Ant colony optimization for the electric vehicle routing problem with time windows

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Keywords: electric vehicles; ant colony optimization

1. Introduction

In recent years, there is a growing interest of logistic companies in utilizing EVs for their daily operations due to the greenhouse effect. Therefore, a problem of routing a fleet of EVs has emerged, namely the electric vehicle routing problem (EVRP). The EVRP aims to find the best possible routes for a fleet of EVs so that they visit a set of customers once and only once making sure that the EVs will never run out of energy. Refer to the comprehensive survey in Erdelić and Carić (2019) for different EVRP variations.

In this paper, we introduce an ant colony optimization (ACO) (Dorigo and Gambardella, 1997) solution approach to the electric vehicle routing problem with time windows (E-VRPTW) (Schneider et al., 2014). The high complexity of this problem makes exact solution methods inefficient for solving realistically sized problem instances (Garey and Johnson, 1979).

2. Problem Description

The E-VRPTW can be defined on a complete weighted graph $G = (N, A)$, where $N = \{0\} \cup I \cup F'$ is a set of nodes and $A = \{(i, j) \mid i, j \in N, i \neq j\}$ is a set of arcs connecting these nodes. A non-negative value $d_{ij}$ is associated with each arc which represents the euclidean distance between nodes $i$ and $j$. Node 0 denotes the central depot. The set $I \subset N$ denotes the set of customers, where each customer $i \in I$ is assigned two positive values $\delta_i$ and $s_i$ indicating the customer’s delivery demand and service duration time. Moreover, a time window $[b_i, e_i]$ in which the service has to start is associated with each customer $i \in I$. A service cannot begin before $b_i$ or after $e_i$, but might end later, such that $b_i \leq t_i \leq e_i$, where $t_i$ is the time of arrival of an EV at node $i$. The set $F' \subset N$ denotes the set of $\beta_i$ node copies of each charging station $i \in F$ (i.e., $|F'| = \sum_{i \in F} \beta_i$), which are used to permit multiple visits to each charging station $i \in F$ (if required) (Erdoğan and Miller-Hooks, 2012). At a charging station, the difference between the current charge level of the EV and the battery capacity $Q$ is recharged with a charging rate of $g$. For simplified reasons, we assume linear recharge.

A fleet of homogeneous EV has a cargo load, $u_i$ ($0 \leq u_i \leq C$), where $C$ is the maximal cargo load of an EV and $u_i$ is the remaining cargo load of an EV on arrival at node $i$. In addition, each EV has a battery charge level $y_i$ ($0 \leq y_i \leq Q$),
where $Q$ is the maximal battery charge level of an EV and $y_i$ is the remaining battery charge level of an EV on arrival at node $i$. Each traveled arc consumes the amount $h \cdot d_{ij}$ of the remaining battery charge level, where $h$ denotes the energy consumption rate of an EV traversing that arc. For simplified reasons, we assume constant consumption rate.

The objective function of the E-VRPTW is to find a set of routes that minimize the total distance traveled where: (a) all EVs start and end at the depot, (b) every customer is visited exactly once by exactly one EV, (c) for every EV route the total demand of customers does not exceed the EV’s maximal cargo load, (d) for every EV route the total energy consumption does not exceed the EV’s maximal battery charge level, (e) all customers are visited within their given time windows, and (f) the charging stations can be visited multiple times by any EV. For simplified reasons, we assume that all EVs leave the depot and the charging stations fully charged.

## 3. Solution Approach

The ACO metheuristic has proven to be a useful and effective solution method to address EVRP problems (Mavrovouniotis et al., 2019). ACO can be applied to the E-VRPTW by associating two measures to each arc of the aforementioned graph $G$: the attractiveness $\eta_{ij}$ and the pheromone trail $\tau_{ij}$ between nodes $i$ and $j$. The attractiveness is computed by taking into account the delivery time of customer $j$ and the time window associated with customer $j$ (Gambardella et al., 1999). In particular, the attractiveness favors the customers with the earliest time windows. The pheromone trails are dynamically modified by the ants during the optimization process. In particular, the pheromone trails give a measure of how desirable it is to insert a given arc in a solution.

In ACO, $\omega$ ants build solutions in parallel, where each ant will represent a complete E-VRPTW solution. Each ant is placed at the depot and builds a solution node by node as follows. Each ant iteratively adds new nodes until all nodes have been added. When ant $k$ is located at node $i$, it chooses the next node $j$ with a probability $p_{ij}$ proportional to $[\tau_{ij}]^\alpha[\eta_{ij}]^\beta$ from the set of feasible nodes $N_i^k$ (i.e., the set of nodes that satisfy all the aforementioned constraints of the E-VRPTW), where $\alpha$ and $\beta$ are two constant parameters. When ant $k$ is not able to serve another customer due to insufficient energy or insufficient cargo load it will visit the closest charging station or return back to the depot, respectively.

Once each ant has built a complete E-VRPTW solution, then that solution is improved by using a local search procedure (i.e., the CROSS exchange (Taillard et al., 1997)). Next, the ant with the best solution found is used to increase the pheromone trails associated with arcs belonging in its solution. Then, the process is iterated by placing again the $\omega$ ants to build new (most probably improved) solutions until a termination condition is met (i.e., either a fixed number of constructed solutions has been generated or a fixed CPU time has elapsed). The described ACO with the local search procedure has shown promising results in our preliminary experiments compared to other approaches.

### Acknowledgements

This work has been supported by the European Union’s Horizon 2020 research and innovation programme under grant agreement No. 739551 (KIOS CoE) and from the Government of the Republic of Cyprus through the Directorate General for European Programmes, Coordination and Development.

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