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RESEARCH ARTICLE

A spatially explicit optimization model for the selection of sustainable transport technologies at regional bus companies

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Abstract
Buses account for almost 60% of the total public transport services in Europe, and most of the vehicles are diesel fuelled. Regional transport administrators, under pressure by governments to introduce zero-emission buses, require analytical tools for identifying optimal solutions. In literature, few models combine location analysis, least cost planning, and emission assessment, taking into account multiple technologies which might achieve emission reduction goals. In this paper, an existing optimal location model for electric urban transport is adapted to match the needs of regional transport. The model, which aims to evaluate well-to-wheel carbon emissions as well as airborne emissions of NO_x and PM10, is applied to a real case study of a regional bus transport service in North Eastern Italy. The optimization has identified electric buses with relatively small (60 kWh) batteries as the best compromise for reducing carbon equivalent emissions; however, under current economic conditions in Italy, the life cycle cost of such vehicles is still much higher than those of Euro VI diesel buses. In this context, our model helps in identifying ways to minimize infrastructure costs and to efficiently allocate expensive resources such as electric buses to the routes where the maximum environmental benefit can be achieved.

Keywords Bus transport · Electric buses · CNG buses · Recharging infrastructure · Location analysis · Extended well-to-wheel analysis

Abbreviations

BAU	Business as usual
BE	Battery electric
BEV	Battery electric vehicle
CNG	Compressed natural gas
FAME	Fatty acid methil esters

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GHG	Greenhouse gases
GWP	Global warming potential (over 100 years)
HP	High pressure (40 bar gas pipeline)
LP	Low pressure (4 bar gas pipeline)
LCA	Life cycle assessment
NO_x	Nitrogen oxides relevant for air pollution
PM10	Particulate matter 10 μm or less in diameter
SCR	Selective catalytic reduction
TTW	Tank to wheels
WTT	Well to tank
WTW	Well to wheels
ZEB	Zero emission bus

Indices

l	Bus route
s	Bus stop
t	Bus technology (diesel, CNG, BEV 60 kWh, BEV 120 kWh)
el	Subset of t including BEV 60 kWh and BEW 120 kWh only
cng	Subset of t including CNG technology only

Variables

$\delta 1, \delta 2, \delta 3\ (s,el)$	[0,1] Variables to determine the total number of charging stations to be installed at stop s (binary)
$\gamma_1, \gamma_2, \gamma_k\ (s,el)$	[0,1] Variable, work as flag to classify the number of routes needing recharging at stop s (0,1,between 2 and k-1, k or above) (binary)
C_{tot}	Annual equivalent total system cost (continuous)
$CO_2eq_{TTW}(t)$	Total annual equivalent CO_2 emissions from Tank to Wheels (positive)
$CO_2eq_{WTT}(t)$	Total annual equivalent CO_2 emissions from Well to Tank (positive)
NB(l,t)	Number of buses of technology t assigned to route l (integer)
NP(s,t)	Number of charging stations of technology t installed at stop s (integer)
TUS(l,t)	[0,1] Variable, equals 1 if technology t is assigned to line l (binary)
US(l,s,t)	[0,1] Variable, equals 1 if charging of technology t for line l is required at stop s (binary)

Parameters

ε	Fixed arbitrary small number
a	Annualization factor
bat_{cost}	Batteries capital cost coefficient (€/kWh)
$b_{cost}(t)$	Bus capital cost (€)
$b_{main}(t)$	Bus maintenance annual cost (€/km)

$c(s)$	[0,1] Scalar, is 1 if two or more trips from different routes are scheduled to stop at *s* at the same time
$cap_{bat}(el)$	Battery storage capacity (kWh)
$co_2eq_{TTW}(t)$	Tank-to-Wheel carbon equivalent emission factor (t/km)
$co_2eq_{WTTfuel}(t)$	Well-to-Tank carbon equivalent emission factor for fuels or energy supplied to vehicles (t/km)
$co_2eq_{WTTbatt}(el)$	Well-to-Tank carbon equivalent emission factor for manufacturing of batteries, for BEV 60 kWh and BEV 120 kWh vehicles only (t/unit)
$co_2eq_{WTTstat}(t)$	Well-to-Tank carbon equivalent emission factor for manufacturing of fuelling/charging stations (t/unit)
$cons(t)$	Fuel economy (kWh/km)
$D(l,s,\ s+1)$	Distance between stop s and successive stop s + 1 on route l (km)
$durationbatt(el)$	Expected lifetime of batteries (y)
$durationstat(t)$	Expected lifetime of charging station (y)
dy	Average total time available for bus operation, in days per year (day/y)
$f(t)$	Fuel cost (€/kWh)
i	Interest rate
$L_{trip}(l)$	Route length (km)
M	Fixed arbitrary large number
n	Project life in years (y)
$n_{trip}(l)$	Number of trips per day for each route
$s_{cost}(t)$	Charging/Fuelling station capital cost- (€)
$s_{main}(t)$	Charging/Fuelling station annual O&M cost (€/y)
SOC_{min}	Minimum state of charge for batteries
$t_{charge}(s,t)$	Charging time allowed for each technology and stop (min)
t_{op}	Average total time available for bus operation, in minutes per year (min/y)
$t_{trip}(l)$	Travel duration on route l (min

1 Introduction

In European urban areas, public transport accounts for 21% of the total number of motorised trips and is responsible for roughly 10% of transport related greenhouse gas (GHG) emissions (UITP 2018). According to the International Association of Public Transport, buses account for 50–60% of the total public transport offer in Europe (UITP 2016) and, according to a recent survey (Corazza et al. 2016), 79% of operational vehicles are diesel fuelled.

Despite the introduction of increasingly restrictive standards on diesel engine emissions, with Euro VI coming into force in 2014, diesel buses continue to make a substantial contribution to urban air pollution. Local governments are calling for the introduction of zero-emission buses (ZEB), which they often view as a means of reducing local air pollution problems, rather than specifically reducing carbon emissions (Bakker and Konings 2018). In fact, an international survey on local bus operators (Corazza et al. 2016) shows that more than 40% of the respondents would opt for increasing the use of electric vehicles, 28% would opt for change in favour of more compressed natural gas (CNG), and 13% towards greater use of vehicles fuelled by bio-methane. Obviously, each of these choices has different economic and environmental implications, and some of them are not explicitly evaluated by local governments or by administrators, whose perceptions may fail to take into account all aspects of the real situation on the grounds (Corazza et al. 2016). To enable informed decision making for the future development of public transport systems, decision support tools may be of help, particularly when multiple technology options need to be given consideration, and when the transition to ZEB requires the development of appropriate but capital-cost-intensive charging infrastructure.

The present study was motivated by the requirement of an Italian regional bus transport company to evaluate the feasibility of improving its environmental performance by introducing alternative bus technologies, including battery electric vehicles, in the intercity regional bus transport network.

To compare different technology options, and particularly different powertrains, several approaches and indicators are adopted in literature, such as life cycle cost analysis (Hellgren 2007), fuel use and primary energy use (Gustafsson et al. 2018), real ecological impact (Esser et al. 2020), well-to-wheel (WTW) analysis (Wang 2002; Edwards et al. 2011), eco-efficiency (Lee et al. 2011) and life cycle assessment (Ercan and Tatari 2015).

The fuel cycle or WTW analysis is one of the earliest and most commonly applied methods to evaluate the environmental impact of alternative fuels and powertrains for buses (Correa et al., 2017). The WTW analysis of a vehicle/fuel system covers all stages of the fuel cycle—from energy feedstock recovery (wells) to making the fuel available at tanks (well-to-tank, WTT), and from the energy supplies which need to be available at fuelling-recharging stations, down to the energy delivered at vehicle wheels (tank-to-wheels, TTW).

However, WTW analyses generally does not account for the embodied energy and indirect carbon emissions associated with component manufacturing, particularly with regard to manufacturing batteries. More comprehensive and complex Life Cycle Assessment (LCA) approaches, which were recently reviewed by Harris et al. (2018) also account for additional stages such as the extraction and processing of raw material, for manufacturing, as well as for the decommissioning of the vehicles themselves. Such analyses predominantly focus on GHG emissions (Harris et al. 2018) while others present more comprehensive impact indicators (e.g. water withdrawal in Ercan and Tatari (2015), toxicity to humans, ionizing radiation, and depletion of minerals and fossil fuels in Petrauskienė et al., (2020)). In this context, a recent trend is the use of extended WTW models, which carefully incorporate LCA data into WTW analyses to account also for the impact of manufacturing and substitution of batteries and for estimating carbon footprint indicators (Moro and Helmers 2017). Some hybrid methods (Ercan and Tatari 2015) also account for the GHG emissions associated with additional infrastructure required for recharging or refuelling new fleets using alternative powertrains.

To obtain more comprehensive cost–benefit analyses, traditional or extended well-to-wheel analyses has usually been complemented by life cycle costing

(Lajunen and Lipman 2016). The performance indicators calculated with these approaches are sometimes incorporated in more comprehensive frameworks, such as external cost frameworks (Mitropoulos et al. 2017), multi-criteria frameworks (Tzeng et al. 2005), fuzzy models (Büyüközkan et al. 2018; Adhami and Ahmad 2020), probabilistic models (Harris et al. 2020; Buakum and Wisittipanich 2020), and optimization approaches (Durango-Cohen and McKenzie 2018). Among the latter, Durango-Cohen and McKenzie, (2018) performed a fleet optimization considering different fuels, hybrid electric and hydrogen fuel cells as options to minimize total cost of ownership, on one hand, and lifecycle NO_x emissions, on the other hand. As observed in Harris et al. (2020) in most cost–benefit analyses individual routes or driving cycles are taken as reference (see e.g. Mitropoulos et al. 2017; Tzeng et al. 2005); often, also one reference vehicle at time is considered. Harris et al. (2020) observe that "when comparing new technologies, a common misleading assumption is that new bus fleets are a like-for-like replacement, regardless of their technological capabilities or route specific energy demands". In some cases, as in Durango-Cohen and McKenzie (2018), entire fleets are considered, rather than a single individual reference vehicle, but it is assumed that fuelling issues, including cost and impacts of fuelling infrastructure, do not affect the issues of re-fleeting. We agree that this is certainly true for traditional fuels, or more precisely those fuels and technologies compatible with existing fuelling stations, such as biodiesel. However, this may not be the case for alternative fuels and powertrains, e.g. CNG and electric vehicles, which require bus companies to install dedicated, capital intensive infrastructure.

Based on the literature we examined, as well as on the needs of companies and public authorities, the present study introduces an optimization model aimed at minimizing the life cycle costs of bus fleets while simultaneously meeting emission reduction constraints. In line with Harris et al. (2020) and Ercan and Tatari (2015), we argue that recharging issues must be considered in cost-benefits analyses and handled at a fleet level, particularly for battery electric buses, costs which were not examined in Durango-Cohen and McKenzie (2018). In fact, for electric buses, and for electric vehicles in general, challenges to installing newcapital intensive charging infrastructure are exacerbated by several factors, including:

- The high specific costs of batteries and their limited capacities;
- Range anxiety, which in the business context of intercity bus transport should be understood as technical anxiety (Noel et al. 2019) that is, the purchaser's concern that real-world mileage range between charges will be significantly lower than expected, and that vehicles won't be able to complete their scheduled runs;
- Uncertainty about the cost effectiveness of alternative or complementary charging technologies (e.g. inductive, conductive, battery swapping) (Chen et al. 2018).

Notwithstanding these barriers, a rapid development of battery electric vehicles and an increasing maturity of fast charging technologies is envisioned in the near future (Pereirinha et al. 2018). Hence, a large body of engineering literature has been devoted to optimizing the location and capacity of battery charging infrastructure, particularly aimed at serving commercial battery electric vehicles (BEVs) such as buses. For further reference note Shen et al. (2019) for a recent comprehensive review of BEVs in general, and He et al. (2019) for a recent review with a focus on electric buses.

From the reviews we examined, it can be inferred that most infrastructure optimization models aim at deploying systems so that total costs are minimized. Such models are generally focused on electric technologies alone. This is e.g. the case of Islam and Lownes (2019), who optimize a course of fleet replacement and recharging infrastructure purchase over the years. They account for the costs of both bus fleets and recharging stations, but they assume that recharging is entirely performed at depot chargers on a one-on-one basis. They do not account for spatial issues in planning recharging stations. A spatially explicit approach is taken by Rogge et al. (2018), who also focus on electric technologies alone and use genetic algorithms to optimize at the same time the composition, the recharging schedule and infrastructure of an electric bus fleet. They minimize total costs of ownerships but do not account for environmental impact. Indeed, only few optimization models (Nie et al. 2016; Xylia et al. 2017) take environmental impact, in particular emissions, into account at the same time, to enable a spatially explicit cost–benefit planning of fleet and infrastructure. To the best of the authors' knowledge, very few models consider both traditional and electric technologies at the same time. Su et al. (2019) take diesel, CNG, and electric buses into consideration when using a continuous approximation approach to optimize the design of an assigned bus route in a Chinese city. Their model is focused on a single corridor and addresses bus stop spacing, service headway, and speed. It should be observed that the model by Su et al. (2019) examines each vehicle type individually: the optimization of the fleet composition is not part of the model itself. The model developed by Xylia et al. (2017) has the unique feature of optimizing the allocation and use of both electric bus technologies and of traditional, internal combustion engine buses fuelled with alternative fuels, on different routes within the same network. This model was applied to the development of the electric buses in the city of Stockholm, particularly the inner city zone (Xylia et al., 2019). Xylia's model is oriented to urban bus transport, which was the case with the electric bus network development models we examined. Several models involving practical case studies on real bus networks were for German settings (Sinhuber et al. 2012; Rogge et al. 2015,2018; Kunith et al. 2017). One (Wang et al. 2017) is for the USA.

As the intercity bus service considered in this study was undertaken within a relatively small province with low population density, travel distances may be comparable with urban problems in larger cities. However, the distance between stops is relatively farther than in urban settings, and the number of daily trips may be quite variable depending on route. These factors may make optimising infrastructure development more challenging. The aim of our model was therefore to identify in which routes and under which specific circumstances electrification could be viable, and how this would affect the composition and costs of the fleet for the regional bus company under examination. For this purpose, the mixed integer linear programming model presented by Xylia et al. (2017) seemed the most promising, although it required adapting to the features of regional bus transport, and to the technologies and emission settings typical to this part of Italy, at the same time as taking a fleet optimization perspective. How this aspect was carried out is discussed in the methodology (Sect. 2), which also addresses the environmental assessment framework developed here. The case study, data, and scenarios definition are presented in more detail in Sect. 3, which is followed by the discussion of the results in Sect. 4.

2 Methodology

In view of the concrete aim of this study, our objective was to consider immediate options available to regional bus companies rather than technologies which may available in the longer term. Hence, as we are discussing in Sect. 2.1, we have focused on fuels and vehicle types generally considered as a valid purchasing option by bus company administrators nowadays. Taking the fleet optimization approach recommended by Harris et al. (2020), the equations presented in Sect. 2.2. Have been added to the model proposed in Xylia et al. (2017). To meet environmental impact targets, the constraints presented in Sect. 2.3 have been introduced.

2.1 Identification of context specific requirements

Unlike Xylia et al. (2017), who focussed on a Scandinavian context aimed at 100% carbon emission abatement using 100% biodiesel as a fuel for conventional engines in combination with battery electric vehicles powered by a Nordic electric mix, we decided to set emission reduction targets at 50% for both GHG and air pollutants. Since public transport serves as a role model with respect to other transport companies, the chosen target is slightly more ambitious than carbon emission reduction targets for this kind of fleets in Italy. In fact, according to Transport and Environment (2019), in 2030 carbon emissions from heavy duty vehicles should be reduced by 45% compared to a 2015 baseline.

Focusing on fuels commonly used to date in regional bus companies in Italy (Camerano et al. 2017), fossil fuel based options such as diesel fuel and compressed natural gas (CNG) have been examined.

An immediate option is the purchase of new buses with the most recent conventional technology (Diesel Euro VI). The current diesel mix entails a 9% mandatory biofuel quota on the overall market, but a blending wall of 7% biodiesel was considered here as a maximum proportion of FAME (Fatty Acid Methil Esters) in conventional diesel (Nylund and Koponen 2012). It was decided not to consider higher shares of biodiesel as feasible options in the mid-term, given the technical limitations and concerns about engine performance and duration reported in Patel et al. (2016). Additionally, there are substantial concerns about actual biodiesel emission factors discussed in literature (Nylund and Koponen 2012), especially if one considers the impact of induced land use change due to the cultivation of crops for biofuel (Kampman et al. 2013).

CNG as a vehicle fuel generally boasts a high market penetration in Italy (Patrizio and Chinese 2016) and has been largely used at urban level by municipal bus transport companies for more than twenty years (Mercuri et al. 2002), with the main aim of reducing local pollutant emissions. CNG is thus considered as a valid short term option by company managers and local authorities owing to the long held belief that natural gas is a "clean" fuel, and also in view of potential conversion to bio-methane. Nevertheless, the current use of CNG in inter-urban transport is minimal (Camerano et al. 2017), primarily because of concerns about driving ranges.

Many authors in Europe (Logan et al. 2020), South America (Correa et al. 2017) and Asia (Khandekar et al. 2018) have called for a massive uptake of battery electric buses, and refer to them as the most interesting alternative for public transport decarbonisation, at least for trip ranges below 100 km (Correa et al. 2017). Given the geographic morphology of Italy and the way local bus company are organized in Italy, such trip ranges are in line with the requirements of regional inter-urban transport. However, additional recharging stations across the network are more likely to be required than in urban settings. The same holds true for CNG vehicles. For BEVs, the key research question for intercity transport is to evaluate whether super-fast charging and smaller volume energy storage with numerous charging stations along the networks are preferable to larger energy storage in vehicles requiring fewer charging cycles (Nylund and Koponen 2012). For this reason, fully electric buses with either a 60 kWh battery or a 120 kWh battery have been considered as alternative options.

2.2 Location and capacity optimization model

As in Xylia et al. (2017), the objective function of the model is to minimize annualized system costs. In our version of the model, costs are expressed by Eq. 1:

$$\begin{aligned} MinC_{tot} = & \sum_{s}\sum_{t}\left(s_{\cos t}(t)\cdot a + s_{main}(t)\right)\cdot NP(s,t) + \sum_{l}\sum_{t} b_{\cos t}(t)\cdot NB(l,t)\cdot a \\ & + \sum_{l}\sum_{t}\left(f(t)\cdot const(t) + b_{main}(t)\right)\cdot L_{trip}(l)\cdot n_{trip}(l)\cdot dy + TUS(l,t) \\ & + \sum_{l}\sum_{el} bat_{\cos t}\cdot cap_{bat}(el)\cdot NB(l,el)\cdot n\cdot a \end{aligned} \tag{1}$$

Integer decision variables are the number *NP* of charging or refuelling stations to be located at bus stop *s* serving technology *t*, and the number of buses *NB* with propulsion technology *t* to be assigned to bus route *l*. The 0–1 binary decision variable *TUS* is equal to 1 if and only if technology *t* is associated with bus route *l*.

The parameter *a* is the annualization factor, calculated according to Eq. 2:

$$a = \frac{(i+1)^n i}{((i+1)^n - 1)} \tag{2}$$

with i = interest rate and n the time horizon of the investment.

The most important model constraints are energy balance equations at stops.

Energy balances at stops essentially impose that:

- the energy in the battery or tank of the bus when coming to a bus stop s equals the energy in the battery or tank at previous stop $s-1$ minus the energy consumed to travel from $s-1$ to s;
- the energy in the battery or tank when leaving bus stop s equals the energy at arrival to the stop plus the energy added from any charging performed at the stop.

The equations are the same as described in the original model (Xylia et al. 2017), to which reference should be made as well for details about the handling of exceptions at start and end stops.

In the following section, we limit our description to the main differences from the original model, that is:

- the number of buses *NB*, which in the original model was a parameter defined for each route as the number of vehicles currently operating on the route, while in the present model version is an integer decision variable.
- the number of electric charging stations, which in the original model was directly given by the binary decision variable *US(l,s,t)*, equalling 1 if vehicles with technology t assigned to route l are due to be recharged at stop s, while in our model is represented by the integer decision variable *NP,* calculated as detailed below.

2.2.1 Number of buses

The underlying assumption in the original model was that the service level on a route would be maintained if the number of buses currently operating on the route was maintained. However, Harris et al. (2020) observe that, depending on the technologies selected for storage and charging, a higher number of vehicles may be required to guarantee the same service. Trade-offs arise between longer charging times (allowing for example to better exploit a smaller number of recharging facilities), and the number of vehicles (which should be increased if too much time is spent in charging). To model this, a detailed approach using timetables could be used as in Wang et al. (2017) and in Rogge et al. (2018) to ensure that current schedule is maintained avoiding any delays or charging station congestion. However, the level of detail and computational effort required for an exact solution with such an approach is compatible with the operational level addressed in Wang et al. (2017) rather than with a long term network planning perspective. In fact, Rogge et al. (2018) resorted to genetic algorithms to solve a similar problem at a strategic level. Given the further complexity of considering several technologies as decision variables, which our case required, we used a simplified approach by calculating the number of buses according to Eq. (3):

$$NB(l,t) \geq \frac{n_{trip}(l)\left[TUS(l,t)\cdot t_{trip}(l)+\sum_{s} US(l,s,t)\cdot t_{charge}(s,t)\right]}{t_{op}} \quad \forall s,l,t \tag{3}$$

where *US(l,s,t)* is, as in the original model, a binary decision variable equalling 1 if vehicles with technology t assigned to route l are due to be recharged at stop s; t_{op} is the available operational time per bus per year, in minutes; $t_{trip}(l)$ is the average travel time on route *l*, and $t_{charge}(s,t)$ is the charging time available at stop *s* for technology *t*. Based on bus schedule, buses have longer idle times at end stations, which can be used for extended recharging: therefore, charging time additionally depends on stops. Inequality 3 basically ensures that, for each route, the number of buses meets the annual average net travel time demand. The approach is approximated, if compared e.g. with the more detailed probabilistic simulation model presented in Harris et al. (2020), where peak and off-peak period are treated differently. Nevertheless, it helps to reduce the risk of underestimating the number of vehicles to be purchased for the new fleet to meet average service requirements.

2.2.2 Number of charging stations

Conversely, there is, however, a risk of overestimation if applying the same approach as in the original model (Xylia et al. 2017) for calculating the number of charging stations for a regional intercity bus company in the Italian context. In fact, in the original model version, the total number of charging stations is apparently calculated as:

$$NP_O(t) \geq \sum_s \sum_l US(l,s,t) \quad \forall t \tag{4}$$

That calculation indicates that charging stations, even those located at junction stops, cannot be shared by vehicles assigned to different routes, as each charging station would need to be dedicated to the corresponding route *l*. What may be reasonable in an urban context with a high number of trips and a high risk of congestion, could lead to excessive investment in charging stations with low utilization rates in an intercity context, where trips on a route can be infrequent. A detailed approach would require solving charging location and scheduling problems at the same time, using the actual timetable, as exemplified by Wang et al. (2017) for the city of Davis, and by Rogge et al. (2018) for the city of Aachen. However, we considered that the computational and data collection effort required to implement such an approach at an intercity level is more in line with the needs of operational planning of electric recharging, rather than with the strategic planning of several alternative technologies on the same network. For this reason, an intermediate approach was implemented. For CNG vehicles, which generally have higher ranges and relatively quicker charging times than electric vehicles, it was assumed that the risk of simultaneous refilling needs for vehicles from different routes at the same charging stations was negligible, and that the infrastructure, which is moreover generally more expensive than power charging, could better be shared among vehicles assigned to different routes. For CNG, the number of stations *NP* is thus determined according to Eq. 5 as:

$$NP(s,cng) = \sum_l US(l,s,cng) \quad \forall s \tag{5}$$

Given the above considerations regarding BEV charging, we concluded that sharing a single charging station between all routes would carry a high risk of congestion and delays only where, based on the timetable, there generally was a high probability of simultaneous arrivals at the charging stop. In that case, the optimization procedure needed to be constrained so that two or more charging stations would be installed at critical charging stops. For this purpose, a simultaneity coefficient *c(s)* was preliminarily calculated for each stop based on the timetable: the coefficient *c(s)* was set to 1 if at least three vehicles from different routes were to coincide at the given stop at least once in any 24-h period, and to 0 otherwise. Within the optimization model, *NP* was then calculated for each stop with the aid of auxiliary binary variables denoted as follows as δ_i and γ_j, and of constants M (fixed arbitrary large number) and ε (fixed arbitrary small number, see e.g. Williams 2003) according to Eqs. 6–16, applying at every stop s:

$$NP(s, el) = \delta_1(s, el) + \delta_2(s, el) + \delta_3(s, el) \tag{6}$$

$$\sum_l US(l, s, el) + \gamma_1(s, el) \geq 1 \tag{7}$$

$$\sum_l US(l, s, el) - (M + \varepsilon) \cdot (1 - \gamma_1(s, el)) \leq 1 - \varepsilon \tag{8}$$

$$\sum_l US(l, s, el) + \gamma_2(s, el) \geq 2 \tag{9}$$

$$\sum_l US(l, s, el) - (M + \varepsilon) \cdot (1 - \gamma_2(s, el)) \leq 2 - \varepsilon \tag{10}$$

$$\sum_l US(l, s, el) + \gamma_k(s, el) \geq k \tag{11}$$

$$\sum_l US(l, s, el) - (M + \varepsilon) \cdot (1 - \gamma_k(s, el)) \leq k - \varepsilon \tag{12}$$

$$\gamma_1(s, el) + \gamma_2(s, el) + \gamma_k(s, el) - 3 \cdot (1 - \delta_1(s, l) \geq 0 \tag{13}$$

$$\gamma_1(s, el) + \gamma_2(s, el) + \gamma_k(s, el) - (M + \varepsilon) \cdot (1 - \delta_1(s, el)) \leq 3 - \varepsilon \tag{14}$$

$$\gamma_1(s, el) + \gamma_2(s, el) - c(s) + M \cdot \delta_2(s, el)) \leq M \tag{15}$$

$$\gamma_1(s, el) + \gamma_2(s, el) - c(s) + (1 + \varepsilon) \cdot (\delta_2(s, el)) \geq \varepsilon \tag{16}$$

$$\gamma_1(s, el) + \gamma_k(s, el) - c(s) + M \cdot \delta_3(s, el)) \leq M - 1 \tag{17}$$

$$\gamma_1(s, el) + \gamma_k(s, el) - c(s) + (1 + \varepsilon) \cdot (\delta_3(s, el)) \geq \varepsilon - 1 \tag{18}$$

The binary variables γ_1, $\gamma_2$and γ_k are used as flags, and according to Eqs. 7–12 they indicate whether the total number of routes requiring recharging at the same stop is equal to:

- zero (all flags at 1);
- 1 (($\gamma_1 = 0$, all other flags at 1);
- an integer value between 2 and *k-1* (γ_1 and γ_2 at 0 and $\gamma_k = 1$);
- an integer value larger or equal to k (all flags at 0).

According to Eqs. 6 and 13–18, the number of charging stations at each stop is set at:

- zero, if no charging is performed on any route;
- 1, if charging is performed for one route, or for at least two routes but with zero risk of simultaneity;
- 2 if charging is performed for 2 to *k-1* routes with some risk of simultaneity;
- 3 if charging is performed for k or more routes with some risk of simultaneity. The procedure can be further generalized for systems with more or less routes intersecting at junction stops. Based on the preliminary analysis of routes, k was set at 5 for our case study.

2.3 Emission assessment framework

Direct carbon equivalent and air pollutant emissions arise only from fuel combustion in internal combustion engines, and are calculated as exemplified in Eq. 19 for tank to wheel CO_2 equivalent emissions.

$$CO_2eq_{TTW}(t) = \sum_l n_{trip}(l) \cdot L_{trip}(l) \cdot co_2eq_{TTW}(t) \cdot TUS(t, l) \cdot dy \tag{19}$$

Emission factors for NO_x, PM10, and carbon equivalent emissions for the technologies of concern are obtained from literature, in particular from the references reported in Table 1, and expressed in g/km. Carbon equivalent emissions are based on 100 years Global Warming Potentials (GWP). NO_x are dangerous for human health in urban environments, but are additionally responsible for acid rain. The Euro VI standard imposes a drastic abatement of NO_x emissions, which is achieved by manufacturers by introducing selective catalytic reduction (SCR), using urea as a reducing agent.

The impact of urea production should thus be included in the assessment of Euro VI vehicles, as shown in Fig. 1, which represents the system boundaries considered for emission assessment for WTT carbon equivalent emissions and for TTW emissions. Besides NO_x, also particulate matter PM10 is considered because of its impact on smog and human health (Donateo et al. 2015). For coherence with the context of application, Italian (Donateo et al. 2015; ISPRA 2014; Chinese et al. 2017) and European (Nylund and Koponen 2012; Nylund 2014) data sources were preferred wherever available, in particular for the electricity mix (Donateo et al. 2015; Chinese et al. 2017), and more generally for assessing WTT emissions. Such

Table 1 CO_2 equivalent and air pollutant emission factors

Parameter	Lifecycle stage	Unit	Propulsion system				Source
			Diesel V	Diesel VI	CNG VI	BEV	
Well-to-tank CO_2 equivalent emission factors	Batteries manufacturing and replacement	g/kWh*	–	–	–	65,111	(Sen et al. 2017)
	Charging /fueling station manufacturing	g/€**	–	–	2671	524	(Ercan and Tatari 2015)
	Urea supply chain	g/kWh	–	–	–	25	(ISPRA 2014)
	Fuel /electricity supply chain	g/kWh	50	50	80	430	(Nylund and Koponen 2012) (Chinese et al. 2017)
Tank-to-wheel emission factors	CO_2eq from fuel combustion	g/km	1207	1033	1055	–	(Nylund and Koponen 2012)
	NO_x from fuel combustion	g/km	6.83	0.475	0.310	–	(ISPRA 2014)
	PM10 from fuel combustion	g/km	0.126	0.076	0.001	–	(ISPRA 2014)

*Per kWh of battery capacity

**Parametrized as function of station cost

§Per kWh of electricity from Italian energy mix or of calorific value of fuel

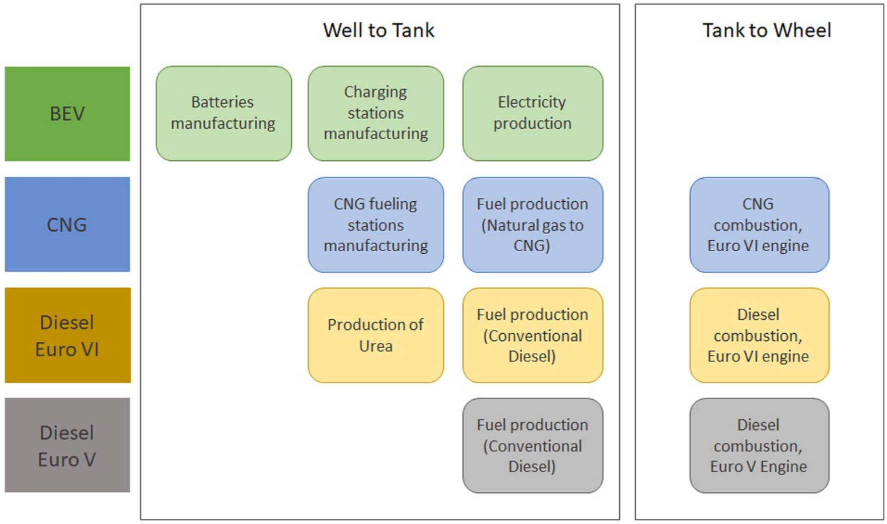


Fig. 1 Activities included in calculation of WTT (CO_2eq) and TTW (CO_2eq, NO_x, PM10) emissions

reference studies are mainly based on the traditional WTW emission calculation approach reported in Edwards et al. (2011) and on the methodology described in the 2009/28/EC Directive (RED methodology) for the assessment of emissions from biofuel quotas. We have integrated these data with American data sources which make use the GREET methodology (Wang 2001) and of a hybrid approach (Ercan and Tatari 2015), respectively, and used this information to derive parametric data about the impact of the manufacturing and replacement of batteries and charging stations. The choice we made was mainly based on to the paucity of data regarding the environmental impact of manufacturing charging stations, and on our desire to enable a comparison at least in terms of relative orders of magnitude.

On the other hand, emissions from vehicle construction were not included in the analysis, which is equivalent to the assumption that they are independent of the technology implemented. This is a limitation of our study, which could be overcome by future research gathering relevant experimental data and by elaborating specific life cycle inventories.

As a result, the assessment of WTT carbon equivalent emissions is achieved for battery electric buses according to Eq. 20:

$$\begin{aligned} CO_2eq_{WTT}(el) = {} & NB(el) \cdot \frac{co_2eq_{WTTbatt}(el)}{durationbatt(el)} \\ & + \sum\nolimits_l n_{trip}(l) \cdot t_{trip}(l) \cdot TUS(l, el) \cdot cons(el) \cdot co_2eq_{WTTfuel}(el) \cdot dy \\ & + \sum\nolimits_s \frac{co_2eq_{WTTstat}(el)}{durationstat(el)} \cdot NP(s, el) \end{aligned} \tag{20}$$

3 Case study and scenarios

At the time of the research, the regional bus transport company investigated as a case study was operating in the South Eastern part of Friuli Venezia Giulia, an Italian region close to the border with Slovenia. The following sections describe the situation of the bus transport service, report the technical and economic data used for the analysis, and summarize the scenarios examined in this study.

3.1 Case study description

As shown in Fig. 2, which represents the route network in black and bus stops as red dots, the company was responsible for bus transport over an area of about 2400 km^2. On average, extra urban buses operate for 19 h a day and 280 days a year, with a total average distance travelled of about 4.2 millions km/year.

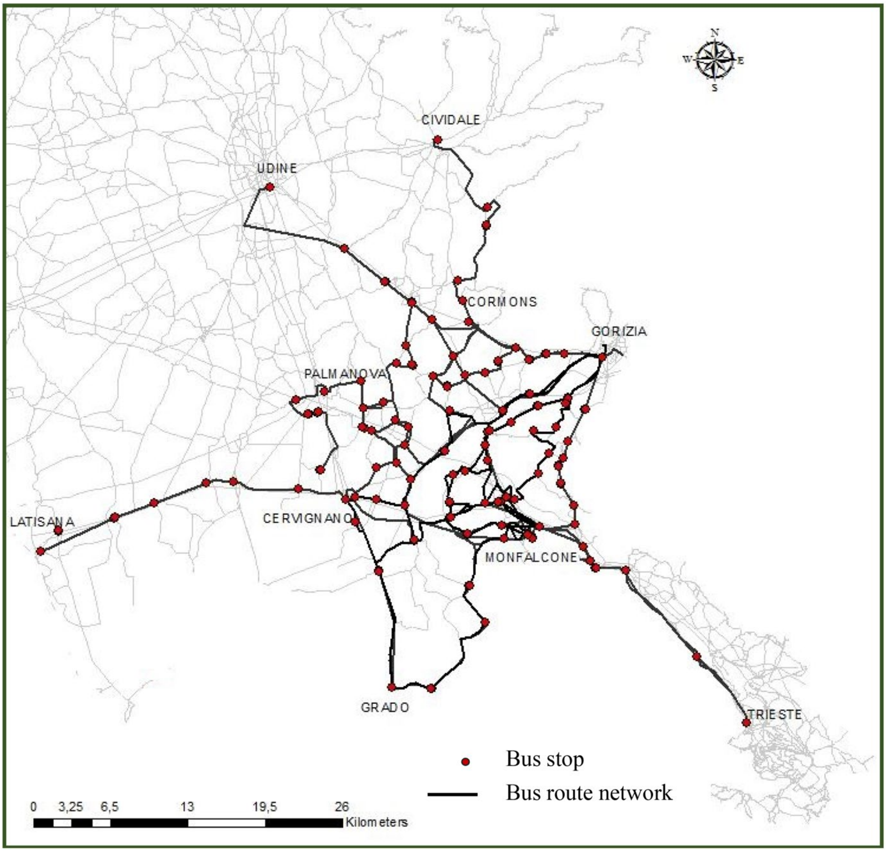


Fig. 2 Map of extra urban bus network and stops

As shown in Table 2, routes are very diverse: they vary in length between some 20 and some 80 km, and the number of services may be very different between different routes, ranging between as little as 1 round trip per day to more than 50 round trips per day. Idling stops at end stations last on average 25 min, whereas two minutes is the idling time generally scheduled for each intermediate bus stop.

The current fleet is made up of diesel vehicles of various Euro emission classes. It was agreed with the technical staff of the company that the current fleet could be roughly considered as a Euro V fleet, as far as fuel economy and emissions are concerned.

3.2 Technical and economic data

The technical and economic data used for the analysis are summarized in Table 3. An agreement was reached with the company administration that a reasonable time horizon for the analysis is $n=15$ years, and $i=8\%$ is an acceptable interest rate. Batteries are assumed to last 5 years (Rothgang et al. 2015; Zhang et al. 2020), thus manufacturing and two replacements are included in the analysis for BEV based options. It must be noted that the capital outlay for BEVs is about 50% higher than that for CNG buses (excluding the cost of batteries), while inversely, the cost of CNG fuelling stations is about 50% higher than for electric fast charging stations. Based on previous studies (Büyüközkan et al. 2018) the cost of CNG filling stations is assumed to be substantially lower when high pressure natural gas transport pipelines exist within proximity of possible locations, as this makes it possible to avoid the additional compression of natural gas required to obtain CNG from low pressure natural gas distribution networks. Low pressure natural gas distribution is available in all the urban centres in the area under consideration.

Table 2 Energy, environmental, and capacity indicators for the existing bus system

Total fuel consumption [MWh/year]			19,262
Total WTW CO_2eq emissions [t/year]			6012
Total NO_x emissions [t/year]			28.6
Total PM10 emissions [t/year]			0.5
Number of buses			51
Number of routes (round trips)			18
	Median	Min	Max
Round trips per route per day	6	1	56
Route length (one way) [km]	36	18	77
Trip duration (one way)[min]	59	25	110

Table 3 Technical and economic data of existing and alternative buses

Parameter	Unit	Propulsion system				Source
		Diesel V	Diesel VI	CNG VI	BEV	
Energy consumption	kWh/km	4.6	4.1	5.2	1.5	(Xylia et al. 2017; Civitas 2016; Lindgren 2015; GTT 2017)
Vehicle energy capacity	kWh	3195	3195	3060	60–120	(Xylia et al. 2017; Nylund 2014; GTT 2017)
Urea consumption	l/km	–	0.02	–	–	(Nylund and Koponen 2012)
Minimum state of charge (SOC_{min}) for batteries	–	–	–	–	15%	(Marcon 2016)
Capacity of charging station	kNm^3/y (CNG) kW (electricity)	–	–	700	300	(Xylia et al. 2017; Chinese et al. 2014)
Capital cost of charging station	€	–	–	358,802 (HP*) 433,719 (LP*)	211,500	(Xylia et al. 2017; Chinese et al. 2014)
O&M costs of charging station	€/y	–	–	26,831	4230	(Lindgren 2015; Chinese et al. 2014)
Rate of charging	kWh/min	898	898	222	5	(Xylia et al. 2017; Emiliana Serbatoi 2017; Galileo Technologies 2020)
Capital cost of bus	€	–	240,000	260,000	390,000	(Lajunen and Lipman 2016; Xylia et al. 2017; Sen et al. 2017)
Capital cost of battery	€/kWh	–	–	–	1000	(Xylia et al., 2017; California Air Res. Board 2016)
Maintenance cost of bus	€/km	0.13	0.15	0.17	0.14	(Nylund and Koponen 2012; Lajunen 2014)
Fuel/Energy cost	€/kWh	0.12	0.12	0.07	0.15	(APT 2017; Rothgang et al. 2015)
Cost of urea	€/l	–	0.5	–	–	(Nylund and Koponen 2012; GTT 2017)

*For the capital costs of CNG refuelling stations, HP indicates that the station is served by a high pressure natural gas network within a radius of 500 m, LP that there is only a low pressure gas distribution network

3.3 Definition of emission constrained scenarios

In order to compare alternative options to improve the environmental performance of the bus network, following scenarios have been defined:

Business as Usual (BAU): in this scenario, the current situation is reproduced by running the model for the Diesel V technology only, in order to estimate the number of buses, energy consumption, emissions and costs. For the sake of comparison, it is assumed that the fleet will operate for fifteen years at the maintenance costs indicated, and that engine performance will not vary over time. It is assumed that existing fuelling stations are to be used for the whole period, and the initial capital costs of diesel fuelling stations, as well as those of the fleet, are to be treated as sunken costs and set to zero. The scenario is developed exclusively for reference and comparison: maintaining current Diesel Euro V buses or purchasing used vehicles are not considered as a feasible option for any of the emission reduction scenarios defined as follows.

50% CO_2 emissions: in this scenario, total yearly WTW carbon equivalent emissions are constrained to be lower or equal to half of the WTW carbon equivalent emissions calculated in the BAU scenario. Here and in all environmental improvement scenarios, the technologies considered for optimization include Diesel Euro VI buses, CNG Euro VI buses and battery electric buses with either a 60 kWh battery or a 120 kWh battery.

Minimize CO_2 emissions: in this scenario, WTW carbon equivalent emissions are minimized.

50% NO_x emissions: in this scenario, total yearly TTW NO_x emissions are constrained to be lower or equal to half of the TTW NO_x emissions calculated in the BAU scenario.

50% PM10 emissions: in this scenario, total yearly TTW PM10 emissions are constrained to be lower or equal to half of the TTW PM10 emissions calculated in the BAU scenario.

4 Results and discussion

The model was implemented according to the flowchart reported in Fig. 3, which also indicates the software tools used for the implementation. Spatial information—including the bus transport network topology represented in Fig. 2, and the topology of the regional natural gas transport networks (Chinese et al. 2014)—has been pre-processed in ArcGIS Desktop 10.5.1 (ESRI 2017). We have thus been able to calculate spatially-explicit input data, including the distances between stops as well as the cost functions for CNG fuelling stations (which depend on the Euclidean distance between each potential refuelling stop and the closest HP natural gas transport network). In the data processing phase, we have also integrated the bus timetables, made available by the bus company as Excel spreadsheets, with the spatial information. In this way, we have been able to evaluate the input data that depends on both the bus schedule and the location of stops. That is the case of the binary indicator for the risk of simultaneous recharging at the

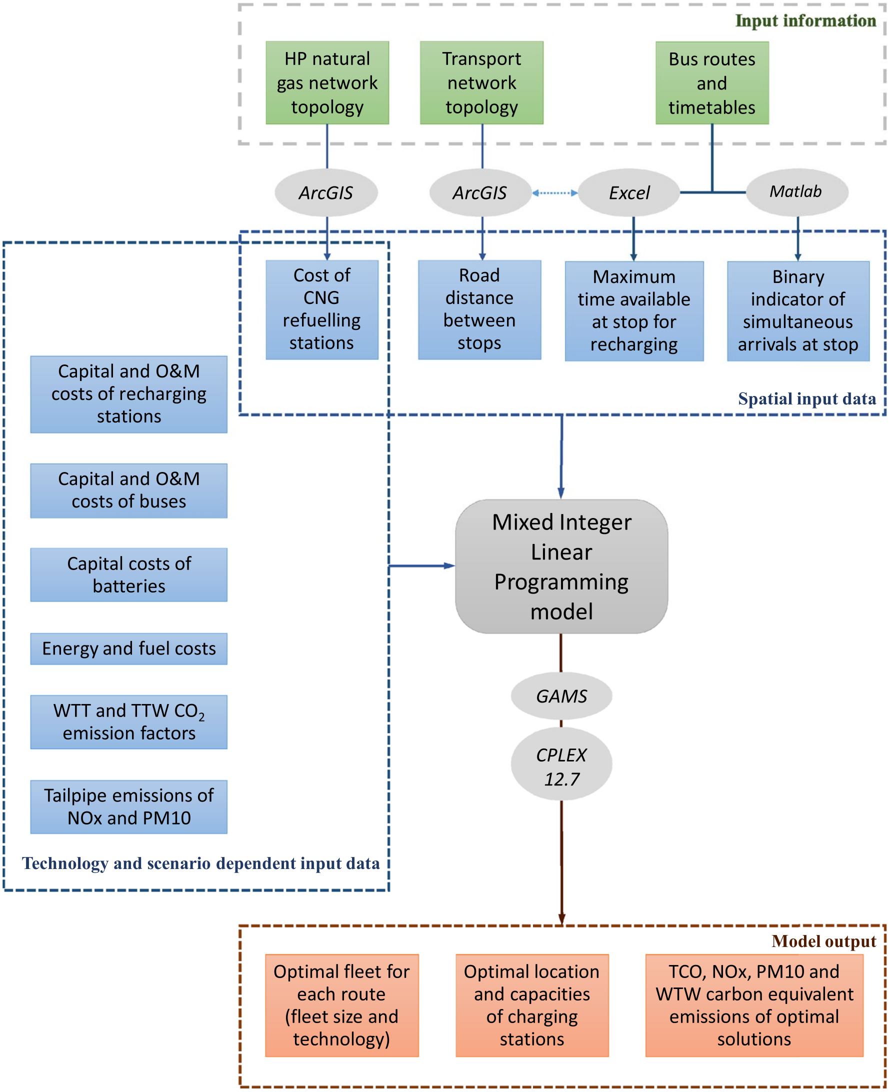


Fig. 3 Flowchart of model calculation processes and software tools used

same stop *c(s)*, which was calculated as described in Sect. 2.2.2. by developing a Matlab script, as well as of the maximum time available at each stop for recharging $t_{charge}(s,t)$, which is estimated as the minimum idling time scheduled at the given stop *s* in any reference-day. The Mixed Integer Linear Programming model was implemented in GAMS, and solved with CPLEX 12.7 (McCarl et al. 2008) for each of the emission constrained scenarios defined in Sect. 3.3. Additionally, technology dependent input data subject to uncertainty have been changed to perform a worst/best case scenario analysis as specified in Sect. 3.4. Computational times on a i7 PC were reasonable, reaching about two hours for the most complex scenarios.

4.1 Optimal system configurations under different emission reduction scenarios

Table 4 shows the fleet composition and the mix of technologies used along the routes in the developed optimization scenarios. It can be deduced that, under the constraint of reducing NO_x emissions alone, the use of Euro VI vehicles instead of the current fleet is, in the main, sufficient for achieving *NO_x* emission reduction targets. The *50% NO_x* scenario in this way corresponds to a full Euro VI scenario without any other technologies.

In order to achieve *50% PM10* emission reduction targets, however, the use of new Euro VI buses alone is not sufficient. For that purpose, the introduction of CNG buses is preferred, which, even accounting for new refuelling stations, are less expensive than the outlay required for battery electric technologies on the network under consideration.

Figure 4 shows the allocation of fuels and infrastructure to the routes of the network in the 50%PM10 scenarios. The routes of the CNG bus network are marked in blue, whereas Euro VI Diesel buses are used on the routes marked in black. Three CNG fuelling stations (red dots in Fig. 4) are introduced at three end stops. The six routes to which CNG is allocated are relatively short routes with a high number of junctions, and an average or above average trip frequency. Having set an emission constraint with a cost minimization objective, the optimal configuration allocates CNG to a restricted number of routes where the need for refuelling stations is minimum and the fuel consumption is particularly high.

Table 4 Optimized allocation of vehicles and technologies to routes in BAU and emission reduction scenarios

	Propulsion system	Scenarios				
		BAU	– 50% CO_2eq	Min CO_2eq	– 50% NO_x	– 50% PM10
Number of buses	Diesel V	51	–	–	–	–
	Diesel VI	–	31	–	51	30
	CNG VI	–	–	–	–	21
	BEV 60 kWh	–	10	–	–	–
	BEV 120 kWh	–	10	51	–	–
Number of routes	Diesel V	18	–	–	–	–
	Diesel VI	–	5	–	18	12
	CNG VI	–	–	–	–	6
	BEV 60 kWh	–	11	–	–	–
	BEV 120 kWh	–	2	18	–	–
Number of charging stations	CNG VI	–	–	–	–	3
	BEV 60 kWh	–	17	–	–	–
	BEV 120 kWh	–	7	28	–	–

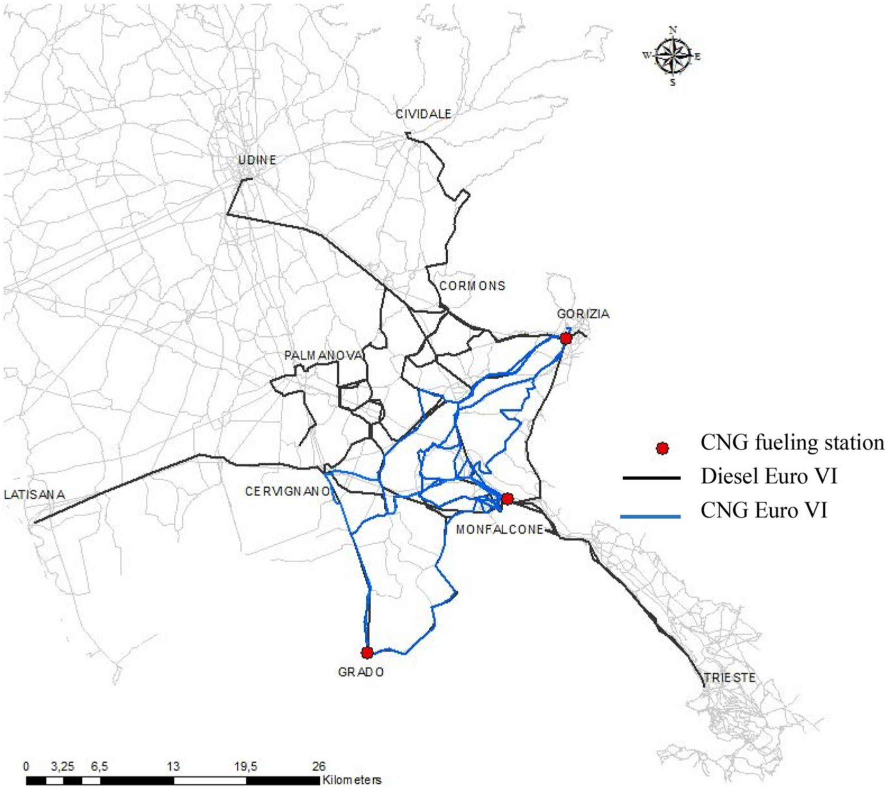


Fig. 4 Map of optimal system configuration for—*50% PM10* scenario

Table 1 shows that the TTW carbon emission performance of CNG Euro VI buses in terms of carbon equivalent emissions may be worse than that of corresponding Diesel Engines, mainly due to the GWP associated with uncontrolled leaks of CH_4.

For this reason, a combination of BEV and Euro VI Diesel is preferred when targeting 50% carbon equivalent emission reduction.

Since the current mix of electricity generation in Italy includes mainly fossil fuel sources (Donateo et al. 2015), more routes need to be electrified to achieve a 50% carbon emission reduction target. In Table 4 and Fig. 5 it can be seen that 13 routes are electrified to halve carbon equivalent emissions at minimum costs (whereas serving only six routes with CNG was enough to achieve a 50% PM10 emission reduction). The optimization tends to favour routes with a relatively lower trip frequency than in the *50% PM10* scenario, in order to keep the number of costly vehicles to a minimum. Longer routes are generally preferred for electrification in the *-50% CO_2* scenario, even though this would require as many as 24 recharging stations. Due to the high cost of storage, 60 kWh systems are generally preferred, apart from the two longest routes (in red in Fig. 5), to which ten 120 kWh battery electric (BE) buses and seven charging stations are assigned.

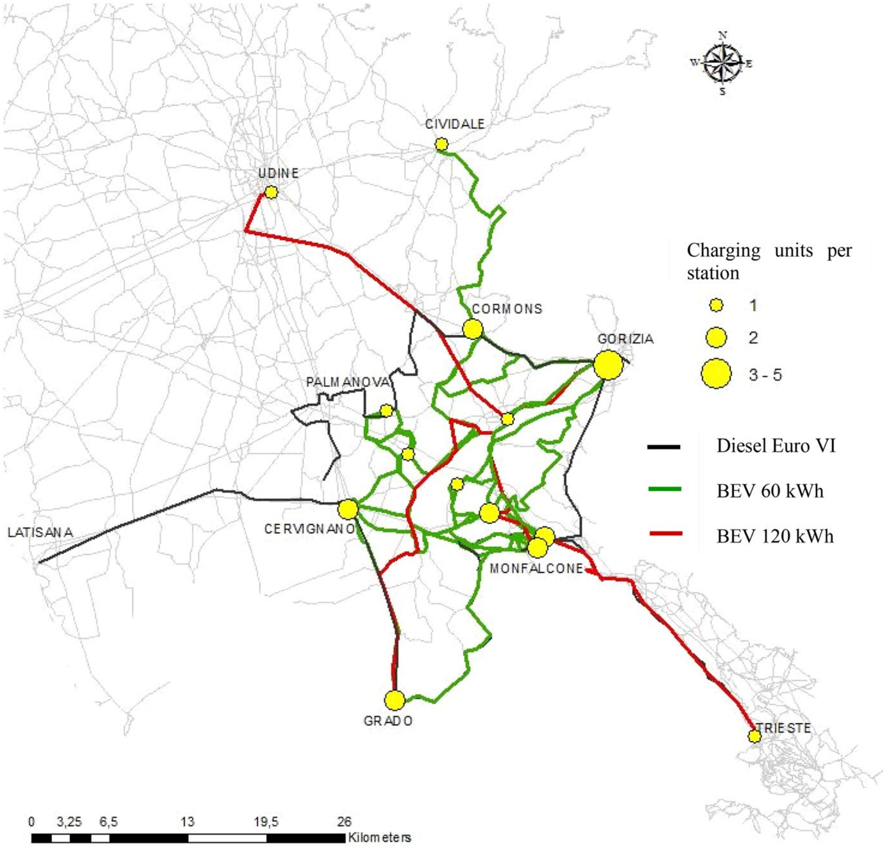


Fig. 5 Map of optimal system configuration for—*50% CO_2eq* scenario

60 kWh electric storage is generally preferred due to the high cost of batteries, but in the "*Minimize CO_2eq emissions"* scenario, in which all routes are electrified, 120 kWh batteries are selected exclusively. In fact, energy consumption being equal, the use of larger storage systems lowers the emissions of GHG on a WTW basis by limiting the requirement for and number of charging systems, whose contribution to WTW emissions is significant.

4.2 Economic performance

That batteries are a main cost component is confirmed by the economic results displayed in Fig. 6, where annual equivalent systems cost for each scenario are compared. The investment required for batteries is greater than that required for charging stations, in particular, more than double that when 120 kWh batteries are selected exclusively. Together with the high cost of battery electric vehicles, which represent the main cost component in the *-50% CO_2 emissions* scenario, this makes electric

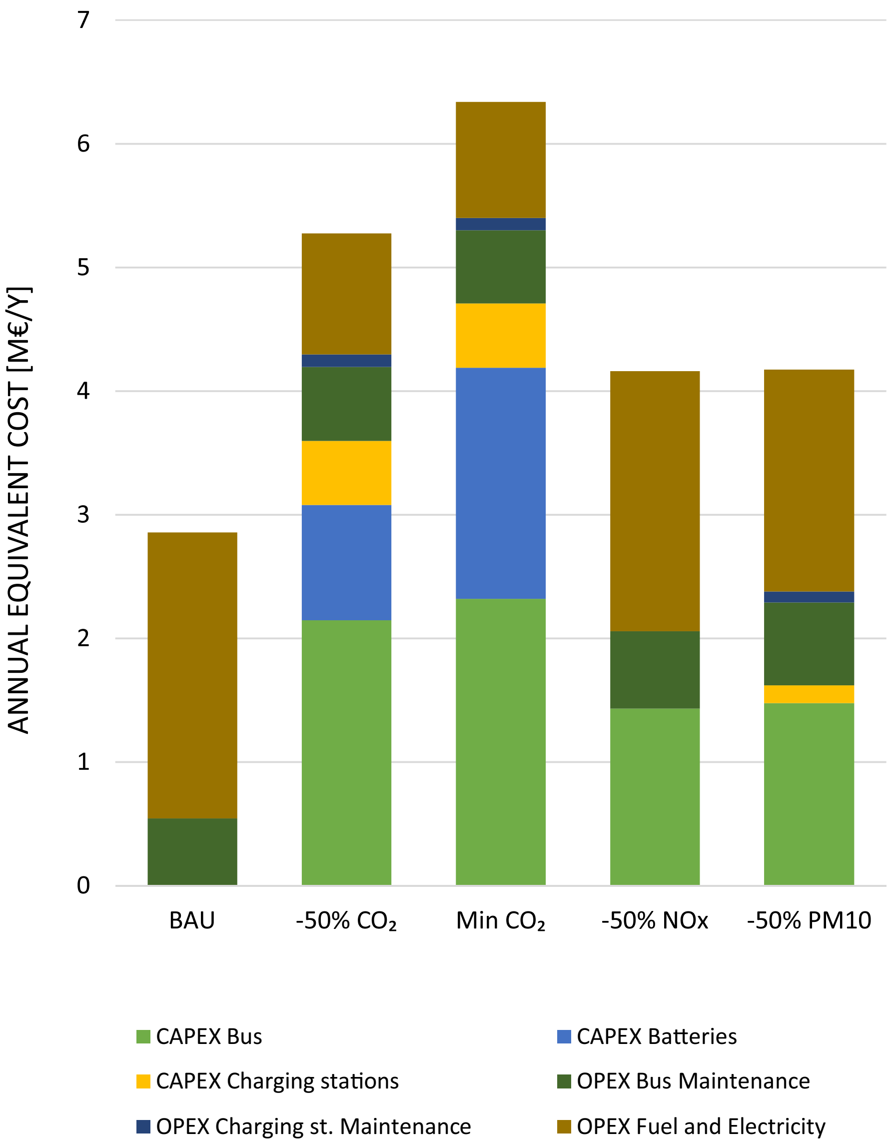


Fig. 6 Annual equivalent system cost for BAU and emission reduction scenarios

vehicle based systems between 25 and 50% more expensive than an entirely new Euro VI bus fleet, depending on the scenario. While the price of electricity (see Table 3) may be deemed relatively high, and corresponding cost share figures are significant, Fig. 6 shows that even if electricity costs were zero, electrified systems (*Min* CO_2 and—*50%* CO_2 emissions scenarios) would be barely competitive with Euro VI or CNG based scenarios.

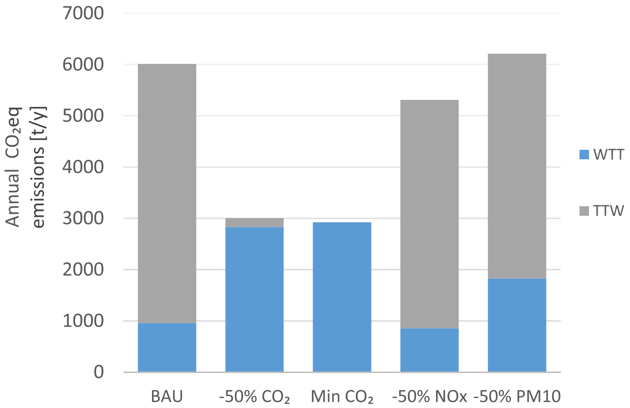
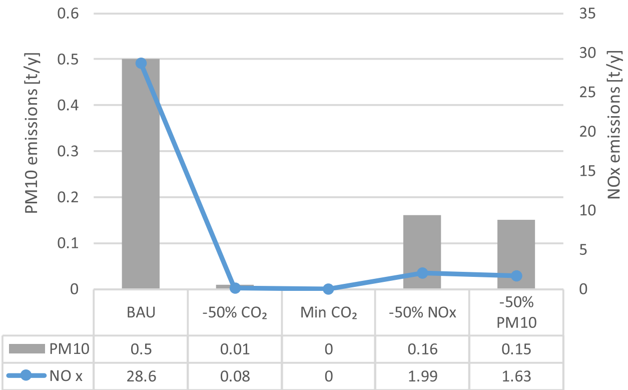


Fig. 7 Annual CO_2 equivalent for BAU and emission reduction scenarios



	BAU	-50% CO_2	Min CO_2	-50% NOx	-50% PM10
PM10	0.5	0.01	0	0.16	0.15
NO x	28.6	0.08	0	1.99	1.63

Fig. 8 Annual NO_x and PM10 emissions for BAU and emission reduction scenarios

4.3 Environmental performance

In terms of CO_2 emissions, even fleet renewal with Euro VI vehicles alone brings about some reduction from BAU, as can be seen in Fig. 7.

Figure 8 shows that the emissions of other pollutants in the *50% NO_x* (Diesel only) and in the *50% PM10* (with CNG) are actually very similar, while they are assumed to be null for electric vehicles, as highlighted in *Minimize CO_2* and *50% CO_2 emissions* scenarios. On the other hand, Fig. 7 also shows that the use of CNG in the *50% PM10* scenario causes an increase in the emissions of GHG even compared with the *BAU* scenario.

The gap is larger when WTW pathway is considered because of WTT related GHG emissions, which mainly occur along the natural gas supply chain and partly for the construction of fuelling stations. While the impact of fuelling or recharging stations may well be uncertain due to lack of data, as discussed above, the results nevertheless confirm that it should at least be investigated for new systems implying the construction of additional infrastructure.

In Fig. 9, a parametric analysis shows the correlation between the environmental benefits of GHG emission reductions in the system studied and the system costs.

The carbon equivalent emission reduction constraint is gradually changed between 11%, which is the maximum reduction achieved by sheer Diesel fleet renewal (represented as a grey square in Fig. 9), and 51%, which is the maximum reduction, achieved with full network electrification in the *minimize CO_2 emissions* scenario (red triangle in Fig. 9). All the intermediate scenarios thus obtained (green dots in Fig. 9) envisage a mix of Euro VI Diesel and battery electric buses.

Additional annual equivalent costs compared with the *BAU* scenario are divided by total emission reduction from the *BAU* scenario, thereby enabling us to calculate the average costs of CO_2eq reduction through optimization of the inter urban regional network of our study. Such costs range between 670 and 1920 €/tonCO_2eq, which is elevated compared with e.g. the implicit carbon price of some renewable energy sources (Marcantuoni and Ellerman 2015) or even with carbon capture costs (see e.g. Mandova et al. 2019 for an industrial application).

Nevertheless, the overall analysis of the scenarios has confirmed that electrification is technically feasible even at the inter-urban, regional scale examined in the present study.

Figure 9 highlights that the average cost of CO_2 abatement for the bus transport system would be maximized by a fleet renewal with Euro VI buses, due to the small reduction in carbon emissions which would be achieved. The minimum average cost is achieved by electrifying the four routes which produce the highest emissions while using Euro VI buses on the remaining routes. A carbon emission reduction of about 44% from the BAU scenario is thus achieved. By electrifying additional routes, carbon equivalent emissions are further reduced, but average CO_2 abatement costs rapidly increase. Overall, aiming at full electrification brings about very limited benefits (see also Fig. 7) at significant additional expense. For a rational planning of fleet and infrastructure deployment, spatially explicit optimization models with an environmental perspective can thus be very useful in directing investment of resources to routes which provide greatest benefits in terms of outlay vs reduction in emissions.

4.4 Sensitivity analysis via worst/best case scenario analysis

The uncertainty inherent in the various estimates of optimization model parameters might be addressed by a sensitivity analysis.

For this purpose, we chose to perform a worse-best case scenario analysis, cited by EC (2017) in the "Better regulation toolbox" as the first potential approach to testing the sensitivity of the final outcome to changes in parameters. Worse/best case scenario analysis is performed by adopting all of the most conservative and all of the least conservative values for the parameters used in the calculation of performance indicators.

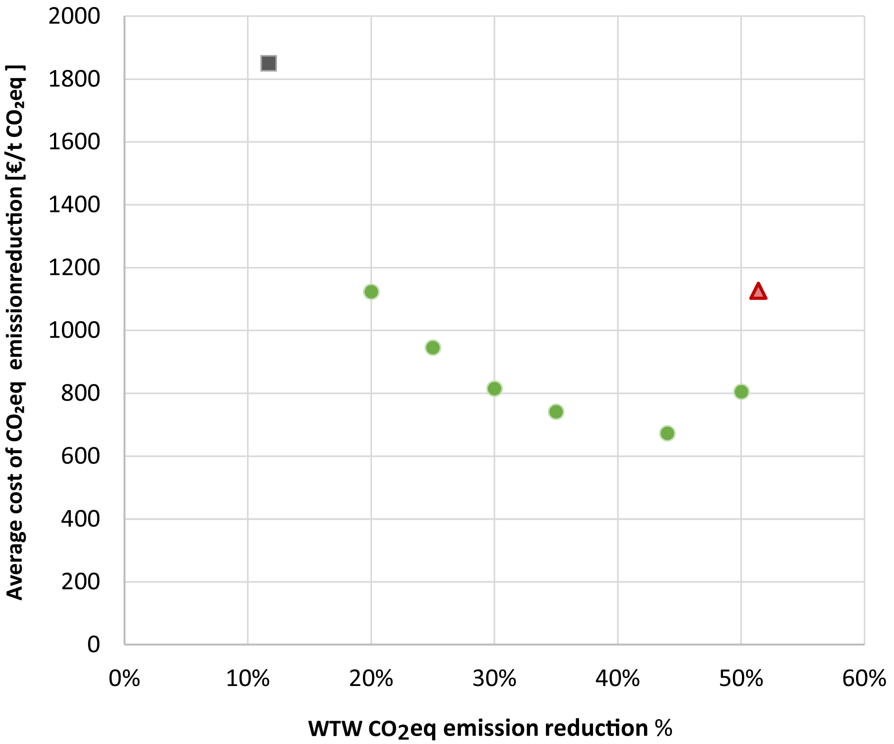


Fig. 9 System average cost of CO_2 equivalent emission abatement depending on achieved reduction percentage

In this study, we performed a worst/best case scenario analysis to determine how the objective function (annual equivalent system costs) and the optimized system configuration (the number of routes served by buses with alternative powertrains) were affected by extreme changes in uncertain parameters. Scenarios were run, using values identified in literature (see Table 5), in which parameters ranged between extremes –more specifically, the most conservative (worst) and the least conservative (best)—for assessing investments in alternative powertrains.

For instance, high costs of CNG and electricity with relatively low diesel oil prices are the most conservative conditions, and are therefore incorporated in the worst-case scenario. On the other hand, the technical and economic values reported in Table 3 are generally in the middle of the range, and are assumed to be the most likely values which correspond to our case study. To test the sensitivity of the model, we performed an unconstrained least-cost optimization, i.e. without the emission reduction constraints described in the scenario definitions above. The results show that Euro VI Diesel buses are the least cost option for re-fleeting in both the worst case and the reference case scenario. In the best case scenario, electric buses with 60 kWh batteries would be preferred on almost all of the 18 routes, with only six routes served by 12 Euro VI Diesel vehicles.

These six routes represent just about 4.3% of the total yearly travelled distance on the bus network. Figure 10 reports the breakdown of the annual equivalent systems costs for the best, worst, and reference case. To give a better insight into what would make alternative powertrains, particularly electric vehicles, competitive with traditional technologies, an additional optimization run is performed by forcing the system to adopt electric buses with 60 kWh batteries on all routes, under worst, reference, and best case conditions. The cost breakdown of this additional, all electric system configuration is also plotted in transparent colours in Fig. 10, from which it is possible to gauge how the costs of batteries and charging stations are subject to the greatest uncertainty, and in worst case conditions make the total system cost of electric buses more than twice as the corresponding Euro VI bus based system costs. Comparison of the optimized and the all-electric configurations under best-case conditions confirms the usefulness of optimization models in identifying uneconomical routes and disregarding these for electrification. Full electrification would increase annual costs by about 9% compared to the optimized configuration. This is mainly due to the additional costs of batteries and recharging stations, which cannot be offset by lower energy cost on such marginal routes due to lower usage, and therefore limited possibility of amortization.

5 Conclusions

There are several environmental and economic factors that need to be evaluated in the strategic planning of alternative propulsion systems for local public transport systems. In this paper, a bus network optimization model for the design of intercity bus transport networks in less intensely served rural areas has been presented. The model was developed to treat the number of vehicles as a decision variable, in order to simultaneously address bus fleet optimization issues. Compared to the multitude of planning models for electric charging stations which have emerged in recent years, the singularity of this approach is in the simultaneous evaluation of several alternative technologies, both electric and fossil-fuel based, conventional or otherwise, which makes the model particularly suitable for strategic network planning. In this study, the model was applied simultaneously to multiple possible scenarios, which led to the deployment of CNG fuelling stations, to the identification of optimal location for electric conductive charging stations, and to the identification of the least-cost fleet composition. Two battery size classes for electric buses were considered, as was the option of next-generation conventional diesel buses.

Being directed to the integrative assessment of several alternative technologies in a long-term perspective, the model also incorporates environmental impact indicators in the form of emission reduction constraints. In our study, a well-to-wheel carbon dioxide equivalent emission assessment based on Italian conditions has been included, as have tailpipe emissions of NOx and PM10, whose impact on local air pollution is of specific concern for local authorities.

Table 5 Optimized allocation of vehicles and technologies to routes in BAU and emission reduction scenarios

Parameter	Unit	Best case	Worst case	Data source
Fuel/Energy price				
Diesel oil	€/kWh	0.14	0.1	Rothgang et al.(2015); APT(2017)
CNG	€/kWh	0.06	0.09	Chinese et al. (2014); Arteconi and Polonara, (2013)
Electricity	€/kWh	0.10	0.2	Pihlatie et al. (2014); Lajunen (2014); APT (2017)
Capital cost of bus				
Diesel Euro VI	€	265,000	225,000	Ercan et al. (2015); Lajunen (2014); Mahmoud et al. (2016)
CNG Euro VI	€	247,500	285,000	Ercan et al. (2015); Lajunen and Lipman (2016)
Electric	€	300,000	420,000	Ebusplan (2018); Rothgang et al. (2015); Kunith et al. (2017)
Maintenance cost of bus				
Diesel Euro VI	€/km	0.17	0.13	Nylund and Koponen (2012); Ally and Pryor (2016)
CNG	€/km	0.15	0.22	Ally and Pryor (2016
Electricity	€/km	0.11	0.16	Pihlatie et al. (2014); Mahmoud et al. (2016)
Battery cost and number of batteries used over lifetime				
Capital cost	€/kWh	800	1200	Pihlatie et al. (2014); Ebusplan (2018); Rothgang et al. (2015
Number of batteries	–	2	4	Lajunen and Lipman (2016); Rothgang et al. (2015); Zhou et al. (2016)
Capital cost of electric charging stations				
Capital cost	€	180,000	320,000	Lindgren (2015); Kunith et al. (2017)
Maintenance cost	€/y	3600	6400	Lindgren (2015)
Capital cost of CNG refueling stations				
Variation from reference case	–	– 10%	+ 20%	Own assumption
Fuel economy				
Diesel Euro VI	kWh/km	5.5	3.6	GTT (2017)
CNG Euro VI	kWh/km	4.5	6	Xylia et al. (2017); Khan et al. (2015)
Electric Euro VI	kWh/km	0.9	2.3	Xylia et al. (2017)

Based on case specific results, obtained here from the application of the model to a regional bus service which manages 18 routes between towns in North Eastern Italy, some policy conclusions can be drawn:

- Trade-offs between different environmental impact reduction objectives emerge frequently when considering different transport alternatives. In our study, this was the case with CNG, which, even accounting for the costs of dedicated refuelling stations, proved to be an economically attractive option when considering the reduction of air particulate, even though CNG vehicles don't perform as well as state of the art conventional diesel buses with regard to emissions of greenhouse gases. One should make decision makers aware of the fact that alternative powertrains or fuels are not equally favourable from every point of view. In this respect, a particularly desirable feature of the model is the simultaneous assessment of various emissions with an extended WTW approach, as well as of costs of outlay and management.
- The analysis of cost trends for carbon emission reduction has confirmed that the potentials of electric propulsion as a decarbonisation option for bus transport are striking, reaching up to as much as 50% in our case-study. When considering environmental benefits vs costs, such potentials are, however, limited by the high capital costs of electric systems. At present electricity prices in Italy make battery electric fleets much more expensive than corresponding conventional propulsion systems (e.g. between 27 and 52% more expensive than Euro VI diesel bus systems, for the case study analysed). If the transition of regional transport to low-carbon systems is sought, policies centred on carbon pricing or carbon taxes would be insufficient or inapplicable, as carbon emission abatement costs related to bus transport are well beyond current and expected carbon prices. Significant specific incentives would then be needed, which could be justified in view of the additional advantages of some technologies in other environmental dimensions. The model proposed in this paper could also be used to guide and support local policy makers in devising targeted incentives such as capital grants or exemption from some energy taxes.
- Especially when support schemes apply, decision makers should give preference to the electrification of the routes most favourable from a cost/benefit point of view, which are more easily identified with the help of the model developed. Minimum support should be given to next generation diesel vehicles, which—when using adequate shares of sustainable biofuels—might nevertheless contribute to the decarbonisation of bus services on marginal routes.
- Joint fleet and network optimization is particularly needed for electric bus fleets, not only because of the costs and local impact of recharging infrastructure, but especially given the initial high outlays for vehicles and batteries: the latter have been found to account for up to 30% of annual equivalent system costs in extreme emission reduction scenarios, where even the longest intercity routes are converted to electric power by increasing the use of high capacity batteries.

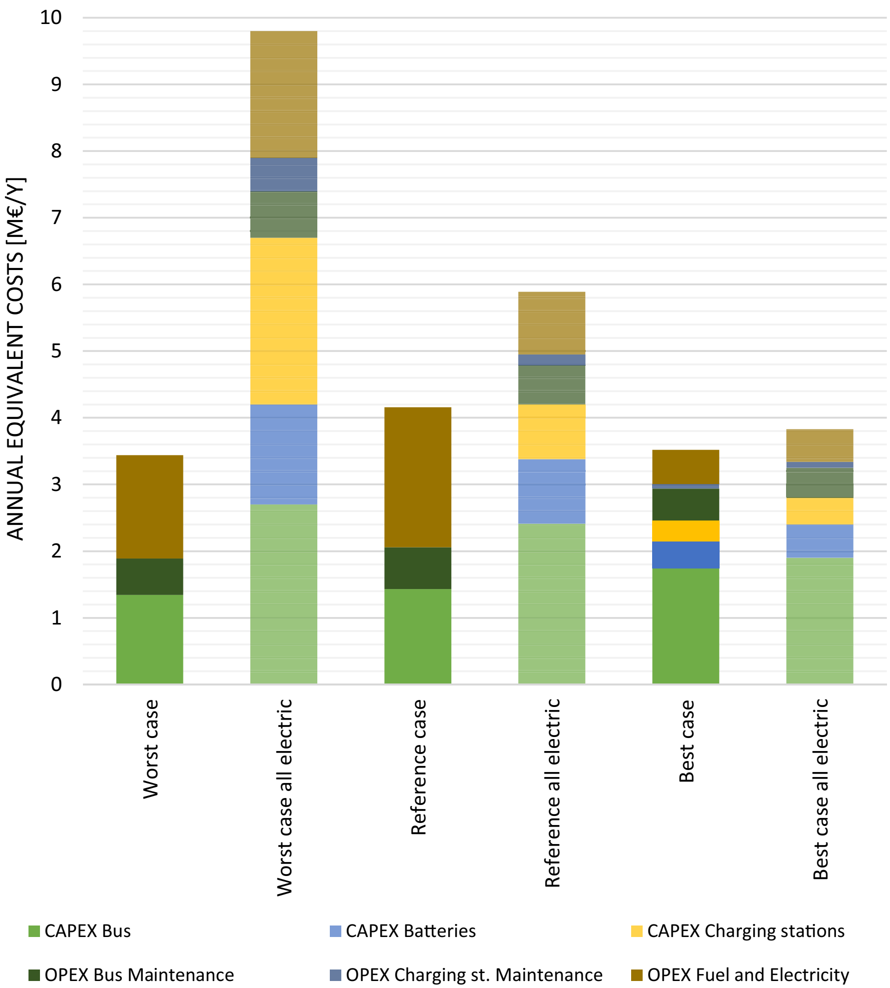


Fig. 10 Annual equivalent system costs for unconstrained, cost optimized configurations and for 60 kWh, all electric configurations under worst-, reference-, and best-case conditions

In this respect, it is plausible that the use of information from the literature and databases, although well documented, might have influenced the results obtained. To improve the accuracy of the model, future developments would benefit from integrating more detailed and realistic models of driving cycles and of energy storage systems aging, in particular, given the significant impact of batteries on the economic and environmental impact of electric bus fleets.

The model application has also confirmed that the environmental impact of manufacturing charging and/or refuelling stations may be limited, but is not inconsequential. It is recommended that the carbon footprint and the environmental impact of recharging stations of various technologies is investigated in specific LCA studies. Data and inventories on the structure and efficiency of alternative charging systems are particularly needed to compare alternative options such as battery swapping or hybrid electric buses.

In future research, the model developed may also be easily extended to incorporate alternative fuels such as first and second generation biofuels for conventional internal combustion engines, or even hydrogen to drive fuel cells; the only limitations being the model size and complexity, and computational times depending on bus network sizes. Based on the outcomes of the current analysis, which considered emission reduction targets separately, incorporating the model into a wider, multi-criteria or multi-objective framework would be an interesting direction for future research.

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Declaration

Conflict of interest The authors declare that they have no conflict of interest.

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