Charger location in electric bus networks

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Motivation

From 1970 to 2010, greenhouse gas emissions increased by 80%. This increment is mainly due to the development of energy-intensive sectors such as industry and transportation. According to the COP21 report (UNFCCC 2016), if no action is taken to stop this rise by 2100, the global temperature is expected to increase by up to 5 degrees Celsius.

This strong rise could have dramatic consequences such as acidification of the oceans, loss of biodiversity, rise of climate refugees, etc. The main greenhouse gas emitted is carbon dioxide CO_2, with up to 70% of the total volume. Each year the transportation sector is responsible for almost 30% of the European Union CO_2 emissions (IPCC 2014). One leverage that governments may use to reduce these emissions is the electrification of public transport, in particular, that of urban buses.

The electrification of transit systems poses several strategic, tactic and operational challenges. Indeed, replacing classical diesel-powered buses by electric buses (e-buses) is not straight forward. The latter have a considerably lower driving range and therefore often need to be recharged between services or even en-route (depending on the technology, length of the line, load, etc.). To cope with these technological constraints, transit agencies must deploy charging infrastructure along the lines, and at end-of-line terminals and depots. This deployment, however, requires significant capital investments. For instance, according to Pelletier et al. (2019), end-of-line and fast en-route chargers for e-buses currently price in the ballpark of USD 100,000 and USD 700,000, respectively. As a consequence, agencies are usually restraint in the number of lines that can be electrified. The latter translates into a strategic optimization problem: how to deploy the charging infrastructure in a way in which electrification (i.e., the distance covered by the fleet using an electric engine) is maximized given a capped investment budget. In this research, we address this problem.

Problem Statement

The battery electric bus system deployment problem can be defined as follows. Let $G(V, A)$ be a graph representing an urban transit network, with V the set of nodes (representing the stations) and A the set of arcs (representing the paths on the road network connecting two stations). Installing a charger at station $i \in V$ incurs a cost c_i. An arc $(i, j) \in A$ has a distance d_{ij} and an energy consumption e_{ij} . Both chargers and buses are assumed to be homogeneous. The latter are hybrid (i.e., they have both an electric engine and diesel-powered engine), have a battery capacity q, and have a charging rate r. Buses can switch driving mode (between electric and diesel) at any station but cannot switch modes while traveling between stations. Let L be the set of bus lines on the network and $G_l(V_l, A_l)$ be the subgraph of G representing the bus line $l \in L$. The entire network is defined by $G(V, A) = \cup_{l \in L} G_l(V_l, A_l)$. The buses drive over line l with a frequency $f_l, l \in L$, and cannot stop at station i to charge their battery for more than w_{li} time units. This maximum waiting time is associated to the service level of the line. For instance, a bus covering a given line may perform a long stop at station at which it typically carries only a few passengers but only a short one at a station at which it is typically full. The goal of the problem is to decide i) the number chargers to install at each station $i \in V$ (hereafter infrastructure decisions), ii) the driving mode m_{ijl} on arc $(i, j) \in A$ of a bus covering line l (hereafter mode selection decisions), and iii) the charging time t_{il} of a bus covering line $l \in L$ at every station $i \in V_l$ serviced by the line (hereafter charging decisions). The objective is to maximize the total distance covered by the fleet in electric mode. Along with the service level constraints, a solution to the problem must verify two additional conditions: the total investment in chargers is lower than a given budget, and the frequency of each line is met.

Related literature

The electrification of urban transport systems is gaining traction in the literature. We are aware of a few attends to solve problems that are closely related to ours. For instance, Kunith, Mendelevitch, and Goehlich (2017) proposed a model to deploy electric buses on independent bus lines. Differently to ours, their model does not considers the possibility of sharing chargers between different lines. Later, Liu, Song, and He (2018) proposed a model for a more general version of the problem considering heterogenous chargers and buses. However, even if they considered charger sharing, they left if to further studies. To the best of our knowledge, only Wei et al. (2018) proposed a full model relaxing that assumption. Nonetheless, they do not explicitly model the charging decisions, so their model cannot guarantee that a feasible dispatching schedule exists.

Solution approach

We model the problem using mixed-integer linear programming and solve it using Branch and Check (Thorsteinsson 2001). Our algorithm iteratively solves two mixed-integer linear programs,

namely, the optimization model and the feasibility model. The optimization model makes infrastructure, mode selection, and charging decisions seeking to maximize the total distance covered in electric mode while verifying the budget and service level constraints. Given a solution to the optimization model, the feasibility model aims to find, for each line, a *dispatching schedule* that guarantees the frequencies.

In our implementation, the optimization model is solved using a commercial solver. Every time the solver improves the upper bound, we call the feasibility problem to find a feasible dispatching schedule. If such a schedule is found, the new incumbent solution is accepted, otherwise the associated node is pruned.

Results

The solution approach was implemented in C++ and used the off-the-shelf CPLEX solver to solve the MILP models. To test our approach, we built a set of instances based on benchmarks from the literature for related problems and data on the characteristics of the buses provided by an e-bus manufacturer. We built 9 sets of 10 instances. The instance had 200, 300 or stations and 3, 5 or 7 lines. Let $|L|$ be the number of lines in the instance, $|L|-1$ stations are "shared" between two or more lines.

Our approach solved 81 out of the 90 instances to optimality. The average running time was 209 seconds with maximum of 0.36 seconds and a minimum of 1623 seconds. On each run, we collected the following statistics: the electrification ratio (kms run on electric mode divided by the total number of kms in the network), the number of installed chargers, the average charging time, the number calls to the feasibility model, and the computation time. Those statistics are summarized in the following table.

$\|V\|$	$\|L\|$	Electrification ratio (%)	Installed chargers	Charging time (s)	Feasibility model call	CPU Time (s)		
						Avg	Min	Max
200	3	60.51	1.0	200.4	8.3	0.467	0.437	0.531
	5	83.68	0.0	0.0	13.0	0.497	0.297	0.828
	7	97.14	0.0	0.0	6.2	0.400	0.359	0.469
300	3	45.51	2.0	408.0	17.0	5.770	0.875	9.016
	5	63.58	1.0	240.0	25.2	820.787	606.781	1146.440
	7	82.07	0.0	0.0	11.3	0.941	0.891	1.000
400	3	34.71	2.0	432.0	9.4	92.638	1.797	229.766
	5	48.2	1.0	240.0	18.9	1080,408	300.000	1623.660
	7	65.19	1.0	238.7	24.0	390.206	33.813	751.172

Table 1 Results obtained from optimal solutions

As we can see in Table 1, when we increase the number of stations, the number of installed chargers, the average charging time, the number calls to the feasibility model and the computation

time increase but the electrification ratio decreases. On the other hand, when we increase the number of lines, the electrification ratio increases but the number of installed chargers and the average charging time decrease.

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