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Ant colony system with characterization-based heuristics for a bottled-products distribution logistics system

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ABSTRACT

The aim of this paper is to show the solution of the Vehicle Routing Problem with Time Windows (VRPTW) as a key factor to solve a logistics system for the distribution of bottled products. We made a hybridization between an Ant Colony System algorithm (ACS) and a set of heuristics focused on instance characterization and performance learning. We mainly propose a method to make a constrained list of candidate customers called Extended Constrained List (ECL) heuristics. Such a list is built based on the characterization of the time-window and the geographical distribution of customers. This list gives priority to the nearest customers with a smaller time window. The ECL heuristics is complemented by the Learning Levels (LL) heuristics, that allows the ants to use the pheromone matrix in two phases: local and global. In order to validate the benefits of each heuristics, a series of computational experiments were conducted using the standard Solomon's benchmark. The experimental results show that, when the ECL heuristics is incorporated in the basic ACS algorithm, the number of required vehicles is reduced by 28.16%. When the LL heuristics is incorporated, this reduction increases to 36.83%. The experimentation reveals that, by a suitable characterization, preexisting conditions in the instances are identified in order to take advantage of both of the ECL and LL.

1. Introduction

Logistics systems applied to transport systems are a current problem in productive and service sectors. Distributors should effectively and efficiently stock customers with products, which constitutes a major challenge for a logistics system, since resources are limited and transportation costs constitute a high percentage of the value added to goods: from 5% to 20% [1]. Solving real-life world transportation problems requires the development of robust methods that support the complexity of these kinds of problems. In order to contribute to this area, we have a methodological solution developed by integrating the main tasks (routing, scheduling and loading) involved in a generic transportation problem, called RoSLoP [2,3].

RoSLoP focuses mainly on routing vehicles applied to the distribution of bottled products in a company located in northeast Mexico [2,4]. The objective of the routing task is to define routes for vehicles so as to minimizing the total cost subject to twelve real world constraints [2]. Considering the difficulty of handling several realistic constraints at the same time, this problem is often called Rich VRP [5,3].

This work extends the solution presented in [2] for RoSLoP, particularly for the VRPTW routing task. The proposal of this research is based on a heuristics hybridization of an ACS algorithm. The purpose of the hybridization is to improve the optimization process by characterizing the problem according to two aspects of customers: geographic distribution

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(topology) and service time distribution (time-window types). The heuristics are: Extended Constrained List (ECL) and Learning Levels (LL) [6,3]. The first heuristics constitutes the main contribution of this work, it provides a higher probability of selection of those customers which are closer and have smaller time-window types, whereas the second heuristics slightly increases the probability for movements which have previously contributed to improve the solution.

Like our work, researchers have presented since the 1960's their proposals related to VRPTW in order to solve this problem. The main work includes Pisinger and Ropke [7], who present an extension of Large Neighborhood Search (LNS) proposed by [8]. Their algorithm, called ALNS, is an adaptation of the LNS algorithm by building partial neighborhoods which compete to iteratively modify the current solution.

Another researcher, Mester [9], proposed a heuristic algorithm based on $(1+1)$ multi-parametric evolutionary strategies. Three operators are used for the removal of customers (purely random removals, removal of one customer from each route, and random ejections from rings generated from two circles centered on the depot with random radiuses), while a cheapest insertion heuristics is applied for re-insertion. Each offspring is further improved using Or-Opt, Exchange, 2-Opt local moves within a parameterized dynamic environment "Adaptive Variable Neighborhood" (AVN). In an effort to prune the neighborhood space, a strategy for selecting neighboring routes, called "Dichotomous Route Combinations" (DRC), is also used to take advantage of the geographical division and topology of the vehicle routes.

A different strategy, but also based on Local Search, is proposed by Prescott-Gagnon et al. [10]; they present a hybridization of a branch-and-price heuristic technique, a LNS method composed by operators related to customer selection known as: Proximity, SMART, and Longest Detour. Another local-search based heuristics was developed by Hoshino et al. [11]; such heuristics is controlled by chaotic dynamics exploiting principles of neural networks. The chaotic search applies by exchanging and relocating local moves. The neurons are updated asynchronously while a single iteration is performed, and finally the route elimination heuristics of [12] is applied periodically for further improvement.

After reviewing state-of-the-art papers, it is concluded that the ECL and LL heuristics are original. Table 4 in Section 5 presents comparative results obtained by our ACS algorithm including the proposed heuristics versus other works presented here.

2. Vehicle routing problem with time windows (VRPTW)

Vehicle routing has been of great interest for the scientific community over the past fifty years. However, open questions remain due to its complexity [13]. VRP, defined by Dantzig in [14], is a classic combinatorial optimization problem. It consists of trying to service a set of customers using a fleet of vehicles, respecting constraints on the vehicles, customers, drivers, and so on. Among the most important variants of VRP is the VRPTW defined by Kallehauge in [15]. This problem consists of finding the optimal routing of a fleet of vehicles from a depot to a number of customers that must be visited within a specified time interval, called a time window. A time and capacity constrained digraph $G = (V, A, c, t, a, b, d, q)$ is defined with the following elements:

- a node set $V = V_* \cup \{0, n+1\}$, where $V_* = \{1, \dots, n\}$ is the set of customer nodes, and the nodes 0 and $n+1$ are the starting depot and the returning depot respectively,
- an arc set $A = A_* \cup \delta^+(0) \cup \delta^-(n+1)$, where $A_* = A(V_*)$ is the set of arcs (i, j) such that $(i, j) \in V_*$, additionally $\delta^+(0) = \{(0, i) | i \in V_*\}$ is the set of arcs leaving the start depot node, and $\delta^-(n+1) = \{(i, n+1) | i \in V_*\}$ is the set of arcs entering the destination depot node,
- durations (traveling time) on arcs $t \in \mathbb{N}^{|A|}$, such that $t_{ij} \le t_{ik} + t_{kj}$, for $i, j, k \in V$,
- start and end service time on nodes $a, b \in \{\mathbb{Z}_+ \cup \{+\infty\}\}^{|V|}$, where $a_0 = a_{n+1} = 0$, $b_0 = b_{n+1} = +\infty$, $a_i \ge t_{0i}$, $b_i \ge a_i$ for $i \in V_*$ and $b_j \ge a_i + t_{ij}$ for $(i, j) \in A_*$,
- demands on nodes $d \in \mathbb{Z}_+^{|V|}$, where $d_0 = d_{n+1} = 0$,
- and a vehicle capacity $q \in \mathbb{Z}_+$, where $q \ge d_i$ for $i \in V_*$ and $q \ge d_i + d_j$ for $(i, j) \in A_*$.

For any path $P = (v_1, \dots, v_k)$ in G, the arrival times of the set of nodes $V(P)$ of the path is the vector $s \in \mathbb{Z}_+^{|V(P)|}$, whose elements are defined as follows: $s_{v_1} = a_{v_1}$, and $s_{v_i} = \max_{i=2,\dots,k}\{s_{v_{i-1}} + t_{v_{i-1}v_i}, a_{v_i}\}$. The demand of the path is $d(V(P))$.

A path $P = (v_1, \dots, v_k)$ in G is feasible if $s_{v_i} \le b_{v_i}$ for $i \in V(P)$ and $d(V(P)) \le q$. A feasible route R from 0 to $n+1$ in G is defined as $R = (0, v_2, \dots, v_{k-1}, n+1)$. We denote by $\Re$ the set of all feasible routes from 0 to $n+1$ in G. For each feasible route a vehicle is required to service the customers included in the route.

Given a time and capacity constrained digraph G, the vehicle routing problem with time windows consists of minimizing the number of required vehicles and the total time required to service all the customers demand.

As VRPTW is a multiobjective problem, in this work a hierarchical technique is applied; i.e., the objectives of the problem are achieved consecutively: minimizing the number of vehicles required, and minimizing the traveling and waiting times required to service all customers.

3. Hybridization of the ant colony system algorithm

Ant algorithms were inspired by the behavior of ants in search for food, because in performing the search, each ant drops a chemical called a pheromone, which provides an indirect communication among the ants. Every algorithm based on an