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Modeling and solving the electric vehicle routing problem with nonlinear charging functions and capacitated charging stations

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1 Introduction

Electric vehicle routing problems (E-VRPs) are receiving growing attention from the operations research community. Electric vehicles differ substantially from internal combustion engine vehicles (ICEVs), the main difference lying in their limited autonomy, which can be recuperated at charging stations (CSs). These are much more scarce than conventional refueling stations for ICEVs, which means that EVs often may need to perform en route detours to reach a CS. The latter is specially true in the context of mid-haul or long-haul routing. Most of the research on E-VRPs implicitly assumes that the charging infrastructure is owned by the EV operator, which is plausible for large transportation companies. Modeling the charging functions is a focal point of E-VRPs. In practice the charging function of an EV is non-linear and the charging quantities are decision variables. However, most of the E-VRP literature relies on models that assume linear charging functions and/or full charging policies. In an effort to overcome these limitations, Montoya et al. [2] recently introduced the E-VRP with nonlinear charging function. In their problem the charging functions are more realistically approximated using piecewise linear functions and partial charging is allowed.

Despite these recent advances, some E-VRP modeling assumptions may still be too

strong to correctly represent reality. For instance, it is common to assume that the CSs are uncapacitated, that is, they are able to simultaneously handle an unlimited number of EVs. In practice, each CS has a limited number of chargers. Needless to say, neglecting the CS capacity constraints may lead to poor decisions in practice. For instance we ran a feasibility test on the 120 BKS for the E-VRP-NL reported in Montoya et al. [2] limiting the number of chargers per CS to 1, 2, 3, and 4. According to our results, nearly 50% of these BKS become infeasible when only 1 charger is available. This figure drops to 11% and 2% for the cases with 2 and 3 chargers. On the other hand, when 4 chargers are available, all solutions remain feasible. It is worth noting that if a company decides to invest in out-of-the-depot charging infrastructure, there are few chances that they decide to install more than a couple of chargers at each CS.

In this research we focus on the E-VRP-NL and we extend it to consider capacitated CSs. We call the resulting problem the E-VRP-NL with capacitated CSs (E-VRP-NL-C).

2 Problem statement

We define the E-VRP-NL-C as follows. An unlimited and homogeneous fleet of electric vehicles (EVs) need to serve a set of customers. At the start of the planning horizon, all EVs are located at a single depot that they leave fully charged. Traveling from a location to another location incurs a driving time and an energy consumption (the triangular inequality holds for both). Each CS has a charging technology (e.g., slow, moderate, fast) associated with a nonlinear charging process that is approximated with a piecewise linear function. Each CS has also a *capacity*, given by the number of available chargers. Feasible solutions to the E-VRP-NL-C satisfy the following conditions: 1) each customer is served exactly once by a single EV, 2) each route starts and ends at the depot, 3) each route satisfies a given maximum-duration limit, 4) each route is energy feasible (i.e., the state of charge of an EV upon arriving at a location or departing from it lies between 0 and the battery capacity), and 5) the number of EVs simultaneously charging at each CS does not exceed the number of available chargers. The objective of the E-VRP-NL-C is to minimize the total time needed to serve all customers. This takes into account driving, service, and charging times. Due to the limited availability of CSs, it also includes the waiting times that may occur at CSs whenever an EV queues for a charger.

3 Mixed integer linear programming formulations

The E-VRP-NL-C is a combined routing (the EVs visiting customers) + scheduling (the charging operations) problem. In addition to a classical CS replication-based formulation (see [1],[3],[4]), we present a model that avoids replicating the charging stations nodes. To extend previous formulations of the E-VRP-NL to include the CS capacity constraints,

we borrowed some ideas from the Resource Constrained Scheduling Problem (RCPSP) literature. There is, however, a major difference between these problems and our CS scheduling problem: in the latter i) the duration of each task (i.e., charging operation) and ii) the number of tasks executed by each resource (i.e., charging station) are decision variables. To the best of our knowledge this case has never been addressed in the scheduling literature before. We propose two formulations of the capacity constraints, a *flow-based* and an *event-based*. As expected, solving our models using a commercial solver allows us to address only small size instances.

4 A two-stage solution method

To tackle the E-VRP-NL-C we propose a *route-first assemble-second* metaheuristic. In this two-stage method, we first build a diverse pool of routes, and then we assemble solutions by selecting a subset of routes from the pool.

In the routing phase of our method, we build a pool Ω of high-quality routes while relaxing the capacity constraints. To generate the pool of routes, we use a local search-based metaheuristic that combines simple components from the routing literature and components specifically designed to consider charging decisions. Specifically, the search uses classical operators focusing on sequencing decisions such as two-opt and relocate. Evaluating a move is not straightforward for E-VRPs and raises challenges. Indeed, altering the sequence of customers in a route (i.e., removing or inserting one or more customers) can make the current charging decisions infeasible or suboptimal. Preliminary computational experiments showed that decoupling the charging decisions from the evaluation of sequencing moves can have undesirable effects. We investigate the impact of exactly evaluating each sequencing move on the efficiency of the method. We tested different strategies. First, we optimally evaluate each move by solving a constrained shortest path problem where the objective is to minimize the path duration and the state of charge of the EV acts as a resource constraint. For this purpose, we use a label-setting algorithm. To reduce the computational time, we examine a heuristic version of this algorithm. For a comparison, we also consider heuristic evaluation procedures including one that consists in disregarding the detour to CSs and the charging times. To improve the efficiency of the exploration of a neighborhood, we adopt two strategies. First, we use short-term and long-term memory structures to avoid evaluating twice the same routes or the same move. Second, we restrict the arcs that can be involved in a sequencing move.

In the assembly phase of our method, we select routes from the pool Ω to build a solution to the problem. Since route-first assemble-second approaches have been mostly applied to problems without route coupling constraints, the assembly phase traditionally consists in solving a set partitioning model over the pool of routes. Due to the CS capacity

constraints, the assembly phase on the E-VRP-NL-C requires a more elaborate treatment. We therefore solve this stage using a Benders' like decomposition method. Specifically, we decompose this assembling problem into a route selection master problem and a CS capacity management sub-problem. The master problem consists in selecting a set of routes such that every customer is covered exactly by one route. Every selection of routes (output of the route selection problem) yields a set of charging operations; each operation being defined by a CS, a starting time, and a recharge amount. The sub-problem checks if the CS capacity constraints can be met. We investigate three different versions of the CS capacity management problem ranging from a simple check of the capacity constraints to the introduction of waiting times to the revision of the charging amounts in the selected routes. To efficiently solve the problem while exploiting this decomposition, we adopt the following approach implemented on top of a commercial solver. We solve the SP model related to the route selection problem using a branch-and-bound algorithm. At each integer node of the branch-and-bound tree, the corresponding solution is sent to the CS capacity management problem. We discard infeasible solutions or solutions for which the objective is underestimated (decisions in the sub-problem may impact the time-based objective of the E-VRP-NL-C) using cuts.

The results suggest that our method performs well on a set of instances adapted from the literature. Results show that using more complex strategies to solve bottleneck issues at CSs does not necessarily increase the computational burden but improves the quality of the solutions. Results also show that the algorithm finds optimal solutions for some instances.

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