Transportation Research Part A 185 (2024) 104103

Contents lists available at ScienceDirect

Transportation Research Part A

journal homepage: www.elsevier.com/locate/tra

Introducing electric buses in urban areas: Effects on welfare, pricing, frequency, and public subsidies

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ARTICLE INFO

Keywords:
Public transport
Electric buses
Optimal pricing
Transit subsidies
Urban transportation
Road tolls

ABSTRACT

We study optimal degree of bus system electrification for Stockholm's longest high-frequency bus line. We evaluate the welfare effects of opportunity and depot charging fleet configurations with batteries charged during dwell times at terminal stations or during the operating pause in the bus depot, respectively. Electric buses (e-buses) significantly reduce carbon and health damaging emissions of transit services. However, e-buses are presently not welfare improving, because their lower external costs do not offset the higher supply costs (e.g., capital cost of charging infrastructures and batteries). Instead, we find that optimising bus fares and frequencies and road pricing is more effective in improving social welfare and carbon emissions. E-buses significantly reduce surplus of bus operators, which thus are reluctant to adopt these technologies without direct public support. Sensitivity analysis shows that: (i) technological developments to substantially reduce capital costs can make e-buses perform well from a social welfare perspective; (ii) efficiency gains obtained in the operation of the service, e.g., by optimizing on-board conditioning systems, but also bus routing and driving style, can have a greater impact on the cost performance of e-bus fleet configurations than simply reducing capital costs. An argument for e-buses is the efforts in coordinating a transition to electrified vehicles, aiming at reducing the risk of futile investments in charging infrastructure.

1. Introduction

The electrification of public transport is accelerating with each passing year, gaining more and more attention from planners and decision-makers worldwide (IEA, 2022). In Europe, the adoption of alternatively powered buses has increased rapidly, driven by technology push policies from local and national authorities (ICCT, 2022a). The total number of electric buses (e-buses) went from about 1,650 in 2018 to over 9,500 in 2022, increasing from 2.5 % to 10 % their sale share (EAFO, 2022). According to certain predictions, especially in urban areas, e-buses will replace their conventional fuelled counterparts in the current decade (Pagliaro and Meneguzzo, 2019).

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https://doi.org/10.1016/j.tra.2024.104103

Available online 30 May 2024

Many public policies aimed at reducing emissions from transport sector involve e-buses. The European Commission (EC) has proposed to make all new city buses zero-emission as of 2030.[1] Governments across the world have been defining multi-billion euro funding programs[2] and a bunch of papers explores the role of public institutions in accelerating the transition to zero-emission buses (e.g., Aldenius et al., 2022; Thorne et al., 2021; Bakker & Konings, 2018). The cost-effectiveness of alternative solutions is undoubtedly one of the most important criteria influencing the decision-makers' choice. Several papers have proposed life cycle cost (LCC) models and total cost of ownership (TCO) assessments for city buses in the last decade comparing, for a given fleet size and kilometres of operation, the increased capital costs of having electric buses and the per-kilometre cost savings (e.g., among others, Avenali et al., 2023; Muñoz et al., 2022; Comello et al., 2021; Harris et al., 2020; Borén, 2020; Lajunen, 2018; Ally & Pryor, 2016). Electric buses significantly reduce carbon emissions generated by public transport (Gustafsson et al., 2021; Holland et al., 2021). Consequently, the environmental impact of transit services is often regarded as a component of the cost model, switching from a private to a social perspective.

In this paper, we complement the debate over cost-effectiveness of e-buses as we build a model for welfare optimal public transport pricing and design by including the optimisation of alternative bus fleet configurations (i.e., conventional diesel or electric). The modelling of the powertrain choice involves various aspects of the transit service provision, including new operating procedures (e.g., charging schedules and energy management) and extra investments (e.g., chargers' installation, electric batteries purchasing). We make contributions to the literature in two aspects: 1) show how introducing e-bus technologies impacts welfare; 2) demonstrate how optimal pricing by travel mode, bus frequency, number of bus stops, and cost recovery change when e-bus fleets are deployed. We study this issue for an urban area along the busiest bus line in Stockholm.

Relying on welfare-oriented optimisation of public transport capacity, rather than on engineering cost studies, allow us to link design variables with the relevant cost analysis behind optimal pricing (Jara-Díaz and Gschwender, 2003). Two types of resources are considered affecting producer and consumer surplus, those provided by the operators and those provided by the users, namely their time. Considering the inputs supplied by the operators, there are operational and capital costs. Regarding the inputs supplied by the passengers, these so-called users' costs are the money values of their travel times, i.e., waiting, access and in-vehicle (Jara-Díaz and Gschwender, 2003).

While doing this, we benchmark the introduction of e-buses towards other policy instruments and address the following questions that seem to remain unanswered: while e-buses intuitively induce, for a given fleet size and kilometres of operation, increased capital costs and per-kilometre cost savings, are other policy instruments – such as optimising bus fares, frequencies (and so fleet size), the number of stops, or road pricing – more effective in improving urban welfare? Do e-buses adoption increase or reduce surplus of bus operators and in turn transit subsidies? While e-buses intuitively reduce emissions of transit services, are other policy instruments more effective in reducing environmental costs? Is the social benefit of reducing the number of car trips by making the bus service more attractive higher than that of simply cutting marginal external damage of bus services by introducing e-buses?

The large literature on optimal welfare pricing and transit subsidies, recently reviewed by Hörcher and Tirachini (2021), has so far neglected electric buses. From Mohring's seminal work (1972) on optimal frequencies, Jansson (1980, 1984) extends the model to look into the optimal fleet size and vehicle size in multiple periods. Later many authors have developed optimal pricing and frequency principles for public transport, e.g., among others, Jara-Díaz and Gschwender (2003), Monchambert and de Palma (2014), Tirachini et al. (2014), de Palma et al. (2015), De Borger and Proost (2015), and Börjesson et al. (2017, 2018). Parry and Small (2009) and Basso and Silva (2014) look at the efficiency of transit subsidies. Recently, Tirachini and Antoniou (2020) complement the debate as they study the effect of automation for optimal vehicle size, frequency, fares and subsidies.

The rest of the paper is organised as follows. Section 2 presents the model components. Section 3 describes the study area and the calibration data. Section 4 presents the main quantitative results and Section 5 provides a sensitivity analysis. Section 6 concludes with some policy recommendations.

2. The model

2.1. General setting

In this model, we study passenger transportation within an inner-city corridor (rather than modelling a full network) in the peak period (two hours in the morning and two hours in the afternoon) of a representative workday. Two different types of trips (j), long ($j = l$) and short ($j = s$), can be demanded along the corridor and travellers can choose between three modes (h): car ($h = c$), bus ($h = b$) and bicycle ($h = v$).[3] The main reason for having short and long trips in the model is that the modal shares, and thereby interaction

[1] 14/02/2023 – Proposal for a regulation of the European Parliament and of the council amending Regulation (EU) 2019/1242 as regards strengthening the CO_2 emission performance standards for new heavy-duty vehicles and integrating reporting obligations, and repealing Regulation (EU) 2018/956. Available at <https://ec.europa.eu/commission/presscorner/detail/en/IP_23_762>.

[2] The National Recovery and Resilience Plan allocates more than 2 billion euro to support zero-emission bus deployment in Italy until 2026 (MIMS, 2022); in Sweden, around 110 million euro from the 2022 budget are allocated for electric buses (Swedish Energy Agency, 2022). Similar plans can be found in China (CATARC, 2020), United States (FTA, 2022), United Kingdom (DfT, 2022), Australia (TfNSW, 2022), and South American Countries (ICCT, 2022b).

[3] The two trips, short and long, are considered as two different separable goods, i.e., the marginal utility (and the consumed quantity) of short trips is independent from the marginal utility (and the consumed quantity) of long trips, implying that we do not model destination choice.

effects, as well as external costs, differ between trip distance.

We assume that the length of the corridor under study is L kilometres (coinciding with the one-way bus route) and that the ns bus stops are uniformly distributed along the bus route. The population is homogenously spread along the corridor and can be divided into four user groups (k) distinguished by income and ability to ride a bike: low-income ($k = low$), mid-income ($k = mid$), high-income ($k = high$), and no-bicycle ($k = nb$). We assume that: (i) the preferences of the first three user groups (defined in Appendix A) differ only according to their income level, while the preferences of the fourth user group (no-bicycle) differ only in the sense that they cannot choose to cycle (disability, age, heavy luggage, trips longer than 12 km, etc.); (ii) the no-bicycle user group has the same value of time as the mid-income group and they make only long trips ($j = l$); (iii) bus is the only available public transport mode in the corridor, and possible overlaps with other options (such as metro or tramway services) are neglected. Note that the preferences vary across groups, but all travellers within a group are assumed to have identical preferences, such that any given group can be treated as a representative individual. The number of trips by user group is assumed to be a continuous variable.

We borrow the street design of the inner-city corridor from Börjesson et al. (2018). The bicycle lane runs between the bus lane and the curb (or parked cars), and it disappears at the bus stop since the bus must reach the stop. When passengers board and alight from the bus, cyclists are forced to divert into the car lane to overtake the bus or to wait for the bus to leave the stop. The result is a temporary conflict between bicycles, buses, and cars which increases road congestion, reducing road capacity and traffic safety.

To model congestion and interactions between the travel modes in a simplified manner, we disregard the dynamics of queue building up and declining. Instead, we assume that all trips made bus, car, and bike during long and short trips are uniformly distributed along the corridor. Furthermore, we make the assumption that congestion is a linear function of vehicle flow, such that the travel time per long trips by car is $TT_c = \alpha_c + \beta_c \cdot \frac{q_c^l + \lambda q_c^s}{n_h cap_c} \cdot \frac{d}{L} + \gamma_c \cdot ns \cdot P_b \cdot P_v$ where α_c is the free-flow driving time, q_c^l and λq_c^s are the number of drivers making long and short trips, d is the distance travelled for long trips (λ is the relative distance of short trips to long trips), n_h is the number of hours in the peak, β_c the congestion parameter and (cap_c) the lane capacity. It means that on an average road section, there are $\frac{q_c^l + \lambda q_c^s}{n_h} \cdot \frac{d}{L}$ cars passing per hour. The final term is the delay time due to the interactions with other modes at the bus stops, where γ_c is the interaction parameter (in terms of time delay), P_b is the probability that there is a bus at the bus stop, and P_v is the probability that a cyclist is passing the bus stop. While these are simplified assumptions, we believe they can be justified for reasonably small changes in car traffic flows. This setting implies that we model congestion and travel times on an average road segment, where different user groups simultaneously travel and the total travel time of a long or short trip depends on the total demand (namely the number of car drivers, bus rides, and cyclists). The reader may refer to Appendix A for all equations related to user costs and preferences.

To analyse the effects of introducing new bus technologies (i.e., electric bus) on urban welfare, we consider four different bus fleet configurations: one diesel case and three full electric options.

The welfare function for the corridor includes: (1) the utility derived from trips, (2) the user cost of these trips, (3) the cost of public transport supply, and (4) the external costs other than congestion. Input parameters for the welfare function can be found in Appendix B. We specify the cost of public transport supply and the external costs other than congestion in Sections 2.2 and 2.3. We present the welfare function in Section 2.4.

2.2. Cost of public transport supply

The key contribution of our model is that we assess the welfare effect of various e-bus systems in addition to standard diesel buses. The electrification of transit services significantly impacts the cost of public transport supply. Importantly, the introduction of e-buses requires both new infrastructure (e.g., bus chargers and electric grid connections must be arranged) and new depot procedures (e.g., power management and charging scheduling must be introduced). Our formulation allows assessing the impact of the charging strategy on fleet size and service frequency, which in turn affect e-bus fleet costs and the related charging infrastructures. This represents a critical step to switch from conventional diesel to e-bus fleets analysis.

2.2.1. E-buses

In order to determine the cost of e-buses, we follow three steps: (1) define the e-bus fleet configurations; (2) determine, for each configuration, the required numbers of buses, i.e., the fleet size; and (3) evaluate the cost function of the bus supply for each configuration.

2.2.1.1. E-bus fleet configurations. The distinction between different e-bus systems is mainly based on the charging strategy that is adopted. We distinguish between:

1. *depot charging* (also known as *overnight charging*), where batteries are charged during the operating pause in the bus depot. For depot charging systems, one of the critical factors is the battery capacity, which sets the daily runtime of the bus before returning to the depot;
2. *opportunity charging* (also known as *end-station charging*), where batteries are repeatedly charged during the day, usually during dwell times at terminal stations. For opportunity charging systems, the critical factors are the C-rate and the number of discharge–charge cycles (the full discharge of a charged battery with subsequent recharge). Note that the C-rate is the time it takes to charge or discharge the battery: 1C (10C) means that the current will completely discharge the battery in 1 h (1/10 h = 6 min).

Depending on the charging strategies, different choices in terms of battery cell types and types of chargers are implemented (Parviziomran and Bergqvist, 2023). The following distinctions hold in terms of battery cell types:

1. *NMC batteries*, which offer the largest capacity currently available on the market (i.e., about 700 kWh for heavy vehicles); NMC batteries are mainly used under depot charging strategies.
2. *LTO batteries*, which provide the best performance in terms of C-rate (up to 10C) and discharge–charge cycles (up to 10,000 per day). LTO batteries are mainly used under opportunity charging strategies.

Similarly, as far as the type of charger is concerned, we distinguish between:

1. *Slow-charger* (SC), where the device battery charges at a lower speed, which not only reduces heat and battery pressure, but also benefits the long-term health of the battery. SC is mainly used at terminals under depot charging strategies. The disadvantages are obvious, i.e., the charging time is longer, and it only meets the vehicles that operate during the day and rest at night.
2. *Fast-charger (FC),* where the charging current is large, which is ten times or even dozens of times the conventional charging current. FC is mainly used at terminals under opportunity charging strategies. The disadvantages are: (i) very high equipment installation requirements and costs; (ii) a greater impact on the battery in a short period of time, which can easily cause the battery's active material to fall off and the battery to heat up.

The key element in e-bus configurations is the energy consumption (E_{km} − kWh/km). It is computed as[4]

$$E_{km} = E_{lw} + \imath w\left(W_b + W_{pax}\right) + P_{HVAC} \cdot \frac{TT_b}{L}, \tag{1}$$

where $W_b = \frac{EB_{c_z}}{EB_{b_z}}$ and $W_{pax} = n_{on} \cdot W_{hb}$.

E_{lw} is the energy consumption of lightweight bodied buses, $\imath w$ is the weight increase parameter (i.e., the additional energy consumption for a weight increase of one kilogram). W_b is the additional weight of the electric battery (kg) – which is the ratio of the capacity of the type z battery EB_{c_z} (kWh) to its energy density EB_{d_z}(kWh/kg), $z = NMC, LTO$. W_{pax} stands for the additional weight of bus passengers (kg) – which is a function of the number of passengers on-board (n_{on}) and the average weight of a human body (W_{hb}). The energy requirement for the HVAC (Heating, Ventilation and Air Conditioning) system of the bus depends on the power required (P_{HVAC} − W) per unit of time (TT_b is the travel time per trip of the bus). Obviously, passenger load and power required by HVAC systems depend on time-of-day, weather conditions, and other contingent factors.

The impact of energy consumption on variable costs in e-bus supply is evident. But this influence extends to various aspects, including changes in fleet size. Indeed, depot charged e-buses may face limitations in completing the daily service provision due to the restricted driving range imposed by the battery. Consequently, an expansion in fleet size becomes necessary to maintain the same bus frequency (see Section 2). Moreover, both the power installed on slow/fast chargers (see Section 4.1) and the capacity of electric batteries (see 5.1) depend on energy demand of the bus route.[5]

Consequently, the cost of charging infrastructure and the cost of bus fleet purchasing, including battery expenses, will change. The difference $E_{km} - E_{lw}$ is the auxiliary energy consumption for non-traction needs, which is mainly related to the HVAC system (Basma et al., 2022, Fiori et al., 2021). In normal weather conditions, auxiliaries account for nearly half of total energy consumption. In winter or hot summer conditions it can reach up to 70 percent of the energy consumption. The primary challenge in reducing energy demand for electrified buses is therefore to minimize consumption for non-traction purposes, directly affecting the fleet size and the power installed on charging stations.

Our paper focuses on three e-bus fleet configurations that combine depot and overnight charging strategies commonly observed in cities that have implemented transit electrification (Li, 2016) (see Table 1).

In the eOCD bus fleet configuration there is a fast charger only in one of the route terminals and then e-buses are also subjected to a depot charge phase during the overnight break by its slow-charger. In the eOCP bus fleet configuration, fast chargers are installed in both bus terminals, so e-buses are charged only during dwell times at the end-stations. In the eDCM bus fleet configuration, we consider a fleet of depot charged e-buses equipped with the highest battery capacity currently available for heavy vehicles (700 kWh). In this case, each e-bus is charged by its slow-charger at the bus depot during the «no departures time», including the whole overnight break and part of the off-peak periods.

[4] Our energy consumption formulation is similar to Vepsäläinen et al. (2018), but we explicitly refer to the impact of passenger load on energy consumption, which is not negligible for e-buses as it is for conventional diesel ones (Rosero et al., 2021).

[5] When assessing the energy consumption needed to compute the fleet size, the power installed on chargers, and the capacity of the battery, we consider the worst operating conditions, i.e., E_{km_max} with passenger full load, W_{pax_max}, and heat/air conditioning on high, P_{HVAC_max}. Conversely, when assessing the energy consumption needed to compute variable costs of e-bus service provision, we consider standard operating conditions, i.e., E_{km_avg} with average load factor, W_{pax_avg}, and average use of HVAC systems, P_{HVAC_avg}.

Table 1
E-bus fleet configurations.[a]

Acronym	Charging strategy	Type of charger	Battery cell type
eOCD	Opportunity charging combined with depot charging	FC (fast-charger) + SC (slow-charger)	LTO
eDCM	Depot charging with max battery capacity	SC (slow-charger)	NMC
eOCP	Opportunity charging at the end-stations	FC (fast-charger)	LTO

[a] Trolleybuses (in-motion charging) are not included in the analysis. Since the main purpose of this research is to assess public policies related to replacing conventional fossil-fuelled buses, we focus on battery electric buses, which can operate on any road. Trolleybuses were operating in this bus corridor before 1950s. At that time, they were replaced by buses because the trolleybuses were deemed to have limited flexibility in terms of route changes or extensions due to their dependence on overhead wires. Even if there are trolleybuses built decades ago successfully operating in Europe and elsewhere in the world, new trolleybuses built in existing old-built city environments will likely encounter problems and opposition.

2.2.1.2. E-bus fleet size. The number of e-buses is defined as:

$$nb_i = \begin{cases} \left\lceil \dfrac{TT_b \cdot f}{60} \right\rceil & for \quad i = eODC, eOCP \\ \left\lceil \dfrac{L \cdot 2 \quad \cdot DD}{dr} \right\rceil & where \quad DD = n_h f + n_{hOP} f \varphi \quad for \ i = eDCM. \end{cases} \tag{2}$$

When opportunity charging is adopted, the required number of buses can be computed as the ratio between the travel time of the bus route (TT_b) and the operation interval, which is the inverse of the bus frequency (f). Conversely, the total number of depot-charged buses depends on the total daily mileage required by the route, which is a function of the route length (L) and the number of daily departures (DD). The number of daily departures, in turn, is function of the frequency (f), the number of hours in peak (n_h) and off-peak (n_{hOP}) periods, and the percentage decrease in frequency for off-peak periods ($\varphi, 0 < \varphi < 1$). The denominator – dr – represents the maximum daily mileage achievable with energy provided by a full charged battery under the worst operating conditions. Note that the driving range of the e-bus decreases as the energy consumption increases, i.e., $dr = dr(E_{km\_max})$ with $\partial dr / \partial E_{km\_max} < 0$.

2.2.1.3. Cost function of e-bus supply. The formulation we adopt in this paper is consistent with other studies on the total cost of electric buses (Lajunen, 2018; Göhlich et al., 2018). In particular, for each e-bus fleet configuration, the total operating cost can be defined as the sum of five main cost components:

(i) total cost of charging infrastructure (TC_{chg}), including installation, grid connection, permits and civil works;
(ii) total cost of bus fleet purchasing (TC_{veh}), including battery expenses;
(iii) total cost of bus stops installation (TC_{bs});
(iv) total variable costs of bus service provision (TC_{var}), including expenses related to energy consumption, vehicle maintenance and bus drivers;
(v) total cost of annual fixed operating expenses (TC_{foc}), which refers to chargers maintenance, e-demand charge, and operational costs of depots and bus stops.

Therefore, we define the following formulation for the cost supply of e-buses:

$$TC_i = TC_{chg} + TC_{veh} + TC_{bs} + TC_{var} + TC_{foc}$$

$$for \quad i = eODC, eDCM, eOCP \tag{3}$$

In the following lines we provide details on each cost component.[6]

Total cost of charging infrastructures (TC_{chg})

This cost item is driven by the power installed on chargers, i.e., fast-chargers vs slow chargers, and is defined

$$TC_{chg} = nc_y \cdot P_{chg_y} \cdot \left[c_{chg_y} + c_{igc_y} (1 + pcw) \right] \tag{4}$$

where nc_y is number of type y chargers installed, $y = FC, SC$, P_{chg_y} is the power installed on type y chargers *(kW)*, c_{chg_y} is the cost per kW of a type y charger ($€/kW$), c_{igc_y} is the cost of installation and grid connection per kW of a type y charger, and pcw stands for the costs relating to permits and civil works that are based on installation and grid connection expenses. The power installed on type y chargers, $y = FC, SC$ (P_{chg_y}), is calculated with respect to the time available to recharge the battery and the charging efficiency:

[6] Note that for capital expenses (i.e., TC_{chg}, TC_{veh}, and TC_{bs}) we refer to their equivalent annual cost, which is further attributed to the peak period. This is reasonable because the bus fleet and related infrastructures are sized with respect to the demand peak, so the capital cost for off-peak period is zero.

$$P_{chg_y} = \frac{E_{km\_max} \cdot dt}{t_w \cdot \eta_{chg}} \tag{4.1}$$

where E_{km_max} is the maximum unit energy consumption and t_w is the available time to recharge the battery, which is the dwell time at the bus terminal for opportunity charging buses and «no departures time» for depot charging ones. The dwell time at the bus terminal is the reciprocal of the frequency (i.e., $t_w = 60/f$, measured in minutes). «No departures time» is the parking time at the depots, computed as the daily duration minus the daily runtime of each e-bus (i.e., $t_w = 24 - 2TT_b/60 \cdot DD/nb_i$), where nb_i is the number of buses for each configuration i as defined in Section 2.2.1.2. The variable dt is the distance travelled by the bus between one recharge and another. The latter differs for opportunity charging configurations, where it matches up with the route length (i.e., $dt = 2 \cdot L$ and $dt = L$ for eOCD and eOCP, respectively), and depot charging one, where it stands for the whole daily service provision (i.e., $dt = 2 \cdot L \cdot DD$). The parameter η_{chg} is the charging efficiency required for consideration of losses in the recharging event.

Total cost of e-bus fleet purchasing (TC_{veh})

This cost item is driven by the capacity of the battery type, i.e., LTO vs NMC batteries, and is defined as

$$TC_{veh} = nb_i(c_{veh} + EB_{c_z} \cdot c_{bat_z}) \tag{5}$$

where nb_i is the number of buses for each configuration i as defined in Section 2.2.1.2, c_{veh} is the unit cost of bus purchase (excluding the battery), EB_{c_z} is the capacity of the type z battery, $z = LTO, NMC$ (kWh), and c_{bat_z} is the unit cost of type z batteries ($€/kWh$).

The capacity of the type z battery, $z = LTO, NMC$ (EB_{c_z}) is sized with respect to the maximum energy that can be consumed between recharges:

$$EB_{c_z} = \frac{E_{km\_max} \cdot dt}{SOC_w}, \tag{5.1}$$

where SOC_w is the state-of-charge window, which is the difference between the maximal and the minimal SOC value that is allowed.

Total cost of bus stops installation (TC_{bs})

This cost item is not directly affected by the electric configuration of the fleet as it depends on the number of bus stops installed. It is defined as

$$TC_{bs} = ns_i \cdot c_{bs} \tag{6}$$

where ns_i is the number of bus stops installed for each configuration i and c_{bs} is the unit cost of bus stops installation.

Total variable costs of e-bus service provision (TC_{var})

This cost item is driven by the average energy consumption and is defined as

$$TC_{var} = \left(c_{dri} \cdot TT_b + E_{km\_avg} \cdot c_{pwr} \cdot L + c_{mnt} \cdot L\right) \cdot f \cdot n_h \tag{7}$$

where c_{dri} is the drivers costs per-hour ($€/hour$), TTb is the travel time of the bus route ($hour$), E_{km_avg} is the average energy consumption per km (kWh/km), c_{pwr} is the unit cost of power ($€/kWh$), L is the length of the bus route (km), c_{mnt} is the maintenance cost of bus ($€/km$), f is the bus frequency ($bus/hour$) and n_h is the numbers hours in peak period.

Total cost of annual fixed operating expenses (TC_{foc})

This cost item is defined as

$$TC_{foc} = c_{chgop} + c_{edc} + c_{dep} + c_{bsop} \tag{8}$$

where c_{chgop} is the chargers maintenance costs, c_{edc} is the annual energy demand charge,[7] c_{dep} is the cost related to bus depot operations and c_{bsop} is the bus stop operational costs.

2.2.2. Diesel buses

In this section we provide details on the benchmark scenario where bus services are provided by means of diesel fuelled (DF) buses only. Specifically, we determine the required numbers of buses, i.e., the fleet size, and evaluate the cost function of the bus supply.

2.2.2.1. Diesel fleet size. Analogously to opportunity charged e-bus configurations, the required numbers of diesel buses can be computed as the ratio between the travel time of the bus route (TT_b) and the operation interval, which is the invers of the bus frequency, namely

$$nb_i = \left\lceil \frac{TT_b \cdot f}{60} \right\rceil \quad for \quad i = DF. \tag{9}$$

[7] The demand charge is a monthly fee related to the cost of maintaining the electric utility's infrastructure required to deliver electricity to the depot. It is based on the peak power demand (kW) during the period (see also Lajunen (2018) for computation of average value).

2.2.2.2. Cost function of diesel bus supply. The conventional diesel bus fleets do not require the same level of supporting infrastructures as e-bus systems, such as fast/slow chargers and other depot facilities (e.g., power grid substations). This means a simpler cost function for diesel buses, consisting of four main cost components:

(i) total cost of bus fleet purchasing (TC_{veh});
(ii) total cost of bus stops installation (TC_{bs});
(iii) total variable costs of bus service provision (TC_{var}), including expenses related to fuel consumption, vehicle maintenance and bus drivers;
(iv) total cost of annual fixed operating expenses (TC_{foc}), which refers to operational costs of depots and bus stops.

Therefore, we define the cost supply of diesel buses as:

$$TC_i = \overbrace{nb_i \cdot c_{veh}}^{TC_{veh}} + \overbrace{ns_i \cdot c_{bs}}^{TC_{bs}} + \overbrace{\left[c_{dri} \cdot TT_b + df_{km} \cdot c_{df} \cdot L + c_{mnt} \cdot L\right] \cdot f \cdot n_h}^{TC_{var}} + \overbrace{c_{dep} + c_{bsop}}^{TC_{foc}} \quad for \ \ i = DF \tag{10}$$

where df_{km} is the diesel fuel consumption per km (*litre/km*) and c_{df} is the unit fuel cost of diesel (*€/litre*). With the exception of the variable costs of the bus service provision (TC_{var}), the other cost components (i.e., TC_{veh}, TC_{bs}, and TC_{foc}) have the same functional form of e-bus cases, where some specific cost items are excluded (i.e., battery expenses in the TC_{veh}, and chargers maintenance and e-demand charge in the TC_{foc}). We define the bus supply cost for a corridor per day by dividing the total (annualised) operating costs by the amount of work days per year, $TC_i/wdays$, where *wdays* is number of work days per year), $i = eODC, eDCM, eOCP, DF$.[8] Fig. 1 shows the linkage between the cost components and the main elements of the various bus fleet configurations.

2.3. External costs

Road transport generates different externalities, such as congestion, carbon emissions, health damaging emissions and accidents. Following the common standards (European Commission, 2020), we consider both GHGs and air pollution, noise pollution and accidents costs related to different urban travel modes. We define daily external costs for car trips (E_c) and the external costs for bus rides for each fleet scenario i (E_{b_i}) as follows:

$$E_c = \left(e_{AP_c} + e_{GHG_c} + e_{N_c} + e_{A_c}\right) \cdot d \cdot \left(q_c^l + \lambda q_c^s\right) \tag{11}$$

$E_{b_i} = \left(e_{AP_i} + e_{GHG_i} + e_{N_i} + e_{A_i}\right) \cdot L \cdot f \cdot n_h$ for $i = DF, eODC, eOCP, eDCM$where e_{AP} is the marginal external cost per vehicle-kilometre (vkm) related to air pollutant emissions in an urban road, e_{GHG} is the marginal external cost per vkm related to greenhouse gas emissions in an urban road, e_{N_i} is the marginal external cost per vkm related to noise pollution in an urban road, and e_A is the marginal external cost per vkm related to accidents in an urban road.

Cycling mode generates both positive and negative indirect effects for its users, namely health benefits and accident risks. However, since these are not external, we do not add them as external costs and benefits as suggested by Börjesson and Eliasson (2012). Similarly, the higher risk of cyclist accidents increases the value of time, reducing cycling volumes. Therefore, in this paper we assume that health and accident risks are fully internalised by the cyclists. While this assumption may be debatable, we believe that fully internalising bicycle externalities is an acceptable approximation.

2.4. Welfare function

For each bus fleet configuration, the social planner maximises social welfare with respect to eight policy variables: the pricing of the six types of trips (short and long car/bus/bicycle trips), the bus frequency, and the number of bus stops. In the absence of any other distortion in the economy, we formulate the welfare function for the corridor served by the bus fleet configuration i (Ω_i) as the gross user surplus net of the total user costs (except for the car tolls and the bus fares), the total costs of public transport supply, and the total external costs other than congestion linked to car and bus trips per day. It is defined as follows:

$$\Omega_i = \sum\nolimits_{j,k} B^{j,k}\left(\cdots, q_h^{j,k}, \cdots\right) - \sum\nolimits_{j,k,h} q_h^{j,k} uc_h^{j,k} - TC_{b_i} - E_c - E_{b_i}$$

$$where \ \ i = DF, eODC, eOCP, eDCM \tag{12}$$

The marginal willingness to pay equals the user cost (including tolls and fares) in equilibrium. Then, we have:

$$uc_h^{j,k} + \tau_h^j = \frac{dB^{j,k}}{dq_h^{j,k}}, \quad \forall j, k \tag{13}$$

[8] For the sake of simplicity, we keep using $TC_{chg}, TC_{veh}, TC_{bs}, TC_{var}, TC_{foc}$ to denote daily costs, i.e., $TC_{chg}/wdays$, $TC_{veh}/wdays$, $TC_{bs}/wdays$, $TC_{var}/wdays$, $TC_{foc}/wdays$ respectively.

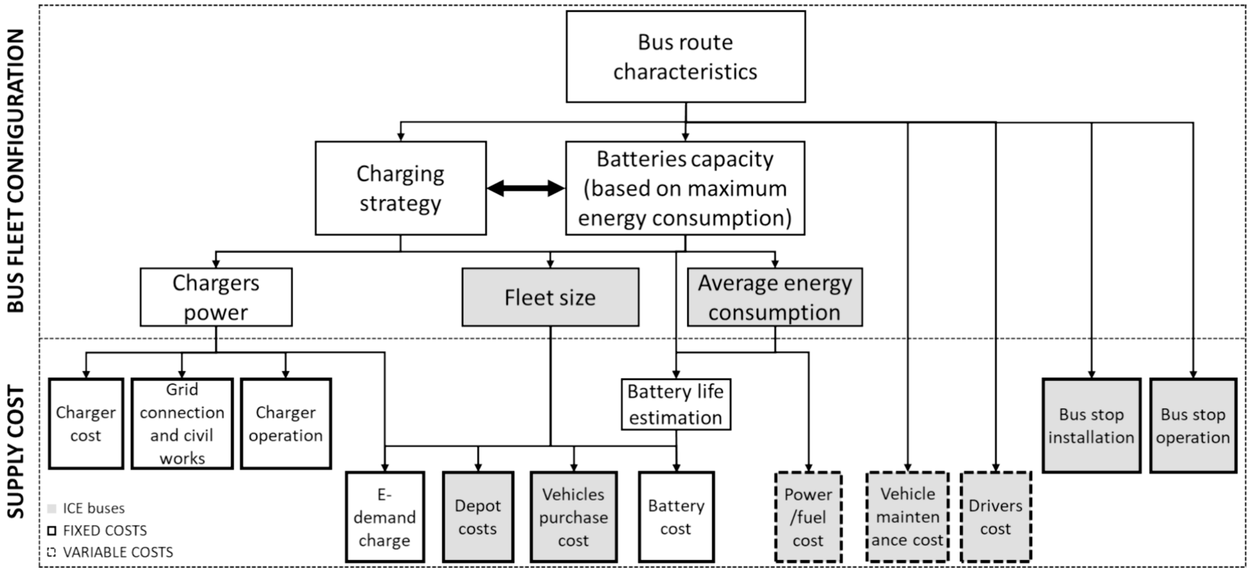

Fig. 1. Diagram of the cost model for public transport supply.

where τ_h^j is the toll/fare for trips of distance j travel mode h.[9]

Note that the sub-utility function $B^{j,k}$ and user costs $uc_h^{j,k}$ are defined in Appendix A.

The pricing of trips of different modes, bus frequencies and the number of bus stops are chosen to assess the maximum welfare with respect to the alternative bus fleet scenarios, given the current allocation of road space over car, bus lanes and cycle lanes. In order to reach the optimal solution by starting from an existing market equilibrium, we need to calibrate the model for a specific case study.

3. Model calibration

We study a corridor within central Stockholm where the busiest and longest high-frequency bus line – no 4, connecting Gullmarsplan and Radiohuset – operates. The route is 12 km long (L), it currently has 31 stops (ns) with a frequency of a bus every 5 min in peak period, and the fleet consists of 18 m articulated buses. During a normal workday, more than 60 thousand passengers are served, and about two-thirds in the 4-hour peak period considered in this paper (7–9 in the morning and 3–5 in the afternoon). This bus line does not really compete with the metro, so the metro is disregarded in our model. Moreover, given the widely proven e-bus cost efficiency in running costs compared to internal combustion counterparts (see, among others, Avenali et al., 2023), it follows that a bus route with a high annual mileage represents a good benchmark for assessing the potential benefits of the bus fleet electrification. Note that, Stockholm has a cordon based congestion charging system since 2006. The charges are not levied in the corridor under study, but we assume that the car trips cross the toll cordon and hence charges are levied.

Based on the present traffic flows and prices, we make forecasts of the traffic flows and prices of 2027, and we used these forecasts to calibrate the model.[10] We make the welfare calculation for the scenario when the transition has been completed. Hence, we disregard that welfare benefits are likely to be lower during the transition to new buses – when all diesel buses have not yet been phased out – than when the full transition has been completed.

The model is calibrated by defining the travellers' preferences according to the market equilibrium condition and the definition of the point elasticity of demand. For each user group we assume that the marginal willingness to pay equals the user costs ($uc_h^{j,k} + \tau_h^j$) and the point own-price elasticity of demand matches the actual value ($\varepsilon_h^{j,k}$). Concurrently, the interaction terms are set such that the resulting cross-price elasticities for the three travel modes (car, bus, and bicycle). Then in order to calibrate the parameters of the sub-utility function (a, b and i) we solve a system of 9 equations in 9 variables for each user group. This baseline case is based on real observations from the inner corridor under study, particularly using four types of data: 1) observed number of travellers by mode, user group and trip distance; 2) monetary costs of trips (including car tolls and bus fares), travel times, and speed-flow functions; 3) values of time; and 4) the price and cross-price elasticities.

[9] Pandey and Lehe (2023) note that when buses experience congestion from the traffic flow by car, a bimodal model with road congestion and responsive frequency can lead to multiple equilibria. However, in our model, this is unlikely to happen since buses have their own lane. Additionally, one of the two equilibria has such a low frequency and ridership that it is very unlikely to lead to higher welfare than the solutions we find.

[10] The bus fleet renewal takes time to complete and the Recovery Plan for Europe – the Next Generation EU – will be completed in 2027 indeed (see https://op.europa.eu/en/publication-detail/-/publication/d3e77637-a963-11eb-9585-01aa75ed71a1/language-en, last retrieved: 15/11/22).

The reader may refer to Appendix B for related estimations. From now on, we will refer to the baseline case as scenario $i = BASELINE$.

4. Results

We optimise welfare with respect to eight policy variables: the pricing of the six types of trips (short and long car/bus/bicycle trips), the bus frequency, and the number of bus stops. The outcome of this optimisation is presented in Table 2 (costs), Table 3 (optimal bus configuration) and Table 4 (effect on the social welfare). We separately optimise welfare for the four bus fleet configurations $i = DF, eODC, eDCM, eOCP$. We use the baseline case ($i = BASELINE$), having diesel buses, current prices, bus frequency, and the number of bus stops as a benchmark. The operational and cost parameters, as well as related data sources, used as input for the analysis are itemised in Appendix B. The reader may refer also to Table C.1 in Appendix C for detailed results of the optimisation.

4.1. Costs

We first focus on the differences in bus supply costs among the bus fleet configurations and next on the external cost components between alternative bus fleet configurations (see Table 2 – in Table 3 we report parameters that are essential to explain cost differentials).

Bus supply costs

The total cost of electric buses, in comparison to diesel buses, is determined by the combination of the higher capital costs (e.g., batteries and charging infrastructure) and the lower variable costs of the electric buses (i.e., energy and maintenance costs).

The bus configuration relying on opportunity charging (i.e., $i = eOCP$) produces a lower total bus supply cost TC_i (−40.1 % compared to the optimised diesel scenario $i = DF$, see Table 2). However, this result is driven by the reduced bus frequency in this scenario, limited to just about 12 buses per hour – see Table 3 – due to the needed charging time at the bus terminals, which is imposed by technological C-rate constraints.[11] For diesel and depot or mixed depot/opportunity charging configurations (i.e., $i = DIE$, *eOCD*, *eDCM*), on the other hand, the optimal frequency keeps almost constant to nearly 22 buses per peak hour in. The total bus supply cost is higher for the e-buses, in spite of the lower variable operating costs TC_{var}, the latter being driven by lower average energy consumption per km – E_{km_avg} – compared to the diesel fuelled bus (see Table 3). Higher costs for the e-buses are induced by:

a) the cost of charging infrastructures TC_{chg} which is entirely incremental for e-buses configurations. This is driven by the power P_{chg_y} installed on type y chargers, $y = FC, SC$;
b) the cost of bus fleet purchasing TC_{veh} (+12.6 % for *eOCD*, and +77.2 % for *eDCM* respectively) which is due to:
    1) expenses for energy capacity of the battery $z = LTO, NMC$ (EB_{c_z}) necessary to complete the bus shift – entirely incremental for e-bus configurations;
    2) higher fleet size nb_i. Note that, an electric bus with depot charging may not be able to complete the daily service provision because of the limited driving range imposed by the battery, and an increase in fleet size nb_i is needed to provide the same bus frequency;
c) the cost of annual fixed operating expenses TC_{foc} (+830.1 % for *eOCD*, and + 503.1 % for *eDCM* respectively compared to the optimised diesel scenario – see Table 2), which is due to chargers' maintenance and e-demand charge costs – entirely incremental for e-bus configurations.

External costs

The electrification of the fleet significantly reduces the external costs of the bus operations, since tailpipe emissions are eliminated, and noise is reduced (by 41.3 %, 39.8 % and 67.7 % in the eOCD, eDCM, eOCP scenarios, respectively, compared to the optimized diesel scenario). However, Table 4 shows that the welfare gain from this reduction is small, because the external costs of the buses are relatively small to begin with. In the baseline, the external cost of cars are 64 times higher, simply because there are so many more cars. According to Table B.1, the number of cars per peak hours is 10,000, which almost 500 times more than the number of buses per hour in the optimized scenario (namely 22 buses per peak hour). Consequently, welfare gains from the reduction of external costs arise mainly when car trips are diverted from car to bus (the external costs of cars decrease from €29,000 in the baseline to €22,000 when the diesel buses are optimised). This result is independent of the bus fleet electrification and relates to the adoption of public transport compared to private cars. Thus, if the goal is to reduce external costs by optimising the bus fleet, it is more effective to attract drivers to switch modes than to deploy cleaner bus services.

[11] The critical factor is the C-rate that is limited to 10C for LTO batteries (Göhlich et al., 2018, see also Section 2.2.1.1). In our case, the upper bound is reached because of the limited dwell time at the bus terminals. Consequently, in the *eOCP* scenario, optimal car tolls and bus fares increase due to the higher external marginal costs related to car lane congestion and crowding in buses. This affects the total number of trips, which is reduced compared to the optimised diesel bus scenario, and hence reduces social welfare compared to other optimised scenarios (see details in Table B.1 in the Appendix B).

Table 2
Cost structure of public transport supply in alternative bus fleet configurations.

Bus fleet configuration	Cost components of public transport supply (€/day)								External costs (€/day)	
	Cost of charging infrastructures	Cost of bus fleet purchasing	Costs of bus stops installation	TOTAL CAPEX (CAPital EXpenditures)	Variable operating costs	Cost of annual fixed operating expenses	TOTAL OPEX (OPerating EXpenditures)	Bus supply cost (TOTAL CAPEX + TOTAL OPEX)	External costs of car trips	External costs of bus trips
	TC_{chg}	TC_{veh}	TC_{bs}	$TC_{chg} + TC_{veh} + TC_{bs}$	TC_{var}	TC_{foc}	$TC_{var} + TC_{foc}$	TC_i	E_c	E_{b_i}
BASELINE	0	3,580	459	**4,039**	4,663	320	**4,983**	**9,022**	**28,574**	**450**
DF	0	6,862	421	**7,283**	8,719	300	**9,018**	**16,302**	**22,319**	**837**
ΔDF/BASELINE	–	91.7 %	−8.1 %	80.3 %	87.0 %	−6.3 %	81.0 %	80.7 %	−21.9 %	86.0 %
eOCD	746	7,729	420	**8,896**	7,222	2,789	**10,011**	**18,907**	**22,327**	**492**
ΔeOCD/BASELINE	–	115.9 %	−8.3 %	120.3 %	54.9 %	771.5 %	100.9 %	109.6 %	−21.9 %	9.2 %
ΔeOCD/DF	–	12.6 %	−0.2 %	22.1 %	−17.2 %	830.1 %	11.0 %	16.0 %	0.0 %	−41.3 %
eDCM	415	12,162	421	**12,998**	7,480	1,808	**9,288**	**22,285**	**22,316**	**504**
ΔeDCM/BASELINE	–	239.7 %	−8.2 %	221.8 %	60.4 %	465.1 %	86.4 %	147.0 %	−21.9 %	12.0 %
ΔeDCM/DF	–	77.2 %	0.0 %	78.5 %	−14.2 %	503.1 %	3.0 %	36.7 %	0.0 %	−39.8 %
eOCP	218	4,272	419	**4,909**	3,962	849	**4,811**	**9,721**	**22,766**	**271**
ΔeOCP/BASELINE	–	19.3 %	−8.6 %	21.6 %	−15.0 %	165.4 %	−3.4 %	7.7 %	−20.3 %	−39.9 %
ΔeOCP/DF	–	−37.7 %	−0.5 %	−32.6 %	−54.6 %	183.2 %	−46.6 %	−40.4 %	2 %	−67.7 %

Table 3
Operational parameters of alternative bus fleet configurations.

Bus fleet configuration				Fleet size (nb_i number of buses)	Frequency (# buses/peak hour)	Total number of trips (Bus trips share)*
		Diesel fuel consumption per km − df_{km} (liter/km)				
DF	0	0.49		46	22.32	107,086 (51.9 %)
	Energy capacity of the battery $z = LTO, NMC$ (EB_{c_z}, kWh)	Average energy consumption per km (E_{km_avg}, kWh/km)	Power installed on type y chargers, $y = FC, SC$ (P_{chg_y}, kW)			
eOCD	112,559	1.73	1,022 (FC), 86 (SC)	46	22.05	106,951 (51.8 %)
eDCM	700,000	1.98	49	60	22.62	107,131 (51.9 %)
eOCP	54,745	1.83	547	25	12.14	99,585 (46.7 %)

* In the diesel baseline scenario the total number of trips is 107,188 (Bus trips share 42 %).

4.2. Social welfare

In this section, we focus on welfare analysis by considering diesel and depot or mixed depot/opportunity charging configurations, since opportunity charging has revealed not suitable for high-frequency bus lines (see details in Table C.1 in the Appendix C). Table 4 shows the resulting total welfare, including the consumer surplus (gross user utility minus user cost), the producer surplus (bus fares revenues minus supply costs), and toll revenues (car/bicycle tolls minus external costs other than congestion).

In these three optimised scenarios (i.e., $i = DF$, $eOCD$, $eDCM$), the welfare gains ranges between 6 % and 7 % compared to the baseline (which means more than 30 thousand euro per day). The main changes relative to the baseline are the higher bus frequency, from 12 to 22 buses per peak hour, and the differentiated road tolls and bus fares with respect to trip distance and travel mode.[12]

Regarding the main marginal effect of bus fleet electrification:

a) consumer surplus does not change significantly, while e-buses are detrimental to producer surplus.[13] Under optimisation, the bus fleet electrification increases bus supply costs, thus the producer surplus/bus supply costs ratio significantly worsens (−16.4 % in $i = eOCD$ and −34.9 % in $i = eDCM$ compared to $i = DF$);
b) external costs of carbon and health damaging emissions are reduced, but it represents a very small component of the welfare.

Hence, we can conclude that while there is no significant welfare gain from electrifying the buses, there is neither any large welfare loss nor a loss for consumers. More transit subsidies are however needed. It is worth noting that neither the depot nor the mixed depot/opportunity charging configurations offer a dominant solution.

We further consider specific combinations of policy variables, exploring different second-best equilibria in Appendix C: 1) the pricing of the bus trips only, the bus frequency, and the number of bus stops are optimised in the "*Bus fares* + *frequency* + *stops*" scenario; (2) the bus frequency and the number of bus stops are optimised in the "*Frequency* + *stops*" scenario; (3) bus frequency is optimised in the "*Frequency*" scenario; (4) bus stops are optimised in the "*Stops*" scenario. The analysis shows that bus fleet electrification reduces bus producer surplus in all policy scenarios, which explains the reluctance of bus operators to e-bus adoption without the opportunity to access peculiar public funding (see also qualitative studies, e.g., Mohamed et al., 2018; Aldenius et al., 2022; Blynn and Attanucci, 2019). Therefore, in non-profitable routes, cost recovery policies by the social planner are needed to compensate deficit to eliminate market failures, then electric buses need an increase in public subsidies.

[12] Explaining the effects of optimal pricing with respect to trip distance and travel mode, including cycling, is beyond the scope of this paper, which focuses on welfare effects of e-buses introduction. Börjesson et al. (2017, 2018) extensively discuss optimal prices and distributional impact by also considering peak and off-peak periods. See details of optimisation in Table C.1 in the Appendix.

[13] Note that in the corridor under study bus operators obtain a surplus and not a loss. Although transit subsidies are widespread across the world in order to compensate produces losses, bus operators can generate a surplus from some specific routes. The main justifications for public incentives to bus services are: positive externalities (the so-called Mohring effect), second-best pricing of road externalities (i.e., under-priced competing modes), and equity reasons (buses are usually used by poorer people). When the Mohring effect is limited because bus demand is already high and the marginal cost of more buses is high due to the congestion on the bus lanes (passengers crowding, extra boarding and alighting, and interaction with other modes), the optimal fares increase, and the bus frequency improvements are limited. Consequently, the bus operators can obtain a surplus from transit services on that route, and this is the case of bus No 4 in Stockholm (case study).

Table 4
Impact of policy variables optimisation on welfare components (/day) – The pricing of the six types of trips, the bus frequency, and the number of bus stops are optimised in scenarios DF, eOCD, eDCM, eDCM (see also Table C.1 for more details).

Results in €/day Scenario *i*	Gross user utility (a)	Total user cost (b)	Bus fares revenues (c)	Bus supply costs (d)	Tolls (car + bicycle) (e)	External costs of car trips (f)	External costs of bus trips (g)	Consumer surplus (=a − b)	Producer surplus (=c − d)	Producer surplus/ Bus supply costs (={c-d}/ d)	Toll revenues (=e − f − g)	Welfare €/day
BASELINE	1,581,468	1,162,425	90,078	9,022	87,103	28,574	450	**419,042**	**81,056**	8.98	**58,079**	**558,178**
DF	1,526,312	1,112,038	72,812	16,302	149,332	22,319	837	414,274	56,510	3.47	**126,176**	**596,960**
ΔDF/BASELINE	−3.5 %	−4.3 %	−19.2 %	80.7 %	71.4 %	−21.9 %	86.0 %	−1.1 %	−30.3 %	−61.4 %	117.2 %	6.9 %
eOCD	1,525,180	1,111,973	73,673	18,907	149,412	22,327	492	**413,207**	54,766	2.90	**126,594**	**594,567**
ΔeOCD/BASELINE	−3.6 %	−4.3 %	−18.2 %	109.6 %	71.5 %	−21.9 %	9.2 %	−1.4 %	−32.4 %	−67.8 %	118.0 %	6.5 %
ΔeOCD/DF	−0.1 %	0.0 %	1.2 %	16.0 %	0.1 %	0.0 %	−41.3 %	−0.3 %	−3.1 %	−16.4 %	0.3 %	−0.4 %
eDCM	1,526,653	1,112,012	72,583	22,285	149,311	22,316	504	**414,641**	**50,298**	2.26	**126,491**	**591,430**
ΔeDCM/BASELINE	−3.5 %	−4.3 %	−19.4 %	147.0 %	71.4 %	−21.9 %	12.0 %	−1.1 %	−37.9 %	−74.9 %	117.8 %	6.0 %
ΔeDCM/DF	0.0 %	0.0 %	−0.3 %	36.7 %	0.0 %	0.0 %	−39.8 %	0.1 %	−11.0 %	−34.9 %	0.2 %	−0.9 %

Lastly, we conduct sensitivity analyses on other parameters of the model, e.g., additional time caused by the interaction at the bus stops (γ_c, γ_v, γ_b), boarding and alighting time per passenger (ζ), bus lane congestion (β_b), free-flow bus travel time (α_b), value of time (VOT_h^k), and social cost of carbon (e_{AP}, e_{GHG}).[14] For the sake of space and readability, we do not present these simulations, however they do not significantly impact the results of the study and thereby we can consider the highlights of the main analysis robust. Notably, even when cross-price elasticities of cycling with other modes are set to zero (i.e., $\varepsilon_{c,v}^{j,k} = \varepsilon_{b,v}^{j,k} = 0$), the core findings regarding the welfare implications of alternative bus fleet configurations remain unchanged. It follows, therefore, that the results concerning the introduction of e-buses transcend localised factors associated with cycling substitution, thereby enhancing their applicability to corridors where cycling usage is less prevalent. We do however present the sensitivity analyses related to the costs associated with e-buses, presented in Section 5.

5. Sensitivity analysis

The technical development of electric vehicles including batteries are progressing fast. But challenges could hamper and slow down the electrification of the road transport sector, for instance the provision of charging infrastructure and the need to accommodate the energy demand of electric vehicles, as well as the supply of raw materials for batteries. There is also a coordination problem in this large-scale transition. Still, the European Green Deal states that achieving climate neutrality by 2050 requires increasing the share of electric vehicles in transportation sector (EEA, 2022). This ambition may reduce some of the coordination problems, as well as speeding up the technological development. Emerging innovative solutions could help to deal with these bottlenecks (EEA, 2022, p.6). We therefore perform a sensitivity analysis to identify the main changes in e-bus fleet supply (i.e., charging infrastructures and electric batteries costs) that can drive an improvement in urban welfare.

Firstly, we assume the following reductions in capital costs until 2050:

(i) a 2 % annual decrease of the charger purchase costs (c_{chg}) for both fast-chargers and slow-chargers, consistently with ICCT (2019) expectations up to 2050; and
(ii) an annual decrease of the cost of electric batteries (c_{bat}) for both cell types (LTO and NMC) according to the downward-sloping curve estimated by Mauler et al. (2021). This latter forecasts a battery cost (per kWh) reduction of about 14 %, 49 %, and 69 % respectively in 2030, 2040, and 2050 compared to the baseline (2027).[15]

However, this simulation leads to a similar result of the main analysis: the introduction of e-bus fleets produces a slightly lower welfare gain compared to the optimized diesel case even in the 2050 scenario. This is because public transport supply costs (see column (d) in Table 4) are relatively small compared to other cost components, i.e., total user costs and external costs of car trips (see columns

[14] The valuation of carbon emissions is the subject of ongoing debate in economics. For example, Cai and Lontzek (2019) argue that the social cost of carbon is a stochastic process with significant variation, and government estimates usually underestimate the risks associated with climate change (Ackerman and Stanton, 2012). Note that in our analysis, the e-bus fleet configurations exceed the welfare gain of optimised diesel (DF) only by assuming an impressive 800% increase in the social cost of carbon (which means, for example, going from €100, assumed by the European Commission (2020), to €800 per ton of CO2).

[15] Note that depot charging configuration (eDCM) is more sensitive to capital cost changes compared to opportunity charging ones (eOCP), since buses are equipped with larger batteries (see also column 2 in Table 2-Cost of bus fleet purchasing).

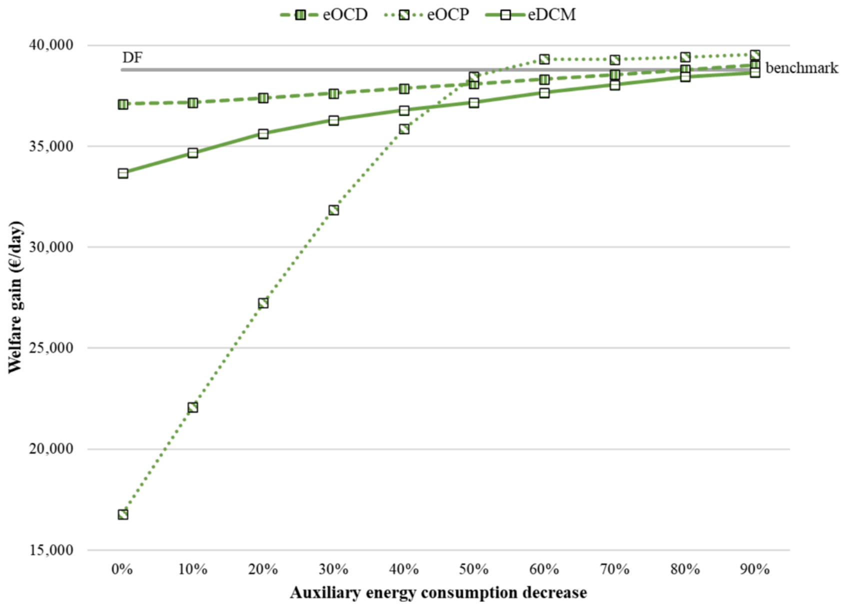

Fig. 2. Sensitivity analysis on welfare gain, relative to the diesel baseline, with respect to reduced auxiliary energy consumption.

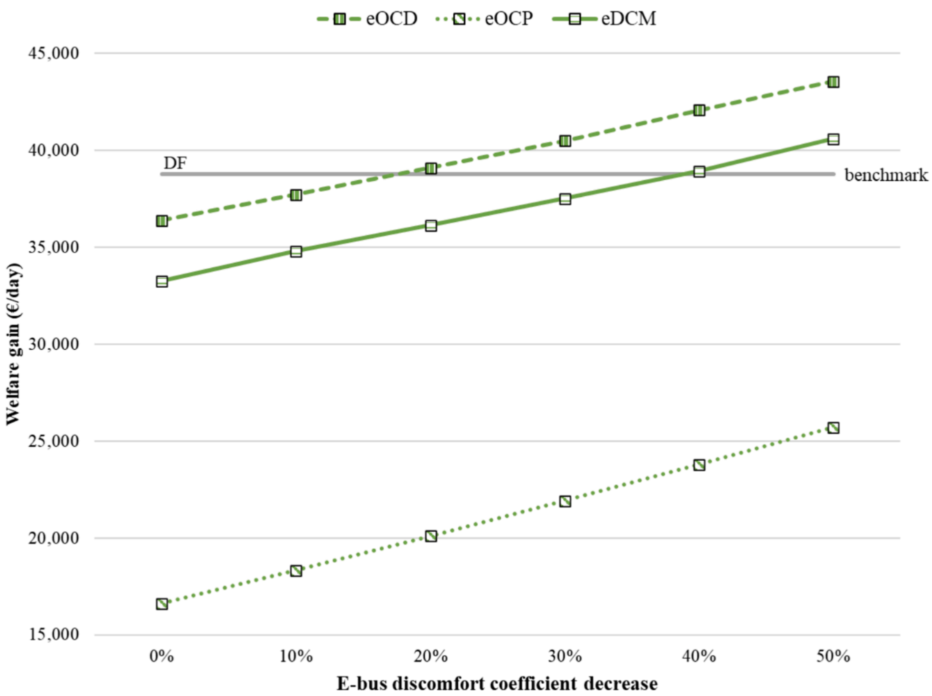

Fig. 3. Sensitivity analysis on welfare gain, relative to the diesel baseline, with respect to improved e-bus comfort.

(b) and (f) in Table 4).

Furthermore, in Fig. 2, we consider a more efficient operations management of the electric bus fleet, which translates into two likely effects:

(i) an annual percentage decrease of the auxiliary energy consumption ($E_{km} - E_{lw}$) for e-bus services; and
(ii) a percentage decrease in the e-demand charge (c_{edc}) linked to an optimised charging schedule (nearly 30 % yearly according to He et al., 2019; Qin et al., 2016).

Fig. 2 shows that the efficiency gains from improving auxiliary energy consumption can have a greater impact on social cost performance of e-bus fleet configurations compare to simply cutting related capital costs. Reduced auxiliary energy consumption is obtained by optimising the HVAC systems, but also bus routing and driving style. This reflects into optimised power installed on chargers and battery capacity available to enhance an extended driving range of e-buses (and hence reducing costs linked to charging infrastructures and reserve bus fleet).[16]

In Fig. 3, we consider a percentage decrease in discomfort coefficient for e-bus trips (dc_b). This is mainly due to the vibration and noise reduction linked to the electric engine (Xylia and Silveira, 2017; Campello-Vicente et al., 2017), other than better technological equipment on average. The improvements in e-bus comfort enhance the consumer surplus by reducing the user costs of bus passengers, thus increasing the welfare gain of e-bus fleet configurations.

Finally, we perform a sensitivity analysis to identify some changes in e-bus fleet demand that can drive an improvement in urban welfare, increasing the attractiveness of the e-bus services by leveraging on users' eco-friendly attitude and better passenger comfort. We consider a percentage decrease in e-bus own-price elasticity and a percentage increase of cross-price elasticities towards e-buses (see Table B.4 for estimated baseline values), which model a potentially higher demand and willingness to pay of users for low carbon buses. Although, public transport users' treasure more the reliability and capillarity of the service (Cantwell et al., 2009), some recent studies assert that the mode travel choice is affected by the environmental factor and that some people are even willing to pay higher fares to switch to e-bus (Lin and Tan, 2017; Flaris et al., 2023; Sunitiyoso et al., 2022; Tan and Lin, 2019). The identification of such as a causal relationship, however, is difficult because findings are not based on observed behaviour but attitudes and statements. Small changes in price elasticities for e-buses allow electrified scenarios to overcome the optimised diesel scenario in terms of welfare gain. This outcome is due to: (i) the increase in consumer surplus, due to a higher marginal utility when travelling by e-buses (consumers contribute to emissions abatement, which is reflected in that own/cross-price elasticity increase); (ii) the increase in bus fares (due to the higher willingness to pay for electrified public transport) and hence in the producer surplus.

6. Conclusion and policy recommendations

This paper develops a stylised model that allows assessing the welfare effects of introducing electric buses in urban areas. The model considers different bus fleet configurations (i.e., one diesel case and three full electric options) under the optimisation of eight policy variables: the pricing of six types of trips (short and long car/bus/bicycle trips), the bus frequency, and the number of bus stops. We do this for the busiest and longest high-frequency bus line – no 4 – in Stockholm. The following policy results emerge for the corridor under study.

1. *Introducing electric buses is not welfare improving for an inner city corridor such that under study*. The main reason is that higher e-bus supply costs are not offset by the gain obtained in terms of reduced external costs.
2. *E-buses significantly reduce carbon and health damaging emissions of transit services.* However, in magnitude, the monetary value of such damage represents a small component of the welfare. The social benefit of reducing the modal share of car trips is much higher than that of simply cutting marginal external damage of bus services. Therefore, other policy instruments such as optimising bus fares and frequencies and road pricing can be more effective in improving both urban welfare and pollution.
3. *E-buses do not introduce significant changes in consumer surplus but significantly worsen producer surplus*. The effect is detrimental to bus operators, which are reluctant to adopt these technologies without direct public support. When producer surplus is negative, cost recovery policies by the social planner are needed to compensate deficit to eliminate market failures. In other words, in non-profitable bus routes, transit service electrification needs an increase in public subsidies. The worsening of the producer surplus with the electrification of the fleet is due to the higher total cost of electric buses compared to diesel buses is the outcome of the higher capital costs (e.g., cost of charging infrastructure), which does not offset the lower variable costs of the electric buses (i.e., energy and maintenance costs). There are some differences between different e-bus fleet configurations. Opportunity charging strategies – where batteries are repeatedly charged during the day, usually during dwell times at terminal stations – limit supply costs growth since they do not involve an increase in bus fleet size; however, relying only such strategies limit the ability to increase the bus frequency and this negatively affects welfare optimisation. Hence, mixed depot/opportunity charging strategies may be suitable for busy and long high-frequency bus lines – such as the one under study.
4. Sensitivity analysis shows that: (i) *technological developments to drastically reduce capital costs (the cost of charging infrastructure and electric batteries) can make e-buses perform well from a social welfare perspective*; (ii) *efficiency gains from improved auxiliary energy consumption can have a greater impact on the social cost performance of e-bus fleet configurations than simply reducing capital costs*

These results highlight the importance of developing technology boost policies for transit electrification in the form of in-kind contributions (e.g., supporting R&D, providing real operational data and simplified guidelines, sharing lessons learned and best practices), which can improve the management of e-bus operations and energy consumption.

An argument for e-buses is that they can facilitate the electrification of private vehicles, which is hindered by the chicken-and-egg problem in transitioning from fuel vehicles to electric vehicles. This problem arises from the interdependence of factors such as expanding charging infrastructure, advancing electric vehicle technology, and investing in production facilities for electric vehicles

[16] The impact is particularly evident in eOCP configuration, where bus frequency is limited by technological C-rate constraints and optimised auxiliary energy consumption makes battery capacity available to enhancing driving range of e-buses.

and batteries, with each development relying on the others. These transitions are complex, time-consuming, and involve various stakeholders. Electrification of city buses can then be seen as helping to coordinate these processes and thus reduce the risk of futile investments. Moreover, e-buses represent a test case to drive clean technology adoption, and the high visibility of e-buses may contribute to raising public awareness of the importance of climate neutrality. In the short term, e-buses could be conceived a valuable aid in facilitating modal shift to public transport, which supports the importance of demand stimulation policies for transit electrification that make non-car modes attractive by exploiting the benefits of e-buses for users. In fact, a growing number of studies show that electrification of public transportation increases commuter demand, that the choice of mode of travel is influenced by the environmental factor, and that some people are even willing to pay higher fares to switch to e-buses, although such studies are not based on observed behaviour but attitudes and statements.

The generalizability of our research findings is influenced by various factors. Firstly, urban passenger transport electrification extends beyond buses, encompassing cars, bikes, and even emerging micro-mobility forms such as e-scooters. Including these aspects would contribute to a more comprehensive assessment of policies aimed at decarbonising mobility. This natural progression should be explored in future research.

Additionally, as in most empirical studies, our results apply to the specific local context under study, such as user preferences and baseline demand. However, while optimal fares and frequencies are always sensitive to such as crowding, congestion, own- and cross elasticities, the results in terms of optimal electrifications should be more robust across corridors. Electric buses should deliver more benefits in terms of less pollution and lower fuel costs relative to the higher capital cost of vehicles and charging infrastructure, the longer distance each bus covers per year. Since the optimal number of buses and yearly distance per bus is endogenously determined the annual distance per vehicle should not vary significantly between contexts. Hence, our results regarding electrification should be fairly transferable to other corridors. However when the transport demand significantly decrease on the corridor is expected an improvement in welfare-effectiveness of e-buses with an opportunity charging configuration linked to the lower optimal bus frequency.

Finally, the bus supply costs may be influenced by technological and macroeconomic uncertainties (such as fuel/energy price fluctuations and electric battery price and weight). To address these uncertainties – and the consequent need to understand what the optimal timing for the introduction of electrification of bus fleets is – there are suitable methods that can be employed in cost assessments that rely on probabilistic approaches (e.g., Monte Carlo simulation and real options). These methods offer valuable insights for future research on cost-benefit analysis of low-carbon solutions for transport sector.

CRediT authorship contribution statement

Mirko Giagnorio: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Maria Börjesson:** Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Tiziana D'Alfonso:** Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Mirko Giagnorio reports financial support was provided by Sapienza University of Rome. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

We are very grateful to the Editor and three anonymous referees for their perceptive and helpful comments on earlier version(s) of the paper. We also thank participants to the 2023 International Transport Economic Association (ITEA) Annual Conference. This research has been partly undertaken at the VTI - The Swedish National Road and Transport Research Institute, which is thankfully acknowledged. Financial support from Sapienza University of Rome (Grants No. 843_009_20_AAT and Researchers Mobility Funding Program 2022) is also gratefully acknowledged.

Appendix A. Preferences and user cost of trips

Preferences of travellers are represented by a quasi-linear utility function U. It consists of the utility derived from other goods (money m) and the sub-utility function for transport trips. The utility that an individual in user group k obtains from making trips by distance $j = \{s, l\}$ by means of mode $h = \{c, b, v\}$, is given by

$$U^k\left(m^k, q_c^{s,k}, q_b^{s,k}, q_v^{s,k}, q_c^{l,k}, q_b^{l,k}, q_v^{l,k}\right) = m^k + B^{s,k}\left(q_c^{s,k}, q_b^{s,k}, q_v^{s,k}\right) + B^{l,k}\left(q_c^{l,k}, q_b^{l,k}, q_v^{l,k}\right) \tag{A.1}$$

The sub-utility function $B^{j,k}$ is a quadratic function representing the gross consumer surplus from all trips. We assume that the demand for short trips is independent from the demand for long trips. Therefore, we have

$$B^{j,k}\left(q_c^{j,k}, q_b^{j,k}, q_v^{j,k}\right) = a_c^{j,k} q_c^{j,k} + a_b^{j,k} q_b^{j,k} + a_v^{j,k} q_v^{j,k}$$

$$-0.5 b_c^{j,k} (q_c^{j,k})^2 - 0.5 b_b^{j,k} (q_b^{j,k})^2 - 0.5 b_v^{j,k} (q_v^{j,k})^2$$

$$-i_{cb}^{j,k} q_c^{j,k} q_b^{j,k} - i_{cv}^{j,k} q_c^{j,k} q_v^{j,k} - i_{bv}^{j,k} q_b^{j,k} q_v^{j,k}, \tag{A.2}$$

where $q_h^{j,k}$ is the daily number of trips of distance j by the travel mode h demanded by the users in the group k. The sub-utility parameters are analogously represented by $a_h^{j,k}$ and $b_h^{j,k}$. The relationships between modes are represented by the interaction parameter i. For instance, $i_{cb}^{j,k}$ refers to the substitution effect between car and bus trips (in this study different modes are substitutes, i.e., $i > 0$).

The quasi-linear function removes the income effect. In this context, it is justified for two reasons. Firstly, the model is calibrated for different income groups, and so the impact of income on preferences is still present. Secondly, transport is only a limited share of household expenditures. The sub-utility parameters of this formulation can be calibrated using a minimum of data (observed generalised prices, number of trips, and price elasticities). The inverse demand function by user group, trip distance and transport mode become linear,

$$\frac{\partial B^{j,k}}{\partial q_c^{j,k}} = a_c^{j,k} - b_c^{j,k} q_c^{j,k} - i_{cb}^{j,k} q_b^{j,k} - i_{cv}^{j,k} q_v^{j,k}$$

$$\frac{\partial B^{j,k}}{\partial q_b^{j,k}} = a_b^{j,k} - b_b^{j,k} q_b^{j,k} - i_{cb}^{j,k} q_c^{j,k} - i_{bv}^{j,k} q_v^{j,k}$$

$$\frac{\partial B^{j,k}}{\partial q_v^{j,k}} = a_v^{j,k} - b_v^{j,k} q_v^{j,k} - i_{cv}^{j,k} q_c^{j,k} - i_{bv}^{j,k} q_b^{j,k}$$

$$\text{for} \quad j = s, l \quad k = low, mid, high, nb. \tag{A.3}$$

The users' marginal cost of a trip is the sum of the monetary costs and time costs. The user costs vary depending on the modes of transport, considering congestion generated by the interaction with users using both the same travel mode and other modes at the bus stop.

Here we present the user cost by excluding tolls and fares. Starting with the user cost of car drivers, it is defined as

$$uc_c^{s,k} = \lambda(c_c d + VOT_c^k TT_c)$$

$$uc_c^{l,k} = c_c d + VOT_c^k TT_c$$

$$\text{where } TT_c = \alpha_c + \beta_c \frac{q_c^l + \lambda q_c^s}{n_h cap_c} \frac{d}{L} + \gamma_c ns P_b P_v, \tag{A.4}$$

where d is the distance travelled for long trips, λ is the relative distance of short trips to long trips, c_c is the fixed monetary cost for a car trip which is proportional to the trip distance d (for long trips), and VOT_c^k stands for the value of driving time (it depends on the user group).

The trip travel time by car (TT_c) is the sum of three components. First, the free-flow driving time (α_c). Second, the delay time depending on the number of drivers ($q_c^l + \lambda q_c^s$) divided by the number of hours in the peak (n_h), the congestion parameter (β_c) lane capacity (cap_c). Third, the delay time due to the interactions with other modes at the bus stop, where γ_c is the interaction parameter (in terms of time delay), ns is the number of bus stops in the corridor, P_b is the probability that there is a bus at the bus stop, and P_v is the probability that a cyclist is passing the bus stop.

The user cost for cyclists follows the same logic as the car drivers' one

$$uc_v^{s,k} = \lambda(c_v d + VOT_v^k TT_v)$$

$$uc_v^{l,k} = c_v d + VOT_v^k TT_v$$

$$\text{where } TT_v = \alpha_v + \beta_v \frac{q_v^l + \lambda q_v^s}{n_h cap_v} \frac{L}{d} + \gamma_v ns P_b P_c, \tag{A.5}$$

where c_v is the fixed monetary cost for a cycling trip, VOT_v^k the value of cycling time (which is group specific), and TT_v is the trip travel time by bicycle. In this case, the delay caused by the interaction with other modes at the bus stop is greater than zero if a bus is boarding and alighting passengers and there is a car in the lane where the cyclist diverts.

The user cost changes for bus passengers are defined as

$uc_b^{s,k} = VOT_b^{ac,k}\frac{L}{2nsv_w} + VOT_b^{w,k}\frac{60}{2f} + \lambda(VOT_b^{inv,k}TT_bDisCom)$ and

$$uc_b^{l,k} = VOT_b^{ac,k}\frac{L}{2nsv_w} + VOT_b^{w,k}\frac{60}{2f} + VOT_b^{inv,k}TT_bDisCom$$

where

$$TT_b = \alpha_b + \beta_b\frac{\sigma(V_b)f}{cap_b} + \gamma_b nsP_v + TS_b, TS_b = ns\left(t_s + \zeta\frac{q_b^l + q_b^s}{fnsn_h}\right)$$

$$\text{and } DisCom = dc_b^{n_{on}/V_b}, \text{ where } n_{on} = r_{on}\left(\frac{q_b^l + \lambda q_b^s}{fn_h}\frac{d}{L}\right). \tag{A.6}$$

Note that the value of time varies across travel time components: access to the bus stop ($VOT_b^{ac,k}$), waiting time at the bus stop ($VOT_b^{w,k}$), and in-vehicle time ($VOT_b^{inv,k}$).

The cost of access time depends on the walking distance, calculated as the ratio between the length of the bus route (L) and the number of bus stops (ns) multiplied by 2 (assuming a uniform distribution of passengers along the corridor), and the walking speed (v_w). The waiting time at the bus stop (in minutes) is equal to the inverse of the bus frequency (f is the number of buses per hour) divided by 2, meaning that bus passengers arrive randomly and do not plan their trip according to the timetable (i.e., a reasonable assumption for high frequency routes). The in-vehicle bus time is the sum of free-flow bus travel time (α_b), the additional travel time arising from congestion in the bus lane, and the delay related to interaction with bicycles at the bus stop. This interaction depends on the bus frequency (f), the equivalent size of a bus ($\sigma(V_b)$), which is a function of the number of seats (V_b), and the presence of other bus routes that share part of the path (it reduces the capacity of the bus lane cap_b). The time spent at the bus stop is the sum of a fixed time cost (t_s) for each stop, which refers to the slowdowns for entering and leaving the stop, and a variable cost depending on the number of passengers boarding and alighting at each stop (parameter ζ is the time need for a passenger to board and alight). In addition, the cost of in-vehicle time for buses is increased by a discomfort factor (*DisCom*), which depends on the number of passengers on-board (n_{on}). This factor is equal to the discomfort coefficient (dc_b) when the number of on-board passengers n_{on} reaches the bus capacity (V_b). Here n_{on} is calculated by multiplying the average number of passenger trips per bus by the on-board ratio ($r_{on} < 1$ since not all bus passengers travel the route throughout).

Empirical evidence shows that bus users do not have a distinct preference for transit services provided through electric vehicles (Cantwell et al., 2009; Mohamed et al., 2018). Therefore, we do not introduce explicit changes on user costs depending on the type of bus, but we explore their potential effects in the sensitivity analysis in Section 6 (e.g., an increase in cross-price elasticities towards e-bus solutions or a decrease in discomfort for e-bus users). The user cost of bus passengers is however influenced by the fleet power type due to the effect that this latter has on the bus frequency (i.e., the higher is the cost of the extra bus supply, the lower is the service frequency provided by transport operators).

Finally, the probability that a bus/car/bicycle is at the bus stop is given by the product between the time spent at the bus stops (TS_b, TS_c, TS_v for cars, bicycles, and buses, respectively) and the total number of trips during the peak period. It is defined as

$$P_c = TS_c\left(\frac{q_c^l + \lambda q_c^s}{60n_h}\frac{d}{L}\right), P_v = TS_v\left(\frac{q_v^l + \lambda q_v^s}{60n_h}\frac{d}{L}\right), P_b = \frac{TS_bf}{60}. \tag{A.7}$$

The effects of these externalities, together with the interaction of the three modes at the bus stop, have been discussed extensively elsewhere (the reader may refer to Börjesson et al., 2018 – Table 1).

Appendix B. Input parameters to the welfare function

The model is calibrated for route no 4 in Stockholm, which connects Gullmarsplan and Radiohuset; Fig. B.1 exemplifies the e-bus fleet configurations within the inner city corridor.

Fig. B1. Assumed bus fleet configuration for bus no. 4 in Stockholm.

The observed trip quantities are gathered from car traffic count, bus automatic passengers count (APC), bicycle count data, and travel surveys. We use the travel survey to split the total demand for each mode into user groups and trip distances. It is worth noting that traffic counts data provided by the city of Stockholm and those from the travel survey match well. We estimate the traffic volume in 2027 by adjusting the current demand according to the population growth forecast for the city of Stockholm. Table B.1 shows the number of trips in both directions in the peak period for the inner corridor, where modal shares are in brackets.

Table B.1
Traffic volumes by user group, travel mode and trip distance in the 4 h peak period for the corridor.

Trip distance	*User group*	Car	Bike	Bus
Short	*low-income*	1,209	1,520	2,064
	($k = l$)	(25.2 %)	(31.7 %)	(43.1 %)
	mid-income	2,560	2,716	2,527
	($k = m$)	(32.8 %)	(34.8 %)	(32.4 %)
	high-income	2,664	1,728	1,538
	($k = h$)	(44.9 %)	(29.1 %)	(25.9 %)
Long	*low-income*	3,275	1,196	6,438
	($k = low$)	(30.0 %)	(11.0 %)	(59.0 %)
	mid-income	9,668	2,417	9,611
	($k = mid$)	(44.6 %)	(11.1 %)	(44.3 %)
	high-income	7,173	1,988	5,094
	($k = high$)	(50.3 %)	(13.9 %)	(35.7 %)
	low-income	15,489	0	11,572
	($k = nb$)	(57.2 %)		(42.8 %)
	Total	42,037	11,565	38,845
		(45.5 %)	(12.5 %)	(42.0 %)

The pecuniary trip costs (i.e., tolls, fares, and operation costs of cars and bicycles) and input parameters of travel time functions are reported in Table B.2. The speed-flow relationships and travel time increases linked to traffic congestion and bus stop delays are calculated by using the same logic adopted in Börjesson et al. (2017, 2018). We specify values assumed for the equivalent size of a bus $\sigma(V_b)$ and the number of seats, 5 and 120, respectively. The on-board ratio (n_{on}) is 0.17 for the bus route under study, and the discomfort coefficient for bus trip (dc_b) is 1.1 when the bus is full load.

The in-vehicle value of time is calculated from the Swedish national travel survey applying the income elasticity of 0.7 (Börjesson & Eliasson, 2014). The cross-price elasticities related to the demand of cycling trips, with respect to travel costs of bus and car, and own elasticities for bicycle are based on estimates carried out by the national transport model (Börjesson & Eliasson, 2014). The own-price elasticity for public transport (−0.4) is confirmed by many studies (e.g., Litman, 2004).

The congestion charging trialhas been used to assign values to cross-price elasticities between bus and car trips, and own-elasticities for car. All values used as input to the model are summarised in Tables B.3 and B.4.

Table B.2
Pecuniary trip costs and travel time parameters.

Parameter	Notation	Value
Monetary cost of car (long) trip	c_cL	2.1
Monetary cost of bicycle (long) trip	c_vL	0.01
Car toll (€ per trip)[a]	τ_c	1.8
Bicycle toll (€ per trip)	τ_v	–
Bus fare (€ per trip)[b]	τ_b	2
Number of car lanes	cap_c	1.5
Number of cycle lanes	cap_v	1
Number of bus lanes	cap_b	0.18
Free-flow driving time in min/(long) trip	α_c	28
Free-flow cycling time in min/(long) trip	α_v	60
Free-flow bus travel time in min/(long) trip	α_b	35
Delay linked to the congestion caused by one more car (sec per car)	β_c	0.36
Delay linked to the congestion by one more bicycle (sec bicycle)	β_v	0.06
Delay linked to the congestion caused by one more bus (sec per bus)	β_b	1.2
Additional time caused by the interaction at the bus stops between car, bicycle, and bus (sec)	$\gamma_c, \gamma_v, \gamma_b$	1.2
Minimum stop time at a bus stop (sec)	t_s	10
Boarding and alighting time per passenger (sec/passenger)	ζ	1.8
Time spent at the bus stops by a car/bicycle (sec)	TS_c, TS_v	2
Walking speed	v_w	1.8
Long trip distance (km)	d	12
Relative distance of short trips to long trips	λ	0.25

[a] We consider the average car toll for peak period in 2014 because is when the national travel survey was conducted. In 2016 the toll was increased to €3.5 per trip.

[b] The average fare is adjusted by taking into account that most of the passengers use monthly tickets and that users can use different bus routes with a single ticket (which is valid 90 min). This is why the bus fare is set to 2 €/trip rather than 3.75 €/trip (namely, the current price of a single ticket).

Table B.3
Values of time by travel mode and income group (€/hour).

	Notation	Income group		
		Low-income	Mid-income	High-income
Value of in-vehicle time, car driver	VOT_c^k	7.53	12.24	16.52
Value of in-vehicle, cyclist	VOT_v^k	6.46	10.50	14.18
Value of access time, bus passenger	$VOT_b^{ac,k}$	6.27	10.20	13.77
Value of waiting time, bus passenger	$VOT_b^{w,k}$	7.50	12.20	16.47
Value of in-vehicle time, bus passenger	$VOT_b^{inv,k}$	4.43	7.20	9.72

Table B.4
Own-price and cross-price elasticities.

Money price elasticities	
Own elasticity, car ($\varepsilon_c^{j,k}$)	−0.54
Own elasticity, bicycle ($\varepsilon_v^{j,k}$)	−0.8
Own elasticity, bus ($\varepsilon_b^{j,k}$)	−0.4
Cross-price elasticity between car and bus trips ($\varepsilon_{c,b}^{j,k}$)	0.13
Cross-price elasticity between car and bicycle trips ($\varepsilon_{c,v}^{j,k}$)	0.081
Cross-price elasticity between bus and bicycle trips ($\varepsilon_{b,v}^{j,k}$)	0.067

At the calibration stage, the price/cross-price elasticities were converted to generalised price/cross-price elasticities, multiplying by the relative ratio between full user cost of a trip (i.e., including the value of time) and the monetary cost of the trip.

The estimated parameters of the sub-utility function are reported in Table B.5.

Table B.5
Sub-utility function parameters estimated through model calibration.

User group	Trip distance	$a_c^{j,k}$	$a_b^{j,k}$	$a_v^{j,k}$	$b_c^{j,k}$	$b_b^{j,k}$	$b_v^{j,k}$	$i_{cb}^{j,k}$	$i_{cv}^{j,k}$	$i_{bv}^{j,k}$
low-income	short	15.60	11.64	8.49	0.0114	0.0046	0.0054	0.0021	0.0014	0.0009
	long	21.06	14.45	13.26	0.0042	0.0015	0.0066	0.0007	0.0005	0.0003
mid-income	short	15.03	12.90	9.39	0.0052	0.0037	0.0030	0.0010	0.0006	0.0007
	long	23.15	17.61	17.19	0.0014	0.0009	0.0033	0.0002	0.0002	0.0002
high-income	short	14.69	13.77	10.19	0.0049	0.0059	0.0047	0.0009	0.0006	0.0010
	long	26.28	20.77	20.93	0.0018	0.0018	0.0040	0.0003	0.0002	0.0003
no-bicycle	long	22.43	17.22	–	0.0008	0.0008	–	0.0001	–	–

Table B.6 reports data used to value the cost of public transport supply for alternative bus fleet scenarios. Parameters relating to both operational and economic performances of different bus systems are based on current literature. When necessary, parameters have been updated and adjusted to the specific operational context under study (i.e., the Stockholm's inner corridor).

Table B.6
Input parameters for the cost function of the bus supply.

Parameter	Notation	Value	Data source
Operational parameters			
Number of work days per year	*wdays*	250	
Number of hours of peak period	n_h	4	Bus line characteristics
Number of hours of off-peak period	n_{hOP}	16	Bus line characteristics
Frequency in off-peak period (%)	φ	70 %	Börjesson et al., 2017

(*continued on next page*)

Table B.6 (*continued*)

Parameter	Notation	Value	Data source
Energy consumption lightweight bus (*Wh/km*)	E_{lw}	795	UITP, 2017
Weight increase parameter (*Wh/kg*)	ιw	0.1	Vepsäläinen et al., 2018
Energy density LTO batteries (*Wh/kg*)	$EB_{d,LTO}$	76	Göhlich et al., 2018
Energy density NMC batteries (*Wh/kg*)	$EB_{d,NMC}$	170	Göhlich et al., 2018
Maximum number of cycles LTO batteries	$n_{c,LTO}$	10,000	Göhlich et al., 2018, Lajunen, 2018
Maximum number of cycles NMC batteries	$n_{c,NMC}$	1,000	Göhlich et al., 2018
Average weight of a human body (*kg*)	W_{hb}	75	
Average power required by HVAC system (*W*)	P_{HVAC_avg}	5,000	Vepsäläinen et al., 2018, Göhlich et al., 2018
Maximum power required by HVAC system (*W*)	P_{HVAC_max}	2,0000	Vepsäläinen et al., 2018, Göhlich et al., 2018
SOC window (%)	SOC_w	0.7	Karlsson, 2016
Charging efficiency (%)	η_{chg}	0.85	Karlsson, 2016
Energy density diesel (*Wh/l*)	ED_{DF}	980	Mauler et al., 2022
Energy consumption diesel bus (*Wh/km*)	$E_{km,DF}$	4,430	Gustafsson et al., 2021
Economic parameters			
Slow-charger cost (€/*kW*)	$c_{chg_{SC}}$	500	ICCT, 2019
Slow-charger installation and grid connection costs (€/*kW*)	$c_{igc_{SC}}$	90	ICCT, 2019
Fast-charger cost (€/*kW*)	$c_{chg_{FC}}$	358	ICCT, 2019
Fast-charger installation and grid connection costs (€/*kW*)	$c_{igc_{FC}}$	286	ICCT, 2019
Permits and civil works costs for charging infrastructures (%)	pcw	30 %	De Briñas Gorosabel et al., 2022
Chargers maintenance costs (%)	c_{chgop}	2 %	Olsson et al., 2016, Lajunen, 2018
Annual energy demand charge (€/*kW*)	c_{edc}	120	Lajunen, 2018
Annual operational cost of bus depots (€)	c_{dep}	9,000	Börjesson et al., 2017
Purchase cost of OC e-bus (€)	$c_{veh_{OC}}$	380,000	Meishner and Uwe Sauer, 2020
Purchase cost of OC e-bus (€)	$c_{veh_{DC}}$	350,000	Meishner and Uwe Sauer, 2020
Purchase cost of diesel bus (€)	$c_{veh_{DF}}$	350,000	Meishner and Uwe Sauer, 2020
Cost of LTO batteries (€/*kWh*)	$c_{bat_{LTO}}$	237	Mauler et al., 2021
Cost of NMC batteries (€/*kWh*)	$c_{bat_{NMC}}$	158	Mauler et al., 2021
Fuel (diesel) costs (€/*l*)	c_{df}	1.40	Borén, 2020
Electricity costs (€/*kWh*)	$c_{pwr_{EB}}$	0.11	Borén, 2020
Drivers costs (€/*hour*)	c_{dri}	35	Olsson et al., 2016
Maintenance costs of diesel bus (€/*km*)	$c_{mnt_{DF}}$	0.292	Börjesson et al., 2017
Maintenance costs of e-bus (€/*km*)	$c_{mnt_{EB}}$	0.183	Olsson et al., 2016
Bus stops installation cost (€)	c_{bsi}	0.183	Börjesson et al., 2017
Bus stop operational costs (€/*year*)	c_{bsop}	15,000	Börjesson et al., 2017
Lifetime parameters			
Useful life of infrastructures (*years*)	I_l	20	
Useful life of vehicles (*years*)	V_l	12	
Useful life bus stops (*years*)	BS_l	10	
Discount rate	dr	4.0 %	Börjesson et al., 2017

Table B.7 reports data on marginal external costs in urban roads used as inputs for the evaluation of externalities (other than congestion) included in the model. We refer to the values estimated by the European Commission (2020).

Table B.7
Input parameters of the external costs function

Externality	Operational context	Car		Diesel VI bus		Electric bus	
		Medium		*Articulated*		*Articulated*	
Air pollution	Metropolitan, urban road	e_{AP_c}	0.006	$e_{AP_{DF}}$	0.024	$e_{AP_{EB}}$	0.006
GHG emissions	Metropolitan, urban road	e_{GHG_c}	0.020	$e_{GHG_{DF}}$	0.132	$e_{GHG_{EB}}$	0.000
Noise	Metropolitan, dense, day	e_{N_c}	0.007	$e_{N_{DF}}$	0.090	$e_{N_{EB}}$	0.081
Accidents	Urban	e_{A_c}	0.022	$e_{A_{DF}}$	0.145	$e_{A_{EB}}$	0.145
TOTAL			**0.055**		**0.391**		**0.232**

Appendix C. Optimal welfare for each policy scenario and second-best equilibria

Table C.1
Comparison of baseline case and optimal welfare for each policy scenario.

Scenario *i*	Welfare €/day	Policy variables								Total number of trips	Bus trips share (%)
		Frequency # buses/peak hour*	Number of bus stops	Road tolls and fares (€/trip)							
				Short car trips toll	Long car trips toll	Short bus trips fare	Long bus trips fare	Short bicycle trips toll	Long bicycle trips toll		
BASELINE	**558,178**	**12.00**	**31.0**	**1.80**	**1.80**	**2.00**	**2.00**	**0.000**	**0.000**	**107,188**	**42.0 %**
DF	**596,960**	**22.32**	**28.48**	**1.07**	**4.29**	**1.13**	**1.34**	**0.17**	**0.69**	**107,086**	**51.9 %**
ΔDF/BASELINE	+6.9 %	86.0 %	−8.1 %	−40.4 %	138.3 %	−43.3 %	−32.8 %			−0.1 %	23.4 %
eOCD	**594,567**	**22.05**	**28.41**	**1.07**	**4.29**	**1.15**	**1.36**	**0.17**	**0.68**	**106,951**	**51.8 %**
ΔeOCD/ BASELINE	6.5 %	83.8 %	−8.3 %	−40.4 %	138.3 %	−42.4 %	−31.7 %			−0.2 %	23.2 %
ΔeOCD/DF	−0.4 %	−1.2 %	−0.2 %	0.0 %	0.0 %	1.4 %	1.7 %	−0.31 %	−0.2 %	−0.1 %	−0.2 %
eDCM	**591,430**	**22.62**	**28.47**	**1.07**	**4.29**	**1.12**	**1.34**	**0.17**	**0.69**	**107,131**	**51.9 %**
ΔeDCM/ BASELINE	6.0 %	88.5 %	−8.2 %	−40.4 %	138.3 %	−43.8 %	−33.1 %			−0.1 %	23.5 %
ΔeDCM/DF	−0.9 %	1.4 %	−0.0 %	0.0 %	0.0 %	−0.9 %	−0.3 %	0.24 %	0.2 %	0.0 %	0.1 %
eOCP	**574,801**	**12.14**	**28.34**	**1.09**	**4.35**	**1.75**	**2.07**	**0.15**	**0.59**	**99,585**	**46.7 %**
ΔeOCP/ BASELINE	3.0 %	1.2 %	−8.6 %	−39.6 %	141.4 %	−12.7 %	3.7 %			−7.1 %	11.2 %
ΔeOCP/DF	−3.7 %	−45.6 %	−0.5 %	1.3 %	1.3 %	54.0 %	54.3 %	−14.3 %	−14.3 %	−7.0 %	−9.9 %

* One might expect that the increase in e-bus supply costs results in a decrease of the optimal service frequency. However, this is not the case of the corridor under study. Intuitively, the benefit in terms of reduced waiting time and crowding costs for bus passengers (connected with higher bus frequency) cover the costs of extra bus supply – even considering the higher costs of electric fleet configurations. Consequently, optimal bus fares are not significantly affected by the introduction of e-bus configurations (see Table 2), which are competitive with diesel case in terms of social welfare maximisation.

This Appendix shows also how the results change when we reduce the policymakers' sphere of action. We consider specific combinations of policy variables, exploring three different second-best equilibria: 1) the pricing of the bus trips only, the bus frequency, and the number of bus stops are optimised in the "*Bus fares + frequency + stops*" scenario; (2) the bus frequency and the number of bus stops are optimised in the "*Frequency + stops*" scenario; (3) bus frequency is optimised in the "*Frequency*" scenario; (4) bus stops are optimised in the "*Stops*" scenario.

Fig. C.1 compares the welfare gain (with respect to $i = BASELINE$) achieved when all variables are optimised to that reached by combining different set of policy variables. Such gain can be roughly divided as follows: 39–50 % from car/bike tolls optimisation, 21–25 % from bus fares optimisation, and 34–39 % from bus frequency. Reducing the number of bus stops produces a small change that does not significantly influence urban welfare.[17]

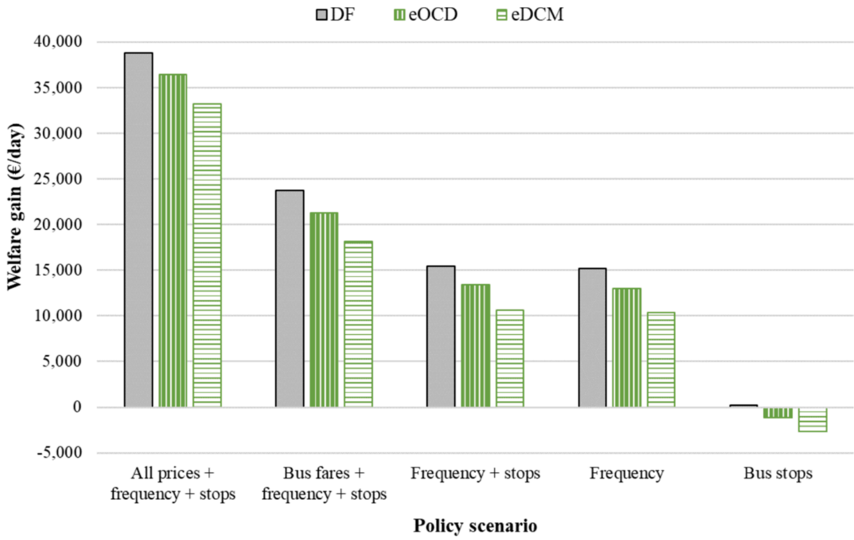

Fig. C1. Comparison of different policy scenarios in terms of welfare gain with respect to $i = BASELINE$.

Fig. C.2 focuses instead on surplus variations (with respect to $i = BASELINE$) for the bus operator and the producer surplus/bus supply costs ratio. Consistently with the discussion in Section 4, producer surplus significantly decreases, when all policy variables are optimised, because of lower bus fares and higher transit frequency (i.e., additional costs). This effect is magnified when: 1) e-buses are introduced, since bus supply costs increase; 2) car/bicycle tolls are not optimised. In this case, there is indeed a reduction in bus fares, which is necessary to reduce the external costs associated with private travel. Note that, the producer surplus increases when only frequency (or frequency and the number of bus stops) is (are) optimised. However, optimisation leads to higher transit frequency (i.e., additional costs) and the cost/benefit ratio is still lower than the baseline case (especially for e-bus systems). Therefore, we can conclude bus fleet electrification reduces/increases producer surplus/deficit in all policy scenarios.

[17] It is worth noting that increasing bus frequency generates less benefit in *eOCD* and *eDCM* scenarios than the diesel case, due to the higher cost of providing an extra bus service. For this reason, the percentage gap between diesel and electric bus fleet scenarios in terms of welfare gain is smaller when all policy variables can be optimised.

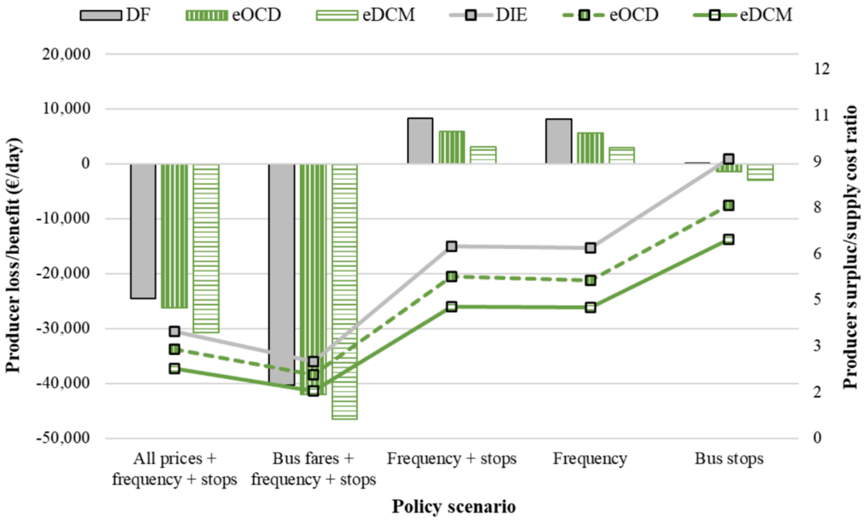

Fig. C2. Producer surplus variations with respect to diesel baseline in different policy scenarios for alternative bus fleet configurations.

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