ji}^{k} \leq 1 \quad \text{for } i = 0 \text{ and } k \in \{1, \ldots, K\} \tag{5}$$

$$\sum_{k=1}^{K}\sum_{j=1}^{N} X_{ij}^{k} \leq K \quad \text{for } i = 0 \tag{6}$$

Objective function (1) minimizes the total distance travelled by the vehicles. Constraint sets (2) and (3) guarantee that each customer is served by exactly one vehicle. Constraint set (4) ensures that the total demand of the customers assigned to a route does not exceed the vehicle capacity. Constraint set (5) indicates that the depot is the start and end node for the trips of each vehicle. Constraint set (6) guarantees that there are maximum K routes for serving the customers.

For comprehensive information about the variants of the vehicle routing problem and their solution procedures, the reader can be suggested to see the first and second editions of the book edited by Toth and Vigo (2002, 2014), and the survey papers by Eksioglu et al. (2009), Laporte (2009) and Braekers, Ramaekers, and Van Nieuwenhuyse (2016). Developing effective solution procedures for the CVRP remains as a challenging research field, however a large number of solution methods have been proposed in the literature during the last 50 years (Jin, Crainic, & Løkketangen, 2014) and CVRP is still far from being satisfactorily solved (Semet, Toth, & Vigo, 2014). CVRP is the basic problem in the literature on vehicle routing, which is also a challenging research field, and thereby any solution procedure developed for the CVRP could be adapted to solve any variant of this problem. For that reason, we have the motivation to solve CVRP instances effectively with an improved search strategy, hybrid LNS-ACO algorithm, within the scope of this paper. Additionally, our proposed hybrid algorithm can be extended to have the capability of solving other variants of CVRP within the context of the succeeding studies.

3. Large neighbourhood search algorithm

Shaw (1998) initially proposed the LNS algorithm for solving vehicle routing problem with time windows (VRPTW). LNS algorithm uses a neighbourhood generation mechanism to explore the solution space of the optimization problem. The neighbourhood generation mechanism of the LNS algorithm depends on two successive operators: destruction of a solution by a removal heuristic and reparation of the destroyed solution by an insertion heuristic. A removal heuristic removes some components of the current solution by considering a criterion, while the insertion heuristic fixes the destroyed solution by reinserting the removed parts via a greedy rule. After that, LNS algorithm evaluates the newly generated solution via an acceptance function in order to decide to accept or reject this solution as the new current solution. LNS algorithm executes these steps successively until the stopping condition is met as can be seen from Fig. 1.

Ropke and Pisinger (2006) successfully modified the basic LNS algorithm by using different types of removal and insertion heuristics during the same search instead of using one method for removal and one method for insertion. They called the new version of the LNS algorithm as adaptive large neighbourhood search (ALNS) algorithm. In addition, there are many successful implementations of the ALNS algorithm in literature such as the papers of Adulyasak, Cordeau, and Jans (2012), Belo-Filho, Amorim, and Almada-Lobo (2015), Demir et al. (2012), Laporte, Musmanno, and Vocaturo (2010), Luo, Qin, Zhang, and Lim (2016),