The Electric Bus Fleet Transition Problem

Samuel Pelletier[1], Ola Jabali[2], Jorge E. Mendoza [1], Gilbert Laporte[1]

[1] HEC Montréal, 3000 chemin de la Côte-Sainte-Catherine, Montréal, Canada H3C 3J7

[2] Politecnico di Milano, Piazza Leonardo da Vinci 32, 20133 Milan, Italy

e-mail addresses: {Samuel.Pelletier, Gilbert.Laporte, Jorge.Mendoza}@hec.ca, Ola.Jabali@polimi.it

Abstract

The use of electric bus fleets has become a topical issue in recent years. Several companies and municipalities, either voluntarily or to comply with legal requirements, will transition to greener bus fleets in the next decades. Such transitions are often established by fleet electrification targets, which dictate the number of electric buses that should be in the fleet by a given time period. In this paper we introduce a comprehensive optimization-based decision making tool to support such transitions. More precisely, we present a fleet replacement problem which allows organizations to determine bus replacement plans that will meet their fleet electrification targets in a cost-effective way, namely considering purchase costs, salvage revenues, operating costs, charging infrastructure investments, and demand charges. We account for several charging infrastructure options, such as slow and fast plug-in stations, overhead pantograph chargers, and inductive (wireless) chargers. We refer to this problem as the electric bus fleet transition problem, and we model it as an integer linear program. We apply our model to conduct computational experiments based on several scenarios. We use real data provided by a public transit agency in order to draw insights into optimal transition plans.

Keywords: electric buses; fleet replacement; integer linear programming.

1. Introduction

In order to improve air quality in metropolitan areas, several bus companies and municipalities, either voluntarily or to comply with legal requirements, will need to transition to greener bus fleets in the upcoming years (see, e.g., Avere-France 2017, Bloomberg New Energy Finance 2018). In the last decade, battery price reductions and performance improvements have led electric buses (EBs) to emerge as a likely solution for the reduction of local air and noise pollution. Several transit authorities have therefore set specific fleet electrification targets that should be met in the next decade or two. For example, the cities of Paris, Los Angeles, and Copenhagen aim to operate only EBs by 2025, 2030, and 2031, respectively (Bloomberg New Energy Finance 2018, ZeEUS project 2017). California as a whole is aiming for 100% zero-emission bus fleets by 2040 (California Air Resources Board 2018). The city of Toronto is committed to a 50% zero-emission bus fleet by 2028-2032, and to operating only EBs by 2040 (Toronto Transit Commission 2019). In France, 50% and 100% of newly purchased buses will need to be low-emission vehicles as of 2020 and 2025, respectively, for municipalities operating at least 20 buses (Avere-France 2017). London and Mexico City are also committed to purchasing only zero-emission buses by 2025 (Bloomberg New Energy Finance 2018). In the Province of Quebec, the cities of Laval and Montreal plan to purchase only EBs by 2023 and 2025, respectively (Montreal Gazette 2018).

Determining bus fleet replacement plans achieving electrification targets is a complex task due to two interrelated issues. The first concerns the timing of EB purchases. Battery prices have been continuously falling in the last decade, while their specific energy (which directly impacts EB driving ranges) and lifespans have been steadily improving. This could be an incentive to wait as long as possible before making significant EB purchases in order to benefit from lower EB purchase costs, and to avoid missing out on further technological improvements. On the other hand, EB energy and maintenance costs are already known to yield significant savings over their diesel counterparts, and such savings may well be amplified in the near future if fossil fuel prices are subject to unexpected hikes. There could therefore also be some value in immediately starting to purchase EBs. Because future battery prices, technological improvements and fossil fuel prices are difficult to predict and are subject to a fair amount of uncertainty, weighing these trade-offs against each other is not straightforward. Sensitivity analyses are therefore required to assess the impact of such uncertain future costs

The second issue concerns the selection of the type of EBs to purchase. For instance, a public transit organization looking to purchase EBs faces the trade-off of purchasing EBs with large batteries that do not require en route recharging, or EBs with smaller batteries that do. The large battery alternative avoids costly investments associated with en route charging infrastructure, but will adversely affect the purchase cost of the vehicles and the number of passengers they can carry (and hence which lines the buses can serve). Moreover, having to charge large batteries at a depot overnight with slower charging equipment may reduce the time during which the buses can operate during the day. The small battery alternative has the opposite pros and cons: smaller purchase costs, larger payloads and less time-related constraints due to depot charging, but a possible need for en route charging infrastructure investments. Furthermore, choosing the small battery alternative implies making additional and non-trivial decisions, such as the kind of en route charging infrastructure to be installed. **Typical alternatives for en route recharging of EBs include fast plug-in stations, overhead pantograph chargers, and inductive (wireless) chargers, but each of these options has its own set of desirable and less desirable characteristics (see, e.g., Bloomberg New Energy Finance 2018, Jang et al. 2016, Chen et al. 2018).**

The scientific aim of this paper is to deal with the aforementioned complexities by introducing a comprehensive optimization-based decision making tool that offers some strategic guidance to organizations having set electrification targets for the next decades. More precisely, we model a bus fleet replacement problem whose solution provides a transition plan that will respect such targets in a cost-effective way. We refer to this problem as the electric bus fleet transition problem (EBFTP). The remainder of this paper is organized as follows. Section 2 provides a short review of the literature related to fleet replacement problems associated with electric vehicles (EVs). Section 3 introduces the EBFTP and presents its mathematical formulation. Section 4 defines the base case for our experiments and reports the corresponding computational results. Section 5 reports the results of sensitivity analyses and presents managerial insights. This is achieved by changing the range of the parameter values used in the base case, and by considering several scenarios regarding uncertain future costs. Finally, Section 6 presents our conclusions.

2. Literature review

Due to the potential societal benefits associated with EVs, several researchers have studied optimization problems involving their use in vehicle fleets. The main transportation research literature on fleet EVs concerns vehicle routing problems, fleet size and mix problems, optimal path problems, charging infrastructure design problems, depot charge scheduling problems, and fleet replacement problems (Pelletier et al. 2016, 2018, Bektaş et al. 2018). The latter involve decisions about purchasing (and potentially salvaging) or leasing vehicles that must be made over the course of a planning horizon. Such fleet replacement problems are closely related to classical equipment replacement problems, in which a sequence of replacement decisions must be made regarding a machine or an asset based on trade-offs between revenues and costs that are generated by the equipment and that depend on the chronological year and the age of the equipment (Dreyfus 1960). Evaluating such trade-offs is particularly complex in the case of parallel replacement problems (as is the case for the EBFTP). In these problems, replacement decisions must be made simultaneously for several assets having economic interdependencies, e.g., a joint demand to satisfy, a fixed cost incurred whenever a purchase is made (regardless of how many assets are involved), or a total purchasing budget to respect (Karabakal et al. 1994). The remainder of this section focuses on the existing fleet replacement studies that are most relevant for the problem studied in this paper, i.e., those involving EVs or low-emission vehicles.

Feng and Figliozzi (2013) developed a deterministic fleet replacement model for fleets with electric and diesel trucks in which vehicles can be purchased and resold on a yearly basis. The objective is to minimize the discounted sum of all costs over a 30-year planning horizon, while satisfying each year's travel demand expressed in miles. The authors investigated several scenarios with varying vehicle use rates and fuel efficiencies for diesel vehicles. Optimal solutions obtained with a commercial solver showed that electric trucks were only profitable in scenarios with high vehicle use rates. Feng and Figliozzi (2014) used a similar model for a case study based on data supplied by a public transit agency that had to choose between replacing their current fleet with diesel or hybrid buses. Ahani et al. (2016) revisited the problem introduced by Feng and Figliozzi

(2013), but modified the objective so as to minimize the sum of deterministic discounted total costs and the weighted variance of total costs when purchase and energy costs are assumed to follow a geometric random walk.

Ansaripoor et al. (2016) formulated a fleet replacement problem with hybrid, electric, and conventional vehicles as a mean-risk model. Vehicles are leased rather than purchased, thus removing salvaging decisions. The objective is to minimize a weighted sum of expected costs and what the authors call the recursive expected conditional value-at-risk. The authors generate scenarios for several uncertain parameters to formulate the deterministic equivalent of the stochastic mixed integer program, which they in turn solve with CPLEX. Numerical results indicated that EVs become more utilized in high mileage scenarios, but that diesel and petrol vehicles remain the dominant choice in general over the course of their considered 2016–2019 planning horizon.

Kleindorfer et al. (2012) studied a fleet replacement problem faced by the French national postal operator, La Poste, in which electric and conventional vehicles must be leased over the course of several periods under uncertain future fuel and battery prices. Diesel prices are modeled as a Brownian motion with drift, while battery prices are stated as an Ornstein-Uhlenbeck process. Periodic demands are given in terms of a required number of vehicles. The problem is formulated as a stochastic dynamic program with the objective of minimizing the expected total costs, and the optimal policy is derived analytically.

Bakır (2017) considered a multi-period deterministic long-haul trucking context in which alternative fuel vehicles (AFVs) must be introduced in a fleet of diesel trucks. The problem consists in determining how many vehicles of each type (i.e., AFV or diesel) to purchase, salvage and assign to each route in each period, and where to open maintenance facilities for AFVs. An AFV cannot perform a given type of route during a given period if no maintenance facility has previously been opened along that route. Moreover, a minimal proportion of operations need to be performed by AFVs in each period. The problem is solved via Benders decomposition and a variable neighbourhood search heuristic.

Stasko and Gao (2010) proposed a fleet replacement model that aims to reduce emissions of a public transit organization in a cost-effective way. Purchase, retrofit, and task assignment decisions are included in the model. Retrofits may be performed on vehicles to reduce their emissions. The model also includes a term for facility upgrades that may be required at the depot for some AFVs. A case study is performed in which conventional, hybrid, and compressed natural gas (CNG) buses may be purchased over the course of the planning horizon. The model was solved with CPLEX. Results showed that the CNG buses were the most cost-effective way to reduce emissions, and highlighted the benefit of adopting a long-term perspective when making replacement decisions.

Finally, Islam (2018) introduced a fleet replacement model for transit agencies similar to that of Feng and Figliozzi (2014), with the addition of yearly emissions constraints, an electrification target that must be met by the end of the planning horizon, and the need to make charging infrastructure investments for EBs. They assumed that only one type of EB and one type of hybrid bus may be purchased to replace the initial bus fleet, and that a depot charger is required for each EB in the fleet at all times. Yearly demands are expressed as a number of buses.

To the best of our knowledge, the problem we introduce in this paper is the first to simultaneously take into account temporal electrification targets, vehicle purchasing and salvaging decisions, several EB types with different charging infrastructure requirements, charger type-specific investments and demand charges, and aggregated task assignment decisions within a fleet replacement optimization framework.

3. Problem description and formulation

The objective of this section is to introduce and formulate the EBFTP. We first provide a general description of the problem, and then formulate it as an integer linear program. Given a set of bus types $K = \{1, ..., m\}$, let $K_E \subseteq K$ denote the subset of bus types that are electric. We assume that $|K_E| > 1$. We consider a planning horizon $T = \{1, \ldots, t_F\}$ of t_F periods, and a target period $t_G \in T$ at which point at least a proportion P of the fleet should consist of EBs. We assume that $t_G \leq t_F$, but that all periods $t \geq t_G$ in the planning horizon should respect the target P.

We adopt an aggregated approach to task assignment decisions similar to that of Stasko and Gao (2010), that is, we assume that the operations in each period of the planning horizon have already been partitioned into assignment runs. Each run is required to be performed by a single bus during its associated period, and possesses certain operational characteristics (e.g., size, typical distance and duration of daily operations, typical weight of the loads to be carried). We assume that during a given period, each bus in the fleet must be assigned to a single run. Task assignment decisions can be further simplified (if required) by clustering the runs based on similarities of operational characteristics. Our motivation for using this approach first stems from the need for realistic demand forecasting. As discussed by Stasko and Gao (2010), predicting the general characteristics of future daily operations may be simpler than predicting specific future routes. Second, simultaneously making fleet composition decisions and traditional vehicle scheduling or routing over a long-term planning horizon quickly becomes intractable. Third, since it is assumed that there are several EB types in K with different charging infrastructure requirements and different distance-, time-, and load-related capacities, we believe it is necessary to express periodic demands in a more granular manner than as a total number of vehicles or kilometers without any form of compatibility considerations between bus types and the operations to which they will be assigned to. The aggregated approach of Stasko and Gao (2010) thus seems like an appropriate compromise between tractability and granularity to express fleet demands.

We denote by R the set of types of runs to be performed over the course of the planning horizon, and by q_{tr} the number of buses that need to be assigned to run type r during period $t \in T$. Note that $q_{tr} \in \{0,1\}$ $\forall r \in R, t \in T$ would correspond to not performing the optional clustering of individual runs mentioned above. We assume that the compatibility between assignment runs and bus types is encapsulated by a binary parameter h^k_{jtr} that takes a value of 1 if and only if a bus of type k and age j can be assigned to run type r during period t. The compatibility between runs and bus types depends on relevant features in the specific context at hand, such as distance, time, load, required charging infrastructure, regulations prohibiting polluting vehicles, etc.

The set $J^k = \{0, 1, \ldots, \kappa^k + 1\}$ contains all possible ages for a bus of type k, with $j \in J^k$ representing an age of j periods. The age $j = 0$ corresponds to a new bus, and a bus of type k is operational until it reaches an age of $\kappa^k + 1$ periods, at which point it must be salvaged. At the start of the planning horizon, the fleet consists of a^k_j buses of type k and age j. A maximum average bus age of Γ periods is imposed in the final period t_F. Let o^k_{jtr} be the total periodic operating cost incurred when a bus of type k is of age j at the start of period t, and executes a run of type r during period t. These operating costs are assumed to account for energy and maintenance expenditures, but can also include any relevant costs for the specific context at hand (e.g., battery degradation costs that depend on the type of run). Let f^k_t be the purchase cost of bus type k at the start of period t. We assume that only new buses are purchased in the model of Section 3.1, but this can of course be modified to account for the possibility of purchasing or leasing used buses as well. Let s^k_{jt} be the salvage value of a bus of type k and age j retired at the start of period t. Significant costs may also need to be incurred near the midlife of vehicles for, among other things, engine overhauls and battery replacements (Blynn 2018). We therefore assume that a bus of type k is subject to midlife costs of mc^k_t when it reaches its midlife age of α^k during period t.

In addition to cost components related to the purchase, operation, and retirement of vehicles, we also account for the fact that different charging infrastructure-related costs will be incurred depending on the chosen EB types. We define set $CT = \{1, \ldots, n_c\}$ as the set of possible charger types to be used to recharge EBs in the fleet. We assume that an EB of type $k \in K_E$ must be recharged using all charger types in a given set $C^k \subseteq CT$. Moreover, the proportion of chargers of a given type $c \in CT$ with respect to the total number of EBs of types $\{k \in K_E | c \in C^k\}$ that are in the fleet must remain above θ^c at all times. For example, suppose that $\theta^c = 0.5$ for a given en route charger type c, $K_E = \{k_1, k_2, k_3\}$ (i.e., there are three types of EBs), $c \in C^{k_1}$, $c \in C^{k_2}$, $c \notin C^{k_3}$, and there are currently 10 EBs of type k_1 in the fleet, seven EBs of type k_2, and five EBs of type k_3. Then we would currently require a minimum of $\lceil 0.5 \cdot (10 + 7) \rceil = 9$ en route chargers of type c. Note that a solution to the EBFTP does not dictate where these nine en route chargers should be located, and that the charging infrastructure requirements are entirely imposed by decisions regarding the fleet configuration (and not by how the vehicles are assigned to the runs). The minimum required number of chargers of a specific type c at any given time therefore depends on the current number of EBs in the fleet that need it, and the associated ratio θ^c. Any incompatibility between vehicles and runs due to the inherent infeasibility of using a specific vehicle type's associated chargers to perform a specific kind of run (e.g., pantographs disallowed in urban areas due to local planning regulations) is assumed to be incorporated in parameters h^k_{jtr}. Hence, in the EBFTP we use the task assignment approach of Stasko and Gao (2010) to determine compatible assignments of buses to run types with respect to parameters h^k_{jtr}, but we additionally ensure that the charging infrastructure is globally sufficient to operate the fleet by deciding how many chargers of each type to purchase in each period so as to respect the θ^c ratios at all times. **We therefore assume that decisions regarding where to actually locate the chosen type of charging infrastructure (for which several existing studies may be of use, e.g., Li et al. 2016, Liu and Song 2017, Xylia et al. 2017, Lin et al. 2019) are made in a subsequent planning stage.**

A charger of type c costs p^c to purchase and retrieves g^c kilowatts (kW) from the grid. It is assumed that e^c chargers of type c are already owned at the start of the planning horizon. Demand charges that are present in some electricity rate plans can also have a significant impact on operational costs of EVs (see, e.g., Pelletier et al. 2018, Gallo et al. 2014). Such monthly fees depend on the largest registered charging power over the course of each month. We assume that there are periodic demand charges of F \$/kW in each location where EB chargers are or can be installed, and we compute demand charges assuming all chargers at a single location will be used simultaneously at some point each month. Due to potential power and space limitations associated with depot charging (Bloomberg New Energy Finance 2018), we assume that charger types in set $DC \subseteq CT$ refer specifically to depot chargers, and that it must be possible to simultaneously use all depot chargers without violating a total grid restriction of G kW during each period of the planning horizon, and that no more than H depot chargers may be installed in total.

A budget b_t is available for purchases (vehicles and charging infrastructure) at the start of period t, which we assume may be increased by salvage revenues earned at the start of t. Finally, let dr be the periodic discount rate used to take into account the time-value of money, and let $\beta = (1 + dr)^{-1}$ be the corresponding one-period discount factor. All cash flows gradually incurred over the course of a period (i.e., operational costs and demand charges) are assumed to be made at the beginning of the period. Therefore, an amount incurred in period t will be discounted by β^{t-1}.

3.1 Integer linear programming model

The decision variables used in the mathematical formulation of the EBFTP are all integer and non-negative, and are defined as follows. Variables x^k_t refer to the number of buses of type k purchased at the beginning of period t. Variables y^k_{jt} indicate the number of buses of type k and age j salvaged at the beginning of period t. Varibales z^k_{jt} represent the number of available buses of type k and age j in period t. Variables w^k_{jtr} are used for task assignment decisions, and refer the number of buses of type k and age j assigned to run type r in period t. Finally, variables u^c_t indicate the number of chargers of type c purchased and installed at the start of period t, and variables v^c_t give

Table 1: Set, parameter and variable definitions of the EBFTP model

Sets	
C^k	Set of charger types that must be used to recharge an EB of type k
CT	Set of charger types
DC	Set of depot charger types
J^k	Set of possible ages for a bus of type k
K	Set of bus types
K_E	Set of EB types
R	Set of run types
T	Set of t_F periods in the planning horizon
Parameters	
a_j^k	Number of buses of type k and age j in the fleet at the start of the planning horizon
b_t	Budget for purchases made at the start of period t
e^c	Number of chargers of type c owned at the start of the planning horizon
F	Periodic demand charges (\$/kW)
f_t^k	Purchase cost of bus type k at the start of period t
G	Total depot grid restriction (kW)
g^c	Power consumption (kW) of charger type c
H	Total depot space restriction
h_{jtr}^k	binary parameter equal to 1 if and only if a bus of type k and age j is compatible with assignment run type r during period t
mc_t^k	Midlife costs incurred when a bus of type k reaches its midlife age α^k during period t
o_{jtr}^k	total periodic operating cost incurred when a bus of type k is of age j at the start of period t, and executes a run of type r during period t
P	Minimal proportion of the fleet that should consist of EBs by the target period $t_G \in T$
p^c	Purchase cost of charger type c
q_{tr}	the number of buses that need to be assigned to run type r during period t
s_{jt}^k	Salvage value of a bus of type k and age j retired at the start of period t
β	One-period discount factor
Γ	Maximum average bus age in the final period t_F
θ^c	Minimal proportion of chargers of type c with respect to the total number of EBs of types $\{k \in K_E \mid c \in C^k\}$ in the fleet
$\kappa^k + 1$	Age at which buses of type k must be salvaged
Decision variables	
u_t^c	Number of chargers of type c purchased and installed at the start of period t
v_t^c	Number of available chargers of type c during period t
w_{jtr}^k	Number of buses of type k and age j assigned to run type r in period t
x_t^k	Number of buses of type k purchased at the beginning of period t
y_{jt}^k	Number of buses of type k and age j salvaged at the beginning of period t
z_{jt}^k	Number of available buses of type k and age j in period t

the number of available chargers of type c during period t.

Table 1 summarizes all set, parameter and variable definitions discussed in this section. The EBFTP is thus stated as the following integer linear program:

$$\begin{aligned}
\text{minimize } & \sum_{t\in T}\beta^{t-1}\sum_{k\in K}\left(f_t^k x_t^k - \sum_{j=1}^{\kappa^k+1} s_{jt}^k y_{jt}^k + \sum_{r\in R}\sum_{j=0}^{\kappa^k} o_{jtr}^k w_{jtr}^k + mc_t^k z_{\alpha^k t}^k\right)\\
& + \sum_{t\in T}\beta^{t-1}\sum_{c\in CT}\left(p^c u_t^c + Fg^c v_t^c\right) + \sum_{k\in K}\sum_{r\in R}\sum_{j=0}^{\kappa^k-1}\sum_{i=1}^{\kappa^k-j}\beta^{t_F+i-1} o_{j+i,t_F,r}^k w_{jt_F r}^k\\
& - \sum_{k\in K}\sum_{j=0}^{\kappa^k}\beta^{t_F+\kappa^k-j} s_{\kappa^k+1,t_F}^k z_{jt_F}^k + \sum_{k\in K}\sum_{j=0}^{\alpha^k-1}\beta^{t_F+\alpha^k-j-1} mc_{t_F}^k z_{jt_F}^k
\end{aligned} \tag{1}$$

subject to

$$\sum_{k\in K_E}\sum_{j=0}^{\kappa^k} z_{jt}^k \geq P\left(\sum_{k\in K}\sum_{j=0}^{\kappa^k} z_{jt}^k\right) \qquad t\in T|t\geq t_G \tag{2}$$

$$\sum_{k\in K}\sum_{j=0}^{\kappa^k} w_{jtr}^k = q_{tr} \qquad r\in R, t\in T \tag{3}$$

$$w_{jtr}^k \leq h_{jtr}^k z_{jt}^k \qquad k\in K, r\in R, t\in T, j\in J^k\backslash\{\kappa^k+1\} \tag{4}$$

$$\sum_{r\in R} w_{jtr}^k = z_{jt}^k \qquad k\in K, t\in T, j\in J^k\backslash\{\kappa^k+1\} \tag{5}$$

$$x_t^k = z_{0t}^k \qquad k\in K, t\in T\backslash\{1\} \tag{6}$$

$$x_1^k + a_0^k = z_{0,1}^k \qquad k\in K \tag{7}$$

$$z_{jt}^k = z_{j-1,t-1}^k - y_{jt}^k \qquad k\in K, t\in T\backslash\{1\}, j\in J^k\backslash\{0,\kappa^k+1\} \tag{8}$$

$$y_{\kappa^k+1,t}^k = z_{\kappa^k,t-1}^k \qquad k\in K, t\in T\backslash\{1\} \tag{9}$$

$$y_{\kappa^k+1,1}^k = a_{\kappa^k+1}^k \qquad k\in K \tag{10}$$

$$z_{j1}^k = a_j^k - y_{j1}^k \quad k\in K, j\in J^k\backslash\{0,\kappa^k+1\} \tag{11}$$

$$\sum_{k\in K}\left(f_t^k x_t^k - \sum_{j=1}^{\kappa^k+1} s_{jt}^k y_{jt}^k\right) + \sum_{c\in CT} p^c u_t^c \leq b_t \qquad t\in T \tag{12}$$

$$v_t^c \geq \theta^c \sum_{k\in K_E|c\in C^k}\sum_{j=0}^{\kappa^k} z_{jt}^k \qquad c\in CT, t\in T \tag{13}$$

$$\sum_{c\in DC} g^c v_t^c \leq G \qquad t\in T \tag{14}$$

$$\sum_{c \in DC} v_t^c \leq H \qquad t \in T \tag{15}$$

$$v_1^c = e^c + u_1^c, \qquad c \in CT \tag{16}$$

$$v_t^c = v_{t-1}^c + u_t^c \qquad t \in T \backslash \{1\}, c \in CT \tag{17}$$

$$\sum_{k \in K} \sum_{j=0}^{\kappa^k} j z_{jt_F}^k \leq \Gamma \sum_{k \in K} \sum_{j=0}^{\kappa^k} z_{jt_F}^k \tag{18}$$

$$y_{jt}^k, z_{j-1,t}^k \in \mathbb{Z}^+ \qquad k \in K, t \in T, j \in J^k \backslash \{0\} \tag{19}$$

$$x_t^k \in \mathbb{Z}^+ \qquad k \in K, t \in T \tag{20}$$

$$u_t^c, v_t^c \in \mathbb{Z}^+ \qquad c \in CT, t \in T \tag{21}$$

$$w_{jtr}^k \in \mathbb{Z}^+ \qquad k \in K, r \in R, t \in T, j \in J^k \backslash \{\kappa^k + 1\}. \tag{22}$$

The objective function (1) minimizes the total discounted cost of the entire transition plan, which includes discounted purchase costs, midlife costs, salvage revenues, operating costs, charging infrastructure investments, and demand charges. The last three terms of the in the objective function are used to mitigate end-of-horizon effects that may arise as a result of decisions being made near the end of the planning horizon without appropriately weighing buses' purchase costs against their operating costs, midlife costs and salvage revenues (see, e.g., Grinold 1983, for a discussion of end-of-horizon effects). The end-of-horizon mitigation terms are based on the assumption that a bus of type k and age j performing a run of type r in period t_F will continue doing so after the end of the planning horizon until it reaches its maximum operating age, and will then be salvaged. For the sake of simplicity, the end-of-horizon mitigation terms assume that salvage values s_{jt}^k, operating costs o_{jtr}^k and midlife costs mc_t^k in periods after the end of the planning horizon remain the same as those in the final period t_F, but if projections are available for periods beyond t_F then these should of course be used instead.

Contraints (2) ensure that the electrification target will be satisfied. The model assumes that the target dictates a minimum percentage of buses that should be electric by year t_G, but this can be easily modified to represent other types of electrification targets as well. As discussed in the introduction of this paper, for some organizations, targets may concern newly purchased buses instead of available buses, and multiple time-varying targets may also need to be met over the course of the planning horizon. Contraints (3) ensure that the number of buses required for each run over time is respected. Note that several types of buses may be used to satisfy these constraints. Constraints (4) state that the run assignments must respect compatiblities with bus types and ages during each period. Constraints (5) mean that all available buses of a given type and age during a given period should be assigned to runs. One could argue that the equality in constraints (5) should be replaced by an inequality to allow for some form of overcapacity. However, organizations would probably prefer having some control over such overcapacities (e.g., to have a specific number of spare vehicles for specific types of operations). The proposed formulation allows for such control, since one can add a specific number of "empty" runs with operating costs of zero in order to have predetermined overcapacities. Moreover, the compatibility parameters h^k_{jtr} of such "empty" runs can be used to impose specific overcapacities for different types of operations. Constraints (6) and (7) ensure that the number of available new buses of each type in each period is equal to the number of buses of that type that were purchased at the start of that period (plus any buses already owned that can be considered as new for the first period). Constraints (8) state that the number of available buses of a certain type and age during a given period $t > 1$ is equal to the number of available buses of that type that were a period younger in $t-1$, minus the number salvaged at the start of t. Constraints (9) and (10) force buses of age κ^k+1 to be salvaged. Constraints (11) impose that the number of available buses of a given type and age during the first period be equal to the number already owned minus the number salvaged at the start of the planning horizon. Constraints (12) state that the amount of purchasing funds available at the start of a period is the sum of the budget and salvage revenues made at the start of that period. Constraints (13) ensure that the ratio of EBs to chargers for each type of charger is respected. Constraints (14) and (15) guarantee that the power and space limitations at the depot(s) are respected in each period. Constraints (16) and (17) track the number of each type of EB charger. Finally, constraints (18) are imposed to further mitigate end-of-horizon effects by setting the maximum average vehicle age to Γ in the final period t_F. Constraints (19)–(22) define the domain of the decision variables. Variables y^k_{jt} are not defined for $j = 0$, while z^k_{jt} and w^k_{jtr} are not for $j = \kappa^k + 1$, i.e., a brand new bus cannot be salvaged (but it can be operated), and a bus of maximal age cannot be operated (but it can be salvaged).

4. Base case experiments

We have performed an extensive computational study in order to validate the proposed formulation and to analyze the sensitivity of transition plans to several problem parameters. To this end, we have generated test instances based on real data obtained from a bus operator in France. All instances were solved using CPLEX 12.9. The models were implemented in C++ and all experiments were conducted on a cluster of 27 machines, each having two Intel(R) Xeon(R) X5675 3.07 GHz processors with 96 GB of RAM running on Linux. Each machine has 12 cores, and each experiment was run using a single thread. All instances were solved to optimality in the stated solution times.

We have assumed a planning horizon that begins in 2019 and ends in 2050, with periods corresponding to years. We are aware that working with such a long planning horizon can present some issues because several technological developments are to be expected, which will of course influence parameters and assumptions in the EBFTP. However, we believe that the benefits associated with using a simplified long-term future (namely to minimize undesirable end-of-horizon effects that could occur if the planning horizon were to end near the target year) outweigh the disadvantages. Moreover, we emphasize that the model is meant to be used in a rolling horizon fashion in order to guide immediate decisions based on currently available information, but should be solved again when new information becomes available as time progresses, e.g., with the availability of new technologies like fuel cell buses or solid state batteries incorporated as inputs to the model.

We first designed and solved a base-case scenario with the model of Section 3.1 and the most likely values for all parameters. The base-case scenario is described in Section 4.1, and its results are reported in Section 4.2. The base-case scenario is then modified in Section 5 to investigate the impact of specific problem features on optimal transition plans.

4.1 Description of the base-case scenario

The operations in our study, as indicated by the set of run types R and their vehicle requirements q_{tr}, are based on data provided by a real transit agency. This agency has supplied us with information regarding their current fleet of buses and the daily runs that must currently be performed by their buses over the course of a multi-day schedule. Aside from a few daily runs for mini-buses (which were excluded from our analysis), there were 84 daily runs in the data, varying by total daily distance and the type of bus that must perform them, i.e., articulated 60 feet (hereafter ft) buses or standard 40 ft buses. In order to represent the typical day of operation of a bus performing a given run, we computed the average daily distance of each run over all days in the schedule. Three runs were also missing the associated bus size information, so we assumed them to be standard-bus runs. The result was that 32 daily runs must be performed by articulated 60 ft buses, and 52 daily runs must be performed by standard 40 ft buses. We then clustered the 84 runs based on similar operational characteristics by grouping them according to the size of the bus required (i.e., standard or articulated), and the nearest multiple of five to their average daily distance, (e.g., a standard-bus run with an average daily distance of 163 km and a standard-bus run with an average daily distance of 167 km were both assumed to be a standard-bus run type associated with an approximate daily distance of 165 km). The final result was a set of 52 types of runs, each type currently required to be performed by a number of buses ranging from one to four.

In order to translate the daily runs into yearly assignment runs, we assumed that each bus will perform the daily run it was assigned to in a given year during 85% of the time (i.e., 310 days), with the run performed by a substitute vehicle in the remaining 15% of the time (i.e., 55 days) while the usual vehicle is pulled from operations for planned checkups and, if required, maintenance activities. We have therefore added two additional types of yearly assignment runs representing the operations of substitute vehicles for the usual standard and articulated buses. We have assumed that each of these two "substitute" run types is associated to a specific bus size (i.e., standard or articulated), and that a bus assigned to a substitute run must be able to perform any of the real daily runs for the associated bus size (i.e., it must be able to act as a substitute for any bus of the same size because it will replace several of such buses in their daily runs over the course of the year). Assuming that each bus performing a substitute run can cover $\frac{310}{55} = 5.64$ vehicles per year while they are pulled for maintenance, we considered requirements of $\lceil \frac{32}{5.64} \rceil = 6$ additional articulated buses performing substitute runs, and $\lceil \frac{52}{5.64} \rceil = 10$ additional standard buses performing substitute runs. The total yearly residual distances of all normal articulated and standard bus runs (i.e., associated with the 55 days during which the usual buses are pulled) were assumed to be evenly distributed among the six articulated and 10 standard buses performing the substitute runs, respectively. We have assumed that the vehicle requirements for each type of run remain the same over the course of the entire planning horizon, resulting in a total fleet size requirement of 100 vehicles in each period.

Our approach to translate daily runs into yearly assignment runs is based on the assumption that a bus will perform the same typical daily run throughout the year (aside from the substitute runs which are associated with several daily runs). However, this does not need to be the case in all instantiations of the EBFTP, which is intentionally formulated so as to leave flexibility when setting run-related parameter values. For example, one may choose to represent a yearly assignment run as a vehicle performing a known sequence of varying daily runs over the course of a repeating multi-day schedule if such sequences are known and can be forecasted for future years.

The initial buses are all diesel buses, and their age distribution, as given by parameters a_j^k, is estimated based on data provided by the transit agency regarding the distribution of cumulative kilometers traveled by buses in their fleet. We assumed each bus to have traveled 60,000 km per year in order to translate cumulative distance traveled to an age in years, which corresponds approximately to the average daily distance of all runs multiplied by 310 days. All other parameters were assigned best found values in the literature. We now discuss our sources and assumptions regarding each of them in the following list.

- **Types of buses** The types of EBs we have considered represent different charging configurations identified by Bloomberg New Energy Finance (2018) as the most likely charging configurations for transit operations in a medium-sized city, in which buses would typically travel approximately 200 km per day. This distance corresponds to the average distance of the daily runs in the data we obtained from the French transit agency. In addition, we have also considered standard 40 ft and articulated 60 ft diesel, hybrid, and CNG buses as alternatives. The set K of bus types we have considered thus contains the following elements:
  - 40 ft diesel bus,
  - 60 ft diesel bus,
  - 40 ft hybrid bus,
  - 60 ft hybrid bus,

  - 40 ft CNG bus,
  - 60 ft CNG bus,
  - 40 ft EB with a 250 kWh battery exclusively using depot charging,
  - 40 ft EB with a 350 kWh battery exclusively using depot charging,
  - 60 ft EB with a 650 kWh battery exclusively using depot charging,
  - 40 ft EB with a 250 kWh battery using depot charging and fast plug-in charging at line terminals,
  - 40 ft EB with a 110 kWh battery using depot charging and pantograph charging at bus stops.

  A terminal refers to a location where several bus lines end and layovers occur, and a depot refers to a location where buses are kept when not in service. As in Bloomberg New Energy Finance (2018), all EBs are assumed to use depot charging, with some requiring additional en route recharging. The lifetime of all bus types was assumed to be 15 years as in Bloomberg New Energy Finance (2018), with the maximum average final age of the fleet Γ set to 7.5 years.

- **Bus purchase costs:** We have used approximate median purchase prices of 40 ft and 60 ft diesel, CNG and hybrid buses derived by Ambrose et al. (2017) from the American Public Transportation Association (APTA) purchase data. We have used the same purchase prices as in Bloomberg New Energy Finance (2018) for 40 ft EBs with battery sizes of 350 kWh, 250 kWh, and 110 kWh. The Bloomberg report does not consider 60 ft EBs, so we have used the median purchase price derived by Ambrose et al. (2017) for 60 ft EBs. We have assumed that the purchase price of diesel, hybrid and CNG buses does not change with time, and that the purchase price of EBs diminishes due to battery cost reductions only. The initial battery price per kWh is assumed to be $600 (in 2017 dollars), as in Bloomberg New Energy Finance (2018). This price is more than that of batteries for passenger EVs because of different packaging, thermal management systems, and lower purchase volumes. To forecast future bus battery prices, we have made the same assumption as Bloomberg New Energy Finance (2018), that is, we assume that the battery prices for EBs decline at the same rate as those for passenger EVs. The evolution of passenger EV battery prices from 2019 to 2050 were taken from Schmidt et al. (2017), who have made such forecasts based on experience rates. The authors first used historical data regarding EV battery prices and cumulative sales to derive an expected experience rate, which is then used to predict future prices as a function of forecasted EV sales. The expected experience rate they identified was used in our base-case scenario.

- **Salvage values**: We have assumed salvage values to be zero for all vehicles in the base-case scenario, as a result of both the difficulty of identifying reliable EB residual values and the little importance salvage values seem to play in non-electric bus replacement decisions (Laver et al. 2007).

- **Operating costs**: We have derived total operating costs (maintenance + energy) per kilometer for each combination of bus type, bus age, and period of the planning horizon. These were assumed to be the same for all types of runs. The total operational cost incurred when performing a given type of run with a given bus type of a given age during a given period was then computed based on the approximate yearly distance associated with that type of run. Our assumptions and sources for maintenance and energy costs are detailed below.

  - **Maintenance costs:**

    * For 60 ft diesel and hybrid buses, we have used maintenance costs based on those found by Feng and Figliozzi (2014), who performed a regression analysis on real data from a transit agency to derive maintenance costs per mile of such vehicles as a function of age. We have assumed that maintenance costs are the same for 40 ft and 60 ft buses of the same type.
    * For electric and CNG buses, our assumptions are based on results from Blynn (2018) and are as follows: 1) the difference between maintenance costs of CNG buses relative to those of diesel buses ranges from −12% to 10%, so we have assumed identical maintenance costs for CNG and diesel buses; and 2) the difference between maintenance costs of EBs relative to those of diesel buses ranges from −60% to −20%, so we have used the medium value of 40% EB maintenance savings.

  - **Energy costs:**

    * We used fuel efficiencies (in miles per diesel gallon equivalent) for 40 ft and 60 ft diesel, hybrid and CNG buses based on median values from Ambrose et al. (2017) for small transit agencies with fewer than 300 buses, which is the case for the transit agency that provided us with data regarding their operations. The fuel efficiencies in miles per kWh for all 40 ft EBs (which vary depending on the battery size) are taken from Bloomberg New Energy Finance (2018). The efficiency of the 60 ft EB is estimated based on BYD's articulated EB (BYD 2018), i.e., it corresponds to a range of 230 miles with a battery of 650 kWh. We have assumed that fuel efficiencies do not change with the age of the buses.
    * Yearly diesel, natural gas and electricity energy prices until 2050 for the transportation sector were taken from the U.S. Energy Information Administration's Annual Energy Outlook 2019 (US EIA 2019) to determine energy costs per unit of distance traveled by each bus type. The reference scenario identified by US EIA (2019) was used in our base-case scenario.

- **Charger types, charger purchase costs, charging powers and bus-to-charger ratios:** We have used values based on the findings of Bloomberg New Energy Finance (2018). The purchase costs and bus-to-charger ratios are exact values used in their total cost of ownership analysis. The charging power of each type of charger is based on the range of charging powers mentioned in the report for each kind of charger.

- **Slow plug-in charger installed at a depot**: \$50,000, bus-to-charger ratio of 2:1, and charging power of 50 kW. The ratio for this type of charger concerns all types of EBs, i.e., they are all assumed to use the same type of depot charger in the base-case scenario.
- **Fast plug-in charger installed at a line terminal**: \$110,000, bus-to-charger ratio of 20:1, and charging power of 120 kW. The ratio for this type of charger only concerns the 40 ft EB with a 250 kWh battery using depot charging and fast plug-in charging at line terminals.
- **Pantograph chargers installed at three bus stops**: \$690,000 (i.e., \$230,000 per pantograph), bus-to-charger ratio of 20:1 (i.e., 1 refers to one group of three pantographs), 900 kW (i.e., 300 kW per pantograph). The ratio for this type of charger only concerns the 40 ft EB with a 110 kWh battery using depot charging and pantograph charging at bus stops.

• **Compatibility between buses and runs**: For a non-electric bus or an EB type that recharges outside the depot (at line terminals or bus stops), the compatibility was assumed to depend only on the size of the bus required for the type of run, i.e., standard (40 ft) or articulated (60 ft). For an EB that does not recharge outside the depot, the range of the bus on a single charge (computed based on the battery size and the efficiency of the bus in miles per kWh) must be more than the approximate daily distance of that run type, in addition to meeting the bus size requirement. We assume that all types of runs leave enough time for overnight charging activities, and that any articulated and standard EB has enough load capacity to handle the number of passengers associated with any articulated-bus and standard-bus run, respectively.

• **Demand charges**: Monthly demand charges vary considerably, with values ranging from \$0.00/kW to \$24/kW reported across the United States for commercial and industrial electricity customers (Gallo et al. 2014). We have used a medium value of \$12 per kW for monthly demand charges in our base-case scenario, which is equivalent to total yearly demand charges of \$144 per kW.

• **Midlife costs**: All midlife costs were set to zero in the base-case scenario since several agencies do not perform midlife rehabilitations to their buses, and some EB manufacturers provide very long battery warranties (Blynn 2018).

• **Electrification targets**: We assumed that 50% of the initial (entirely) diesel fleet must be electrified by 2035 in the base-case scenario. We chose a target year of 2035 in order to allow the option of keeping any initial vehicle in the fleet until the end of their lifetime, which is at most 15 years after the first period (i.e., 2019).

- **Yearly budgets and grid/space limitations for depot chargers**: We have assumed all these parameters to be unbounded, given that we could not obtain data for them or find reliable values in the literature.

- **Finance**: All identified monetary values from the literature were converted to 2018 dollars and used as such in the model. A yearly discount rate of 3% was used (Blynn 2018).

4.2 Base case results

The results for the problem setting described in Section 4.1 are reported in Table 2. For ease of presentation, instead of reporting annual results, we chose to present them in buckets of five years. The fleet configuration (in terms of vehicles and EB chargers) is reported for 2020, 2025, ..., 2050. We also report the solution's different cost values (in millions of dollars), as well as the solution time in seconds. The results suggest that the optimal transition plan is to 1) rely heavily on EBs to accomplish runs that need to be performed by standard 40 ft buses; and 2) use CNG buses as a near-term diesel replacement before transitioning to EBs for the majority of runs to be performed by articulated 60 ft buses in the long-term as well. Indeed, as early as 2025, 30 of the 62 required standard buses consist of EBs, and by 2035 each of the 62 standard buses is electric. On the other hand, because of the hefty purchase premium of the 60 ft EB alternative, 60 ft CNG buses are chosen to replace aging 60 ft diesel vehicles in the initial fleet. However, with the decline of battery prices in the long term, the cost associated with the large battery of the articulated EBs decreases significantly, and the 60 ft EB begins to be incorporated into the fleet between 2025 and 2030, with 12, 24, and 32 of the 38 articulated bus runs covered by EBs in 2035, 2040 and 2045, respectively. Neither of the 40 ft or 60 ft hybrid buses is incorporated into the fleet over the course of the entire planning horizon.

Regarding the choice among the different EB alternatives, the optimal replacement plan clearly suggests that among all 40 ft EB alternatives, combining the medium-sized battery of 250 kWh with fast charging at line terminals in this case is the optimal configuration. Although the 350 kWh alternative has the benefit of being compatible with 47 of 62 standard-bus runs without any investments in en route charging infrastructure, the purchase price premium resulting from the larger battery seems to outweigh the additional charging infrastructure investments at line terminals. On the other hand, the 110 kWh EB benefits from a low purchase cost compared with the other 40 ft EBs, but has a short driving range of approximately 90 km. It therefore requires the expensive pantograph charging configuration to grant more operational flexibility, a proposition deemed unprofitable according to the optimal replacement plan. Ultimately, the best compromise is to pay a premium for the 250 kWh battery compared to the 110 kWh battery in order to be able to employ the cheaper en route fast charging infrastructure at line terminals, all the while avoiding the most expensive 40 ft EB with the 350 kWh battery.

Table 2: Optimal transition plan for the base-case scenario

Year:	2020	2025	2030	2035	2040	2045	2050
Bus types:							
Diesel 40 ft	58	32	21	0	0	0	0
Diesel 60 ft	38	25	14	0	0	0	0
Hybrid 40 ft	0	0	0	0	0	0	0
Hybrid 60 ft	0	0	0	0	0	0	0
CNG 40 ft	0	0	0	0	0	0	0
CNG 60 ft	0	13	21	26	14	6	6
Electric 350 kWh 40 ft DC	0	0	0	0	0	0	0
Electric 650 kWh 60 ft DC	0	0	3	12	24	32	32
Electric 250 kWh 40 ft DC	0	0	1	3	3	2	4
Electric 250 kWh 40 ft DC+FC	4	30	40	59	59	60	58
Electric 110 kWh 40 ft DC+PC	0	0	0	0	0	0	0
Charger types:							
Depot plug-in charger (DC)	2	15	22	37	43	47	47
Fast plug-in charger at line terminal (FC)	1	2	2	3	3	3	3
Pantograph charger at three bus stops (PC)	0	0	0	0	0	0	0
Costs:							
Bus purchase cost (M$):	92.80						
Charger purchase cost (M$):	2.02						
Operating cost (M$):	95.24						
Demand charge (M$):	4.90						
End-of-horizon cost (M$):	6.78						
Total cost (M$):	201.74						
Solution time (s):	354.31						

5. Sensitivity analyses and managerial insights

In order to better understand how specific problem parameters influence optimal transition plans, we have solved several variations of our problem by making incremental modifications to the base-case scenario described in Section 4.1. In what follows we present and discuss characteristics of optimal transition plans obtained for various scenarios concerning en route charging configurations, articulated EB charging infrastructure requirements, demand charges, future energy and battery prices, EB maintenance savings, and midlife costs. In all tables and figures hereafter, the following abbreviations are used to refer to bus types:

- D-40: 40 ft diesel bus,
- D-60: 60 ft diesel bus,
- H-40: 40 ft hybrid bus,
- H-60: 60 ft hybrid bus,
- CNG-40: 40 ft CNG bus,
- CNG-60: 60 ft CNG bus,
- E350-40: 40 ft EB with a 350 kWh battery exclusively using depot charging,
- E650-60: 60 ft EB with a 650 kWh battery exclusively using depot charging,
- E250-40: 40 ft EB with a 250 kWh battery exclusively using depot charging,
- E250-40 FC: 40 ft EB with a 250 kWh battery using depot charging and fast plug-in charging at line terminals,
- E110-40 PC: 40 ft EB with a 110 kWh battery using depot charging and pantograph charging at bus stops,
- E110-40 WC: 40 ft EB with a 110 kWh battery using depot charging and wireless charging at bus stops.

5.1 En route charging configurations

While the combination of the medium-sized 250 kWh battery with fast plug-in charging at line terminals was clearly the preferred EB type for standard 40 ft buses in the base-case scenario, it is worth investigating what an optimal transition plan would be if this option were not available. Indeed, fast charging at line terminals will only be possible if the distance of individual routes that are part of a given daily run can be performed on a single battery charge, and if the operating schedule allows enough time to sufficiently recharge the battery between such routes at line terminals. If either of these conditions is not met, it may be that the only feasible en route charging configurations will involve very fast (and expensive) chargers at bus stops while passengers are boarding. Thus, in Table 3 we report characteristics of optimal transition plans for the base-case scenario and for two other scenarios. In the first, it is assumed that the only possible en route charging configuration is the EB with the 110 kWh battery to be charged at the depot with plug-in charging and at bus stops with pantograph chargers. Pantograph charging is the preferred option for charging smaller batteries at bus stops since it is cheaper and more efficient than wireless charging, the other type of charging considered to be feasible for bus stops. However, it may not always be possible to install pantograph chargers at bus stops due to space restrictions and local planning regulations, although some of these drawbacks can be overcome by opting for wireless charging (Bloomberg New Energy Finance 2018). Thus, the second additional scenario reported in Table 3 assumes that the only possible en route charging configuration is an EB with a 110 kWh battery to be charged at the depot with plug-in charging and at bus stops with wireless chargers. An investment in a unit of wireless charging infrastructure is assumed to correspond to installing wireless chargers at five bus stops, and has the following characteristics based on Bloomberg New Energy Finance (2018):

- **Wireless chargers installed at five bus stops**: Purchase cost of \$2,000,000 (i.e., \$400,000 per wireless charger), bus-to-charger ratio of 20:1 (i.e., 1 refers to one group of five wireless chargers), charging power of 1000 kW (i.e., 200 kW per wireless charger).

The results indicate that when pantograph charging is the only feasible en route charging infrastructure for EBs, the EB with the 110 kWh battery using depot charging and pantograph chargers at bus stops is prefered to the EB with the 350 kWh battery for most of the standard-bus runs with large daily distances. While the 250 kWh option with fast charging at line terminals is almost exclusively used to cover the 62 standard-bus runs in the base-case scenario, the 110 kWh option with pantograph charging is used to cover only 40 of these in the first additional scenario, with the 250 kWh battery alternative using depot charging called upon to perform approximately a third of the standard-bus runs (i.e., those it can cover with its 200 km range before being charged overnight at the depot) in the target year and beyond. The costly 350 kWh alternative with depot charging is also used to cover a few standard-bus runs with large daily distances (the 350 kWh alternative has a range of approximately 270 km) in order to avoid having to purchase more pantograph chargers. The cost breakdown shows that the total discounted cost increases by about five million compared to the base-case scenario, mostly due to the larger demand charges incurred as a result of the large charging powers drawn by the pantograph chargers.

The number of standard-bus runs performed by EBs utilizing en route charging infrastructure further drops in the second scenario investigated, due to the even more expensive wireless chargers involved. Nevertheless, the model still opts for the 110 kWh battery EB using the wireless chargers to cover about a third of the standard-bus runs, which in most years corresponds to about 20 fewer runs than those covered by the 110 kWh battery EB using pantograph charging in the first new scenario. These 20 runs are now assigned to the 350 kWh alternative, whose purchase price is worth incurring to take advantage of its large driving range and to avoid investing in more costly wireless chargers. As in the base case results, in both new scenarios approximately 75% of the fleet is electrified by the target year of 2035 despite only 50% being required to be, and the initial 40 ft diesel buses are replaced entirely with EBs.

Table 3: Optimal transition plans under several en route charging assumptions

Bus types:	D-40	D-60	H-40	H-60	CNG-40	CNG-60	E350-40	E650-60	E250-40	E250-40 FC	E110-40 PC	E110-40 WC
Fast plug-in charging at line terminals and pantograph charging at bus stops (base case)												
2025 fleet configuration:	32	25	0	0	0	13	0	0	0	30	0	N/A
2030 fleet configuration:	21	14	0	0	0	21	0	3	1	40	0	N/A
2035 fleet configuration:	0	0	0	0	0	26	0	12	3	59	0	N/A
2040 fleet configuration:	0	0	0	0	0	14	0	24	3	59	0	N/A
2045 fleet configuration:	0	0	0	0	0	6	0	32	2	60	0	N/A
2050 fleet configuration:	0	0	0	0	0	6	0	32	4	58	0	N/A
Bus purchase cost (M$):	92.80											
Charger purchase cost (M$):	2.02											
Operating cost (M$):	95.24											
Demand charge (M$):	4.90			**Total cost (M$):**			201.74					
End-of-horizon cost (M$):	6.78			**Solution time (s):**			354.31					
Pantograph charging at bus stops only												
2025 fleet configuration:	38	27	0	0	0	11	0	0	4	N/A	20	N/A
2030 fleet configuration:	17	14	0	0	0	21	0	3	6	N/A	39	N/A
2035 fleet configuration:	0	0	0	0	0	26	2	12	20	N/A	40	N/A
2040 fleet configuration:	0	0	0	0	0	16	3	22	19	N/A	40	N/A
2045 fleet configuration:	0	0	0	0	0	6	3	32	19	N/A	40	N/A
2050 fleet configuration:	0	0	0	0	0	6	1	32	21	N/A	40	N/A
Bus purchase cost (M$):	92.06											
Charger purchase cost (M$):	2.92											
Operating cost (M$):	96.62											
Demand charge (M$):	8.29			**Total cost (M$):**			206.73					
End-of-horizon cost (M$):	6.82			**Solution time (s):**			710.35					
Wireless charging at bus stops only												
2025 fleet configuration:	36	27	0	0	0	11	2	0	4	N/A	N/A	20
2030 fleet configuration:	21	14	0	0	0	21	12	3	9	N/A	N/A	20
2035 fleet configuration:	0	0	0	0	0	26	21	12	21	N/A	N/A	20
2040 fleet configuration:	0	0	0	0	0	16	30	22	17	N/A	N/A	15
2045 fleet configuration:	0	0	0	0	0	6	28	32	14	N/A	N/A	20
2050 fleet configuration:	0	0	0	0	0	6	21	32	21	N/A	N/A	20
Bus purchase cost (M$):	93.81											
Charger purchase cost (M$):	3.61											
Operating cost (M$):	97.48											
Demand charge (M$):	6.74			**Total cost (M$):**			208.58					
End-of-horizon cost (M$):	6.95			**Solution time (s)**			347.36					

5.2 Charging infrastructure requirements for articulated electric buses

It may seem optimistic to assume that the articulated EB with the 650 kWh battery can be charged with a 50 kW depot charger (as is the case in the base-case scenario), since it takes approximately 13 hours to fully recharge this battery with such a charger. However, the range of the 650 kWh EB is approximately 370 km and the average daily distance of the articulated-bus runs is just over 200 km, so charging half the battery capacity each night (or charging it fully every two nights) should be sufficient for several articulated-bus runs. Nevertheless, given the knowledge of the context at hand (namely regarding when overnight depot charging can occur and how much time is available for it), one could instead assume that there are different types of depot chargers that must be used by different buses. For example, in some contexts it may be more appropriate to consider a type of depot charger to be used specifically by the 60 ft EBs and that is more expensive and power-consuming, or that requires a higher bus-to-charger ratio than does the type of depot charger associated with 40 ft EBs.

In order to see whether the decision to adopt articulated EBs in the long term is sensitive to such charging infrastructure requirements, we modified the base-case scenario so as to assume that the 60 ft EB with the 650 kWh battery has more stringent depot charging infrastructure requirements. We first considered a new type of depot charger identifical to the slow depot chargers described in Section 4.1, but is to be used exclusively by 60 ft EBs with a bus-to-charger ratio of 1:1. We also considered two additional scenarios in which the 60 ft EB is only compatible with a new (and this time faster) type of depot charger having the same cost and charging power characterisitcs as the fast chargers at line terminals, i.e., a purchase cost of \$110,000 per charger and a charging power of 120 kW. We tested a problem setting with the faster depot chargers under two bus-to-charger ratios dictating how many of such fast depot chargers are required according to the number of 60 ft EBs in the fleet: 2:1 and 1:1. The results for each of these three new scenarios are reported in Table 4 and show that the long-term profitability of the considered 60 ft EB is indeed sensitive to such depot charging infrastructure requirements. The first two scenarios presented in Table 4 have similar effects: they delay the addition of 60 ft EBs to the fleet compared with their adoption rate in the base-case scenario, and the 60 ft EBs represent a far smaller proportion of the fleet than they do in the base-case scenario during the second half of the planning horizon. The scenario with fast depot chargers and a 2:1 ratio seems more detrimental to the business case of the large EB than the scenario with slow depot chargers and a 1:1 ratio. The last scenario with the fast depot chargers and the 1:1 ratio clearly ruins the business case of the large electric bus, which is then never added to the fleet over the entire planning horizon. In this scenario, the initial 60 ft diesel buses are only replaced with 60 ft CNG buses.

5.3 Cost scenarios

We now turn our focus to several cost scenarios, namely regarding demand charges, future energy and battery prices, EB maintenance savings, and midlife costs. In what follows we analyze the optimal transition plan obtained when each of these parameters is modified individually in the base-case scenario. For each considered cost scenario, the obtained optimal fleet configurations in 2030, 2035 and 2040, as well as the entire transition plan's total discounted cost are presented in Figures 1, 2, 3 and 4, respectively. In the remainder of this section we discuss in more detail how each cost scenario was designed, as well as its associated optimal transition plan based on the results presented in Figures 1–4.

Table 4: Optimal transition plans under more stringent charging infrastructure requirements for articulated electric buses

Bus types:	D-40	D-60	H-40	H-60	CNG-40	CNG-60	E350-40	E650-60	E250-40	E250-40 FC	E110-40 PC
Slow plug-in depot chargers for articulated electric buses with a ratio of 1:1											
2025 fleet configuration:	32	26	0	0	0	12	0	0	0	30	0
2030 fleet configuration:	20	14	0	0	0	24	0	0	2	40	0
2035 fleet configuration:	0	0	0	0	0	33	0	5	4	58	0
2040 fleet configuration:	0	0	0	0	0	27	0	11	4	58	0
2045 fleet configuration:	0	0	0	0	0	15	0	23	2	60	0
2050 fleet configuration:	0	0	0	0	0	11	0	27	3	59	0
Bus purchase cost (M$):	90.63										
Charger purchase cost (M$):	2.26										
Operating cost (M$):	98.08										
Demand charge (M$):	5.04			**Total cost (M$):**			202.82				
End-of-horizon cost (M$):	6.81			**Solution time (s)**			202.01				
Fast plug-in depot chargers for articulated electric buses with a ratio of 2:1											
2025 fleet configuration:	32	25	0	0	0	13	0	0	0	30	0
2030 fleet configuration:	16	13	0	0	0	25	0	0	1	45	0
2035 fleet configuration:	0	0	0	0	0	34	0	4	3	59	0
2040 fleet configuration:	0	0	0	0	0	30	0	8	3	59	0
2045 fleet configuration:	0	0	0	0	0	20	0	18	2	60	0
2050 fleet configuration:	0	0	0	0	0	16	0	22	5	57	0
Bus purchase cost (M$):	90.50										
Charger purchase cost (M$):	2.18										
Operating cost (M$):	98.44										
Demand charge (M$):	5.01			**Total cost (M$):**			203.06				
End-of-horizon cost (M$):	6.92			**Solution time (s)**			512.15				
Fast plug-in depot chargers for articulated electric buses with a ratio of 1:1											
2025 fleet configuration:	32	23	0	0	0	15	0	0	0	30	0
2030 fleet configuration:	16	11	0	0	0	27	0	0	1	45	0
2035 fleet configuration:	0	0	0	0	0	38	0	0	3	59	0
2040 fleet configuration:	0	0	0	0	0	38	0	0	3	59	0
2045 fleet configuration:	0	0	0	0	0	38	0	0	2	60	0
2050 fleet configuration:	0	0	0	0	0	38	0	0	4	58	0
Bus purchase cost (M$):	88.23										
Charger purchase cost (M$):	1.54										
Operating cost (M$):	101.19										
Demand charge (M$):	4.08			**Total cost (M$):**			203.58				
End-of-horizon cost (M$):	8.53			**Solution time (s)**			288.16				

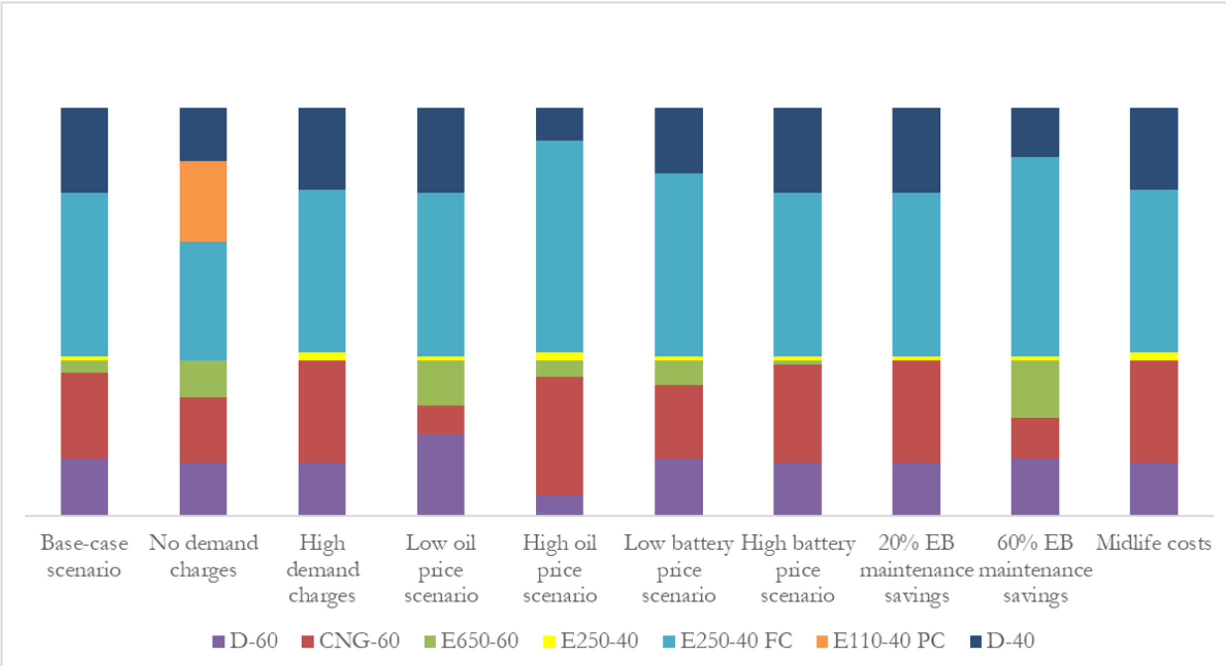

Figure 1: Optimal 2030 fleet configuration under several cost scenarios

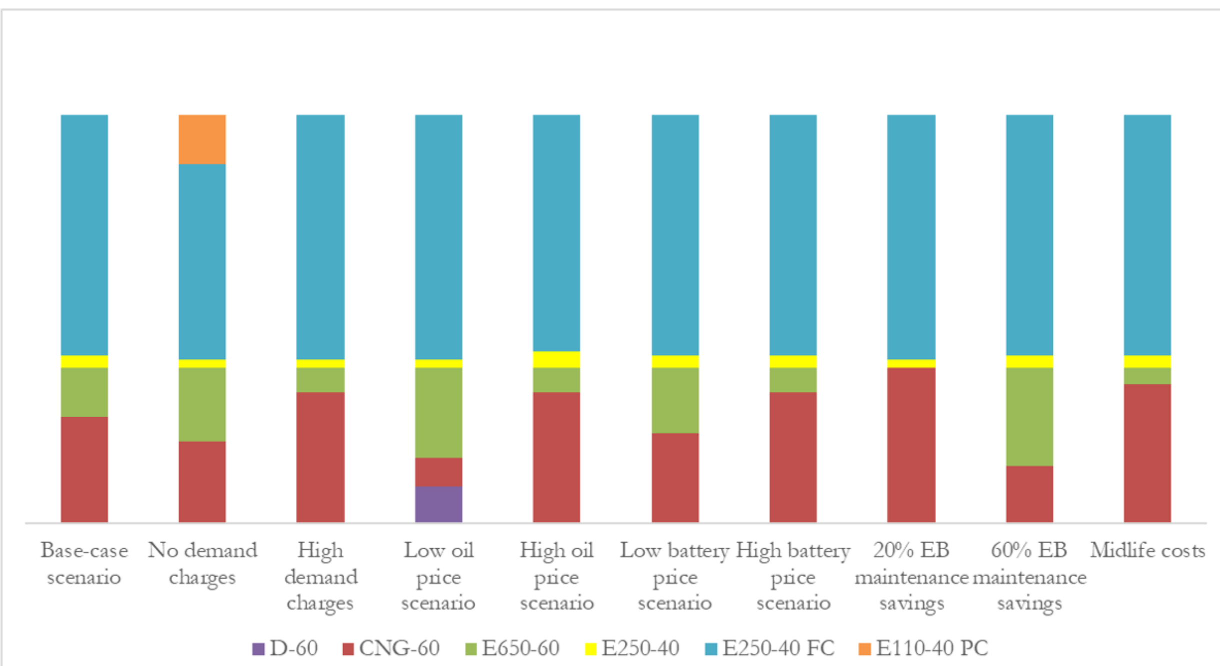

Figure 2: Optimal 2035 fleet configuration under several cost scenarios

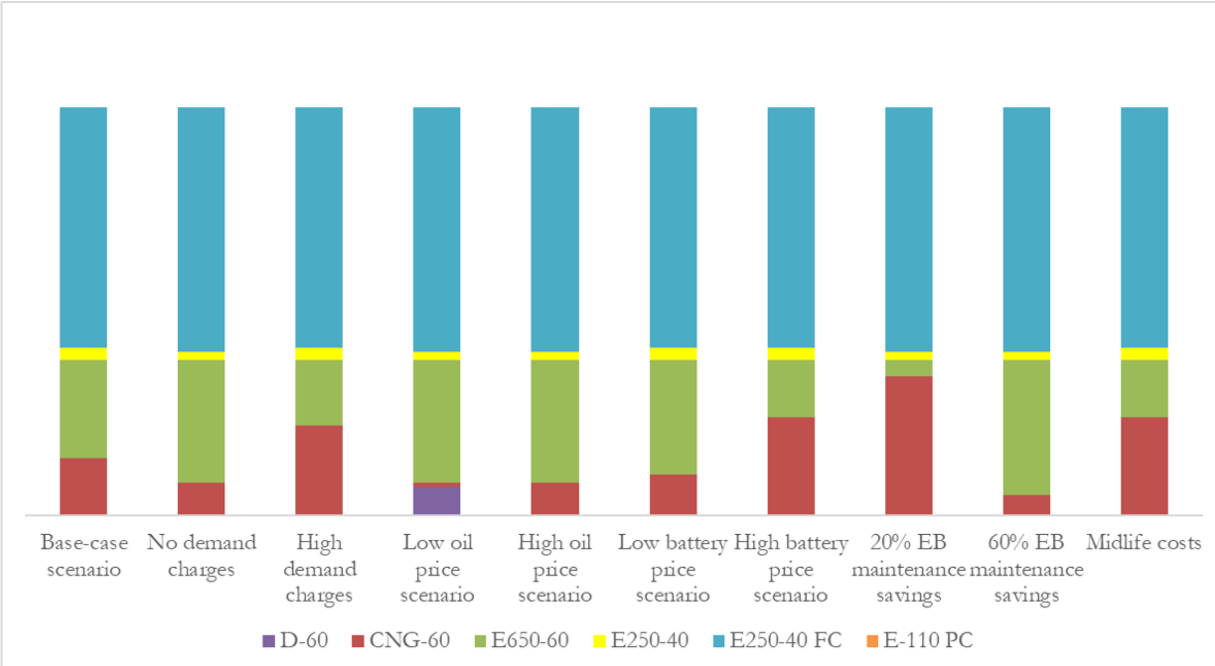

Figure 3: Optimal 2040 fleet configuration under several cost scenarios

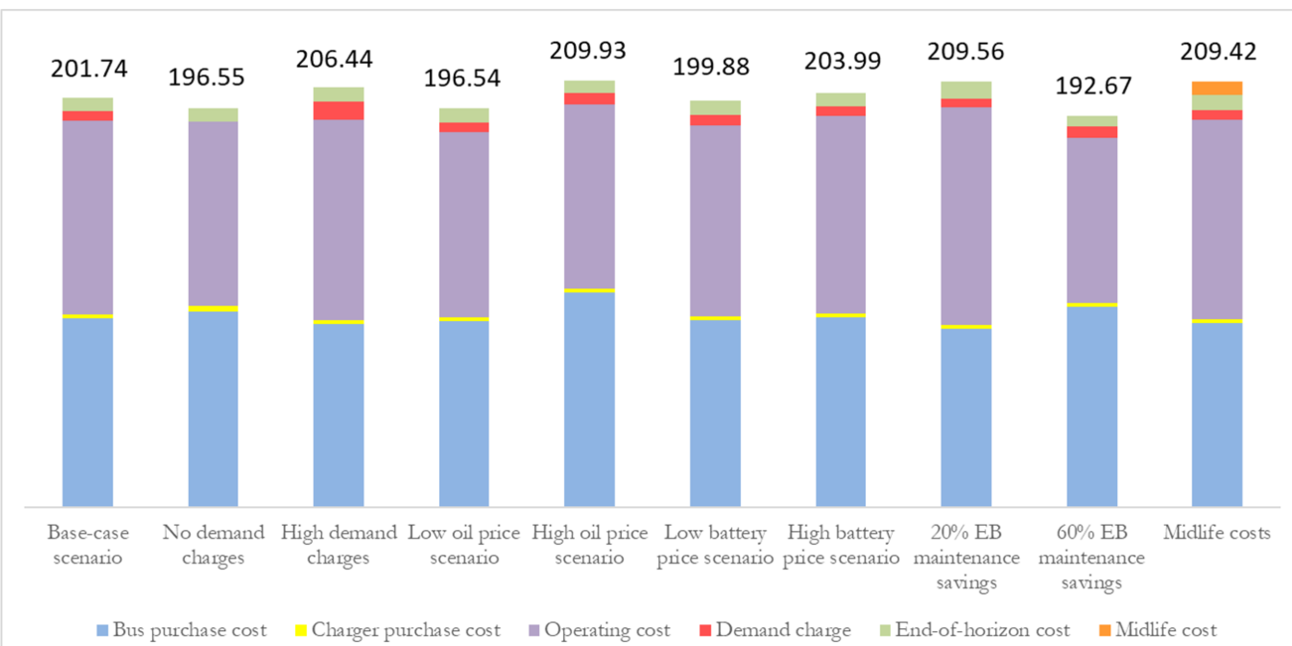

Figure 4: Total cost (M$) breakdown under several cost scenarios

Demand charges

Demand charges that are based on the largest charging power retrieved from the grid over the course of each month can have a significant impact on total energy costs associated with fleet EBs (Pelletier et al. 2018, Gallo et al. 2014). However, monthly demand charges can vary significantly. Gallo et al. (2014) report values ranging from $0/kW to $24/kW across the United States for commercial and industrial electricity consumers. In the base-case scenario, demand charges were therefore set to a medium value of 12$/kW per month. To explore how demand charges affect EB replacement decisions, we now solve the base-case scenario without demand charges and with high demand charges (i.e., $24/kW). The results suggest that demand charges can indeed hinder the use of certain high-power en route chargers. While the 110 kWh EB using high-power pantograph chargers is never used in the base-case scenario, it is used when removing demand charges (see Figures 1–2). This is done in the first half of the planning horizon when the purchase costs of EBs with larger batteries have not yet substantially decreased. Removing the demand charges incurred with the pantograph chargers seems to render the costly investments in the pantograph charging infrastructure at bus stops worthwhile. The incorporation of the 60 ft EBs is also done at a faster rate when removing the demand charges compared with the base-case scenario. The opposite observations apply in the scenario assuming the highest demand charges. **Indeed, in Figures 1–3, there are always fewer 60 ft EBs in the scenario with high demand charges than in the base-case scenario.** Nevertheless, the high demand charges are not enough to move away from the 250 kWh alternative combined with fast plug-in charging at line terminals, which remains the dominant type of bus used for standard-bus runs **in the high demand charge scenario of Figures 1–3**, as in the base-case scenario.

Energy prices

The evolution of energy prices is not only critical to the business case of fleet vehicles, but is also subject to a fair amount of uncertainty. In the base-case scenario, energy prices were based on yearly diesel, natural gas and electricity price forecasts up to 2050 for the transportation sector made by the U.S. Energy Information Administration's Annual Energy Outlook 2019 (US EIA 2019) in their reference scenario. The US EIA (2019) has also made such forecasts for high and low oil price scenarios, which we now use to evaluate the base case solution's sensitivity to energy price developments. The yearly price forecasts of diesel fuel, natural gas, and electricity in the reference, high, and low oil price scenarios are depicted in Figures 5–7.

The high oil price scenario, although detrimental to the diesel buses' business case, is actually accompanied by lower natural gas prices up to 2030 than in the reference scenario, resulting in a few extra 60 ft CNG buses being purchased early in the planning horizon instead of EBs. The natural gas prices are however higher beyond 2030 in the high oil price scenario than in the reference

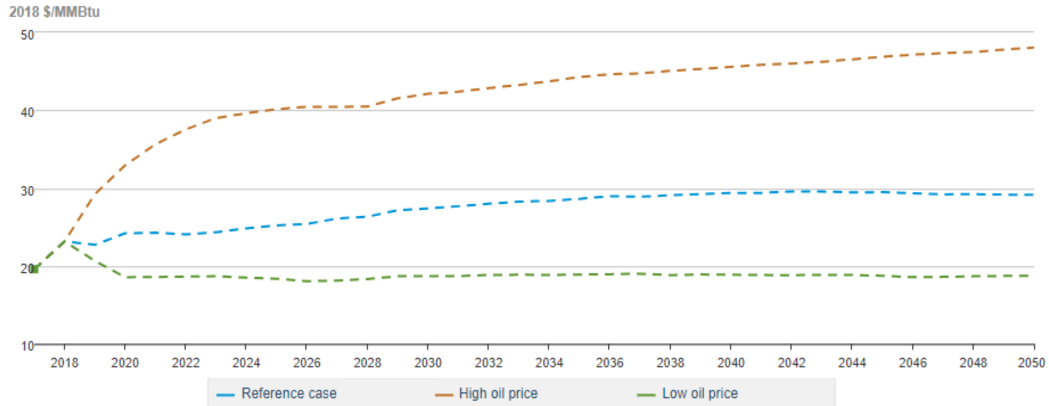

Figure 5: Diesel fuel price forecasts (Source: US EIA 2019)

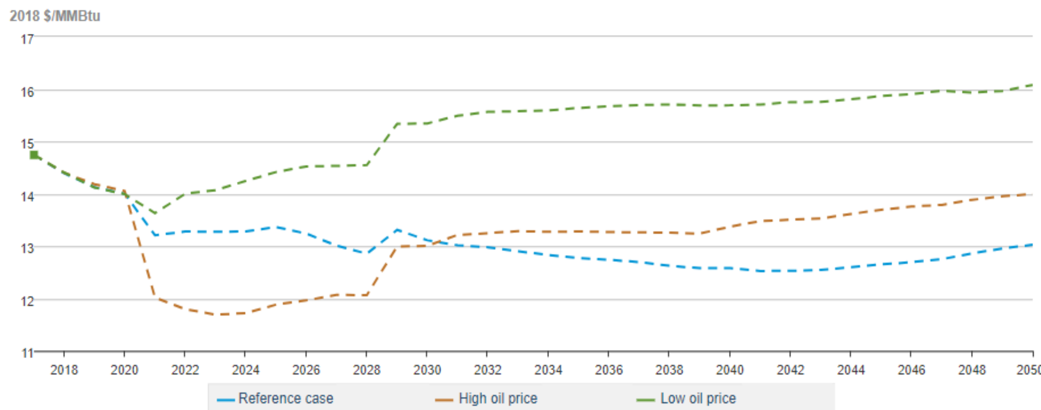

Figure 6: Natural gas price forecasts (Source: US EIA 2019)

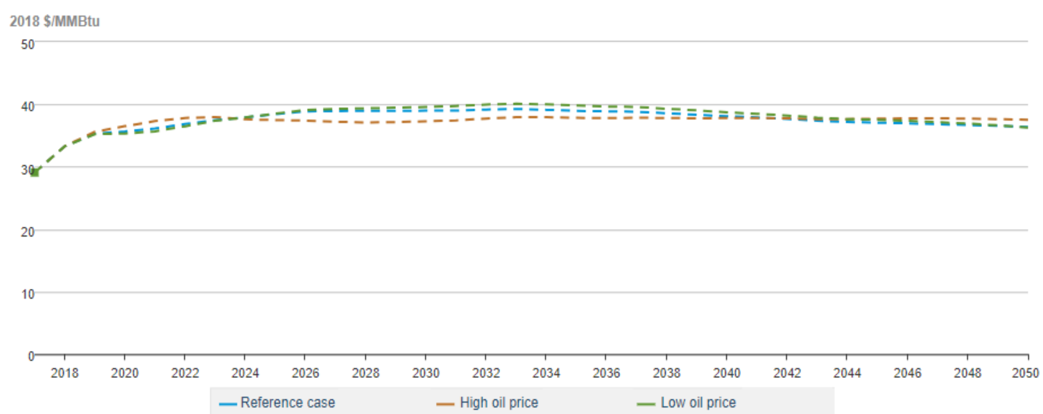

Figure 7: Electricity price forecasts (Source: US EIA 2019)

scenario, and thus by 2040 (see Figure 3) there are more 60 ft EBs in the fleet than there are in the base-case scenario. The lower natural gas prices in the high oil price scenario up to 2030 are, however, not enough to justify replacing the 40 ft diesel buses in the initial fleets with 40 ft CNG buses, given that a dozen extra 250 kWh 40 ft EBs using fast charging at line terminals are in the fleet in 2030 compared to the base-case scenario's 2030 fleet configuration **(see Figure 1)**. Because the low oil price scenario is accompanied by higher natural gas prices than in the reference scenario over the entire planning horizon, the transition to EBs for operations required to be carried out by articulated buses is accelerated (at the expense of CNG 60 ft buses). Almost twice as many 60 ft EBs are purchased by the target year of 2035 compared to the base-case scenario (see Figure 2). Moreover, the lower diesel prices result in a few 60 ft diesel buses being maintained in the fleet over the entire planning horizon in this scenario. The high oil price scenario is accompanied by a total discounted cost increase of over eight million dollars compared with the base-case scenario, while the low oil price scenario allows reducing such costs by approximately five million dollars (see Figure 4).

Battery prices

Another important component of the business case of fleet EBs that is subject to a fair amount of uncertainty is the price of lithium-ion batteries. The rate at which these prices fall directly impacts the purchase cost premium connected to EBs. In the base-case scenario, we assumed that the battery prices for EBs decline at the same rate as those for passenger EVs, and we used the evolution of passenger EV battery prices from 2019 to 2050 from Schmidt et al. (2017) under the expected experience rate that they derived from historical data. Schmidt et al. (2017) have also made passenger EV battery price projections that take into account the uncertainty surrounding the experience rate, which we use in this section to investigate how EB adoption varies under several future battery price scenarios. The authors identified a 95% confidence interval for the experience rate under expected market growth rates for EB batteries. The lowest and highest experience rates of the confidence interval are used to derive high and low battery price scenarios, respectively. As with the energy price scenarios, **Figures 1–3 show that the battery price scenarios mostly impact decisions surrounding 60 ft buses, with articulated EBs being added to the fleet more and less agressively in the low and high battery price scenario, respectively, compared with the base-case scenario**. The battery price scenario does not seem to influence standard 40 ft bus replacement decisions, **which remain almost identical in the new battery price scenarios compared with the base-case scenario in Figures 1–3. The only difference occurs in the 2030 fleet configurations presented in Figure 1, in which there are five more 40 ft EBs in the low battery price scenario than in the base-case scenario, and five fewer 40 ft diesel buses**.

EB maintenance savings

Blynn (2018) reports maintenance savings for EBs that range from 20% to 60% compared with those of diesel buses. In the base-case scenario, we assumed a mid-value of 40% savings relative to diesel maintenance costs for EBs. We now study the optimal fleet replacement plans obtained when the maintenance savings of EBs are set to the low and high ends identified by Blynn (2018). As for the previous cost scenarios, the results in Figures 1–3 suggest that decisions surrounding standard 40 ft buses are robust with respect to the new EB maintenance savings scenarios as well. Regardless of maintenance savings for EBs, the 250 kWh battery combined with fast charging at bus line terminals remains the prefered option for standard-bus runs, but the choice of bus types for the articulated bus requirements is sensitive to the maintenance savings scenario. Aside from one of the scenarios considered in Section 5.2 with stringent depot charging infrastructure requirements for 60 ft EBs, the low EB maintenance savings scenario is the only one considered thus far that does not include any 60 ft EB in the fleet by 2035 (see Figure 2). **By relying much less on EBs for the articulated bus runs, the total operating cost increases by about 12 million dollars in the low EB maintenance savings scenario compared to the base-case scenario in Figure 4, while the total bus purchase cost decreases by approximately five million dollars**. On the other hand, 14 articulated EBs are already in the fleet by 2030 in the high EB maintenance savings scenario, which is the highest number of 60 ft EBs in the 2030 fleet out of all scenarios considered thus far (see Figure 1). **The more intensive use of 60 ft EBs in this scenario thus results in the total operating cost and the total bus purchase cost decreasing by 14 million dollars and increasing by six million dollars, respectively, compared with the base-case scenario in Figure 4**.

Midlife costs

Finally, we also investigated a scenario with midlife costs by assuming that such costs are incurred for buses when they reach an age of eight years. The midlife costs for non-EBs are taken from Blynn (2018) and represent engine overhauls. The midlife costs for EBs are assumed to represent battery replacements, and their values are therefore the price of a new battery (of the size associated with the specific EB type) with battery costs of the current period. The optimal fleet configurations for the scenario with the additional midlife costs in Figures 1–3 suggest that such costs have similar impacts to those of other parameters studied in the sensitivity analyses: the adoption of 60 ft EBs takes place at a slower rate than in the base-case scenario, this time due to the large fees associated with replacing the 650 kWh battery over the course of the bus lifetime. **Figure 4 shows that the sole addition of midlife costs to the base-case scenario causes the total discounted cost of the transition plan to increase by about eight million dollars.**

5.4 Robustness of choice to replace 40 ft diesel buses with electric buses

The fact that EBs have been so consistently chosen to carry out most of the standard-bus runs raises the question of whether this would be the case even under simultaneous worst-case scenarios for demand charges, battery prices, and maintenance savings for EBs, and without requiring any minimal proportion of the fleet to consist of EBs by the target year of 2035. Because it is unclear which oil price scenario is most detrimental to EBs considering how such scenarios also influence the adoption of CNG buses, we first tested each oil price scenario with base-case electric bus-to-charger ratios, high demand charges, low EB maintenance savings, and high battery prices. The results of this experiment are reported in Table 5 and illustrate that even in such worst-case scenarios and without any electrification requirements, EBs remain the prefered option to replace the 40 ft diesel buses in the initial fleet, with 60 ft EBs being the EB type that is at the mercy of such uncertain parameters. Not a single 60 ft EB is added to the fleet during the entire planning horizon in the worst-case scenarios with reference and high oil prices.

The required electric bus-to-charger ratios could very well deviate from those assumed in our base-case scenario for 40 ft EBs as well. When the same "worst-case" scenarios for EBs described above are tested while also doubling all electric bus-to-charger ratios from the base-case scenario (the results of which are reported in Table 6), the standard EBs finally lose their competitive edge at the expense of 40 ft CNG buses in the short and medium term. Nevertheless, even in this case, 40 ft EBs represent a significant portion of the fleet near the end of the planning horizon with increasing natural gas prices and reduced battery prices in the long term.

6. Conclusions

We have introduced the EBFTP, whose solution provides strategic guidance to organizations having set fleet electrification targets for the future. We have modeled the EBFTP in the form of an integer linear program. The formulation simultaneously takes into account temporal electrification targets, vehicle purchasing and salvaging decisions, several types of EBs with different charging configurations, charger type-specific infrastructure investments and demand charges. The model also considers aggregated task assignment decisions, and the mitigation of end-of-horizon effects. We have also shown how simple modifications can be made to incorporate other extensions according to the operating context, such as midlife costs and charger maintenance costs.

We have analysed a strategic bus fleet replacement problem based on data obtained from a bus operator in France. Our analyses suggest that EBs with medium-sized batteries charged at depots overnight and at bus line terminals with fast plug-in chargers during the day are consistently chosen as the 40 ft buses in this context. The optimal transition plan also suggested that while 60 ft EBs present a promising business case in the longer term, articulated CNG buses are the most

Table 5: Optimal transition plans under base case bus-to-charger ratios, worst-case scenarios for EBs in terms of demand charges, battery prices, and maintenance savings, and without electrification requirements

Bus types:	D-40	D-60	H-40	H-60	CNG-40	CNG-60	E350-40	E650-60	E250-40	E250-40 FC	E110-40 PC
Reference oil price scenario with worst case demand charges, battery prices and maintenance savings for EBs											
2025 fleet configuration:	42	25	0	0	0	13	0	0	0	20	0
2030 fleet configuration:	20	13	0	0	0	25	0	0	2	40	0
2035 fleet configuration:	0	0	0	0	0	38	0	0	2	60	0
2040 fleet configuration:	0	0	0	0	0	38	0	0	2	60	0
2045 fleet configuration:	0	0	0	0	0	38	0	0	2	60	0
2050 fleet configuration:	0	0	0	0	0	38	0	0	2	60	0
Bus purchase cost (M$):	86.42										
Charger purchase cost (M$):	1.49										
Operating cost (M$):	109.41										
Demand charge (M$):	7.65				**Total cost (M$):**		214.91				
End-of-horizon cost (M$):	9.94				**Solution time (s):**		432.73				
High oil price scenario with worst case demand charges, battery prices and maintenance savings for EBs											
2025 fleet configuration:	26	10	0	0	2	28	0	0	0	34	0
2030 fleet configuration:	12	5	0	0	2	33	0	0	0	48	0
2035 fleet configuration:	0	0	0	0	0	38	0	0	2	60	0
2040 fleet configuration:	0	0	0	0	0	38	0	0	2	60	0
2045 fleet configuration:	0	0	0	0	0	38	0	0	2	60	0
2050 fleet configuration:	0	0	0	0	0	38	0	0	15	47	0
Bus purchase cost (M$):	97.71										
Charger purchase cost (M$):	1.57										
Operating cost (M$):	108.87										
Demand charge (M$):	8.45				**Total cost (M$):**		224.78				
End-of-horizon cost (M$):	8.18				**Solution time (s):**		1170.53				
Low oil price scenario with worst case demand charges, battery prices and maintenance savings for EBs											
2025 fleet configuration:	42	31	0	0	0	7	0	0	0	20	0
2030 fleet configuration:	21	22	0	0	0	16	0	0	2	39	0
2035 fleet configuration:	0	7	0	0	0	31	0	0	2	60	0
2040 fleet configuration:	0	3	0	0	0	31	0	4	2	60	0
2045 fleet configuration:	0	2	0	0	0	22	0	14	2	60	0
2050 fleet configuration:	0	9	0	0	0	7	0	22	2	60	0
Bus purchase cost (M$):	86.95										
Charger purchase cost (M$):	1.76										
Operating cost (M$):	105.76										
Demand charge (M$):	8.19				**Total cost (M$):**		211.65				
End-of-horizon cost (M$):	8.99				**Solution time (s):**		360.64				

Table 6: Optimal transition plans under doubled base case bus-to-charger ratios, worst-case scenarios for EBs in terms of demand charges, battery prices, and maintenance savings, and without electrification requirements

Bus types:	D-40	D-60	H-40	H-60	CNG-40	CNG-60	E350-40	E650-60	E250-40	E250-40 FC	E110-40 PC
Reference oil price scenario with doubled charger ratios and worst case demand charges, battery prices, and EB maintenance savings											
2025 fleet configuration:	41	25	0	0	21	13	0	0	0	0	0
2030 fleet configuration:	21	13	0	0	41	25	0	0	0	0	0
2035 fleet configuration:	0	0	0	0	61	38	0	0	1	0	0
2040 fleet configuration:	0	0	0	0	51	38	0	0	2	9	0
2045 fleet configuration:	0	0	0	0	31	38	0	0	2	29	0
2050 fleet configuration:	0	0	0	0	11	38	0	0	11	40	0
Bus purchase cost (M$):	88.24										
Charger purchase cost (M$):	1.47										
Operating cost (M$):	118.25										
Demand charge (M$):	3.08			**Total cost (M$):**			220.95				
End-of-horizon cost (M$):	9.91			**Solution time (s):**			114.10				
High oil price scenario with doubled charger ratios and worst case demand charges, battery prices, and EB maintenance savings											
2025 fleet configuration:	31	10	0	0	31	28	0	0	0	0	0
2030 fleet configuration:	14	5	0	0	48	33	0	0	0	0	0
2035 fleet configuration:	0	0	0	0	48	38	0	0	4	10	0
2040 fleet configuration:	0	0	0	0	38	38	0	0	4	20	0
2045 fleet configuration:	0	0	0	0	21	38	0	0	4	37	0
2050 fleet configuration:	0	0	0	0	10	38	0	0	18	34	0
Bus purchase cost (M$):	98.66										
Charger purchase cost (M$):	1.64										
Operating cost (M$):	118.09										
Demand charge (M$):	4.64			**Total cost (M$):**			231.03				
End-of-horizon cost (M$):	8.00			**Solution time (s):**			163.64				
Low oil price scenario with doubled charger ratios and worst case demand charges, battery prices, and EB maintenance savings											
2025 fleet configuration:	43	31	0	0	19	7	0	0	0	0	0
2030 fleet configuration:	24	23	0	0	28	15	0	0	0	10	0
2035 fleet configuration:	10	8	0	0	28	30	0	0	4	20	0
2040 fleet configuration:	17	3	0	0	9	35	0	0	6	30	0
2045 fleet configuration:	14	0	0	0	0	38	0	0	8	40	0
2050 fleet configuration:	8	9	0	0	0	23	0	6	14	40	0
Bus purchase cost (M$):	85.05										
Charger purchase cost (M$):	2.05										
Operating cost (M$):	115.35										
Demand charge (M$):	7.14			**Total cost (M$):**			219.52				
End-of-horizon cost (M$):	9.94			**Solution time (s):**			264.18				

cost-effective intermediate alternative to articulated diesel buses until battery prices have fallen sufficiently. This is, however, contingent on the depot charging requirements for 60 ft EBs. These findings may be of interest to other transit fleets operating in similar operational contexts (i.e., medium-sized cities with buses traveling an average of 200 km per day). Our sensitivity analyses have also shown that the choice of 40 ft EBs to replace the initial diesel buses in the fleet is quite robust to parameters subject to uncertain future developments, but that such parameters can have a significant impact on the time frame associated with the incorporation of 60 ft EBs into the fleet. No hybrid buses were used in any optimal solution, which suggests that using such vehicles as an intermediate step towards full electrification may not be a cost-effective strategy.

Acknowledgements

This research was partly supported by the Canadian Natural Sciences and Engineering Research Council under grants 463834-2014, 436014-2013 and 2015-06189. This research was also partly funded by the French Agence Nationale de la Recherche through project e-VRO (ANR-15-CE22-0005-01). This support is gratefully acknowledged. Thanks are due to the referees for their valuable comments.

References

Ahani, P., A. Arantes, S. Melo. 2016. A portfolio approach for optimal fleet replacement toward sustainable urban freight transportation. *Transportation Research Part D: Transport and Environment* **48** 357–368.

Ambrose, H., N. Pappas, A. Kendall. 2017. Exploring the costs of electrification for California's transit agencies. Report No. UC-ITS-RR-2017-03, University of California Institute of Transportation Studies. URL `https://cloudfront.escholarship.org/dist/prd/content/qt0fn8s2jh/qt0fn8s2jh.pdf`. Last accessed May 2019.

Ansaripoor, A.H., F.S. Oliveira, A. Liret. 2016. Recursive expected conditional value at risk in the fleet renewal problem with alternative fuel vehicles. *Transportation Research Part C: Emerging Technologies* **65** 156–171.

Avere-France. 2017. Développer le transport en commun en véhicule électrique URL `http://www.avere-france.org/Site/Article/?article_id=5893`. Last accessed May 2019.

Bakır, İ. 2017. Large scale optimization methods for fleet management in long-haul transportation networks. Ph.D. thesis, Georgia Institute of Technology, GA.

Bektaş, T., J.F. Ehmke, H.N. Psaraftis, J. Puchinger. 2018. The role of operational research in green freight transportation. *European Journal of Operational Research* **274**(3) 807–823.

Bloomberg New Energy Finance. 2018. Electric buses in cities: Driving towards cleaner air and lower CO2. On behalf of: Financing Sustainable Cities Initiative, C40 Cities, World Resources Institute, Citi Foundation. URL `https://data.bloomberglp.com/professional/sites/24/2018/05/Electric-Buses-in-Cities-Report-BNEF-C40-Citi.pdf`. Last accessed May 2019.

Blynn, K. 2018. Accelerating bus electrification: Enabling a sustainable transition to low carbon transportation systems. M.Sc. thesis, Massachusetts Institute of Technology, MA.

BYD Motors. 2018. K11 electric transit bus. URL `https://en.byd.com/bus/k11-electric-transit-bus/`. Last accessed April 2019.

California Air Resources Board. 2018. California transitioning to all-electric public bus fleet by 2040. URL `https://ww2.arb.ca.gov/news/california-transitioning-all-electric-public-bus-fleet-2040`. Last accessed May 2019.

Chen, Z., Y. Yin, Z. Song. 2018. A cost-competitiveness analysis of charging infrastructure for electric bus operations. *Transportation Research Part C: Emerging Technologies* **93** 351–366.

Dreyfus, S.E. 1960. A generalized equipment replacement study. *Journal of the Society for Industrial and Applied Mathematics* **8**(3) 425–435.

Feng, W., M. Figliozzi. 2013. An economic and technological analysis of the key factors affecting the competitiveness of electric commercial vehicles: A case study from the USA market. *Transportation Research Part C: Emerging Technologies* **26** 135–145.

Feng, W., M. Figliozzi. 2014. Vehicle technologies and bus fleet replacement optimization: Problem properties and sensitivity analysis utilizing real-world data. *Public Transport* **6**(1-2) 137–157.

Gallo, J.-B., T. Bloch-Rubin, J. Tomić. 2014. Peak demand charges and electric transit buses. CALSTART. URL `http://calstart.org/wp-content/uploads/2018/10/Peak-Demand-Charges-and-Electric-Transit-Buses.pdf`. Last accessed May 2019.

Grinold, R.C 1983. Model building techniques for the correction of end effects in multistage convex programs. *Operations Research* **31**(3) 407–431.

Islam, A. 2018. Minimization of carbon footprint of transit agencies by adopting alternative fuel technologies. M.Sc. thesis, University of Connecticut, CT.

Jang, Y.J., S. Jeong, M.S. Lee. 2016. Initial energy logistics cost analysis for stationary, quasi-dynamic, and dynamic wireless charging public transportation systems. *Energies* **9**(7), 483.

Karabakal, N., J.R. Lohmann, J.C. Bean. 1994. Parallel replacement under capital rationing constraints. *Management Science* **40**(3) 305–319.

Kleindorfer, P.R., A. Neboian, A. Roset, S Spinler. 2012. Fleet renewal with electric vehicles at La Poste. *Interfaces* **42**(5) 465–477.

Laver, R., D. Schneck, D., Skorupski, S. Brady, L. Cham. 2007. Useful life of transit buses and vans. Report No. FTA VA-26-7229-07.1, US Federal Transit Administration.

Li, S., Y. Huang, S.J. Mason. 2016. A multi-period optimization model for the deployment of public electric vehicle charging stations on network. *Transportation Research Part C: Emerging Technologies* **65** 128–143.

Lin, Y., K. Zhang, Z-J.M. Shen, B. Ye, L. Miao. 2019. Multistage large-scale charging station planning for electric buses considering transportation network and power grid. *Transportation Research Part C: Emerging Technologies* **107** 423–443.

Liu, Z., Z. Song. 2017. Robust planning of dynamic wireless charging infrastructure for battery electric buses. *Transportation Research Part C: Emerging Technologies* **83** 77–103.

Montreal Gazette. 2018. Montreal, Laval team up in Canada's largest order of electric buses. URL https://montrealgazette.com/news/local-news/montreal-laval-team-up-in-canadas-largest-order-of-electric-buses. Last accessed May 2019.

Pelletier, S., O. Jabali, G. Laporte. 2016. 50th anniversary invited article – Goods distribution with electric vehicles: Review and research perspectives. *Transportation Science* **50**(1) 3–22.

Pelletier, S., O. Jabali, G. Laporte. 2018. Charge scheduling for electric freight vehicles. *Transportation Research Part B: Methodological* **115** 246–269.

Schmidt, O., A. Hawkes, A. Gambhir, I. Staffell. 2017. The future cost of electrical energy storage based on experience rates. *Nature Energy* **2**, Article No. 17110.

Stasko, T.H., H.O. Gao. 2010. Reducing transit fleet emissions through vehicle retrofits, replacements, and usage changes over multiple time periods. *Transportation Research Part D: Transport and Environment* **15** 254–262.

Toronto Transit Commission. 2019. TTC Green Initiatives. URL http://ttc.ca/Riding_the_TTC/green_initiatives.jsp. Last accessed May 2019.

U.S. Energy Information Administration. 2019. Annual Energy Outlook 2019. URL https://www.eia.gov/outlooks/aeo/. Last accessed May 2019.

Xylia, M., S. Leduc, P. Patrizio, F. Kraxner, S. Silveira. 2017. Locating charging infrastructure for electric buses in Stockholm. *Transportation Research Part C: Emerging Technologies* **78** 183–200.

ZeEUS project. 2017. ZeEUS eBus Report #2: An updated overview of electric buses in Europe. URL https://zeeus.eu/uploads/publications/documents/zeeus-ebus-report-2.pdf. Last accessed May 2019.