The Bi-objective Electric Autonomous Dial-A-Ride Problem

Yue Su[1,2], Sophie N. Parragh[3], Jakob Puchinger[4,1], Nicolas Dupin[5]

[1] Université Paris-Saclay, CentraleSupélec, Laboratoire Génie Industriel, 91190, Gif-sur-Yvette, France
[2] CERMICS, Ecole des Ponts ParisTech, Champs-sur-Marne, France
yue.su@centralesupelec.fr
[3] Institute of Production and Logistics Management, Johannes Kepler University Linz, 4040, Linz
sophie.parragh@jku.at
[4] EM Normandie Business School, Métis Lab, 92110, Clichy, France
jpuchinger@em-normandie.fr
[5] Univ Angers, LERIA, SFR MATHSTIC, F-49000 Angers, France.
nicolas.dupin@univ-angers.fr

Mots-clés : *Dial-A-Ride Problem, Electric Autonomous Vehicles, Bi-objective Optimization.*

1 Introduction

The prevalence of ride-sharing services presents a fundamental trade-off between the operational costs and the users' convenience. While ride-sharing operations reduce operational costs, users may experience certain inconveniences, such as longer ride times when sharing their rides with others. Along with the development of ride-sharing services, the emergence of new techniques, such as electric vehicles and autonomous techniques, has drawn academic interests in operations research to apply a more eco-friendly and comfortable mode of transport. The Electric Autonomous Dial-A-Ride Problem (the E-ADARP) was first introduced by [1], which consists in designing a set of minimum-cost routes for a fleet of electric autonomous vehicles (EAVs) by scheduling them to provide ride-sharing services for users specifying their origins and destinations. In this work, we emphasize the conflicting interests of service providers and users in the objective function of the E-ADARP and investigate the Bi-objective E-ADARP (hereafter BO-EADARP). The two objectives of the BO-EADARP are the total travel time of all vehicles and the total excess user ride time of all users. We apply the ϵ-constraint method and the generalized B&P algorithm to solve the BO-EADARP. Numerical results with regard to different methods are summarized, as well as the managerial insights that we observe from the obtained efficient solutions.

2 The BO-EADARP and the bi-objective B&P algorithm

The problem is defined on a complete directed graph $G = (V, A)$, where V represents the set of vertices and $A = \{(i, j) : i, j \in V, i \neq j\}$ the set of arcs. V can be further partitioned into several subsets, i.e., $V = P \cup D \cup S \cup O \cup F$. P and D represent the set of all pickup and drop-off vertices, S is the set of recharging stations, and O and F denote the set of origin depots and destination depots, respectively. Each user request is a pair $(i, n + i)$ for $i \in P$ and has a maximum user ride time of m_i. The travel time on each arc $(i, j) \in A$ is denoted as $t_{i,j}$. Detailed MIP formulation of the E-ADARP can be found in [1]. The two objectives are :

$$\min \sum_{i,j \in V} t_{i,j} x_{i,j}^k \tag{1}$$

$$\min \sum_{i \in P} R_i \tag{2}$$

where $x_{i,j}^k$ is a binary decision variable which denotes whether vehicle k travels from node i to j. R_i denotes the excess user ride time of request $i \in P$ and is formulated as the difference between the actual ride time and direct travel time from i to $n+i$.

2.1 Bi-objective branch-and-price (BOBP) algorithm

The principle of the bi-objective B&P is extended from the single-objective B&P ([3]), which aims to divide the original problem into easier subproblems and store them in the form of *"nodes"*. We denote each subproblem of the BO-EADARP as $P(\eta)$, where η represents the associated node. The main ingredients of the bi-objective B&P are presented as follows :

1. **Calculate lower bound set and update upper bound set :** On each node, we calculate the lower bound set with the dichotomic method, where we apply the CG algorithm presented in [3] to solve each weighted-sum objective problem. Once the lower bound set of the analyzed node η (denoted as $\mathcal{L}(\eta)$) is calculated, we first check if new non-dominated points are obtained. If this is the case, the upper bound set $\mathcal{U}$ is updated.
2. **Lower bound filtering and node fathoming :** Then, the lower bounds in the set are filtered with the current upper bound set $\mathcal{U}$, which stores each candidate point that corresponds to the integer solution that is not dominated by other points in the set. The *filtering* process compares the current $\mathcal{L}(\eta)$ with $\mathcal{U}$ and returns a set of non-dominated portions. If no portion is generated after the filtering process, then the analyzed node η can be fathomed, as it is fully dominated by the current upper bound set $\mathcal{U}$.
3. **Branching procedure :** If the analyzed node cannot be fathomed, branching is applied to generate child nodes. We consider different of branching strategies and apply them to each disjoint non-dominated portion. After branching, a set of child nodes is added to the unprocessed node set $\mathcal{T}$. The tree search terminates when there is no unprocessed node remaining in $\mathcal{T}$.

3 Numerical Experiments and Discussion

In this work, we solve the BO-EADARP, where the total travel time and the total excess user ride time are considered as separate objectives. To tackle the BO-EADARP, we introduce the BOBP algorithm based on the framework of [2], where the lower bound set is calculated by the CG algorithm ([3]). In the computational experiments, the BOBP algorithm is shown to be more efficient and generate more efficient solutions in a less average computational time, compared with the classic ϵ-constraint method. Then, we analyze the obtained efficient solutions, which offer the following managerial insights for different service providers : (1) for profitable service providers, it is possible to significantly improve service quality while keeping near-optimal operational costs ; (2) for non-profitable service providers, there exist efficient solutions of high service quality while at lower operational costs. These efficient solutions are very interesting for this kind of service provider. To sum up, the obtained efficient solutions can help decision-makers select Pareto-optimal transportation plans according to their priorities and preferences.

Références

[1] Claudia Bongiovanni, Mor Kaspi et Nikolas Geroliminis. “The electric autonomous dial-a-ride problem”. In : *Transportation Research Part B : Methodological* 122 (2019), p. 436-456.

[2] Sophie N Parragh et Fabien Tricoire. “Branch-and-bound for bi-objective integer programming”. In : *INFORMS Journal on Computing* 31.4 (2019), p. 805-822.

[3] Yue Su et al. “A Column Generation Approach for the Electric Autonomous Dial-a-Ride Problem”. In : *arXiv preprint arXiv :2206.13496* (2022).