Optimizing the selection of sustainable transport technologies at regional bus companies with a spatially explicit approach

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ABSTRACT

Buses account for almost 60% of the total public transport offer in Europe, and most of them are diesel fuelled. Regional transport companies, pressed by governments to introduce zero-emission buses to reduce air pollution, need tools to identify optimal solutions. In literature, few models combine least cost planning and emission assessment for multiple technologies. In this paper, an existing localisation model for electric urban transport is adapted to match the needs of regional transport and to evaluate well-to-wheel carbon emissions as well as TTW airborne emissions of NOx and PM10. The model is applied to a real case study of a regional bus transport company in North Eastern Italy. Electric buses with relatively small (60 kWh) batteries are identified as the best compromise to reduce CO2eq emissions, however, under current economic conditions in Italy, their life cycle cost is still much higher than those of Euro VI diesel.

KEYWORDS

Transportation, Electric buses, CNG buses, Recharging, Location analysis, Well-to-Tank, Thank-to-Weel, Optimization

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 [1]. According to the International Association of Public Transport, buses account for 50-60% of the total public transport offer in Europe [2] and, according to a recent survey [3], 79% of operational vehicles are diesel fuelled. In spite of more and more restrictive standards on diesel engine emissions, with Euro VI coming into force in 2014, diesel buses contribute to urban air pollution, and local governments call for the introduction of zero-emission buses (ZEB). Local authorities mostly view ZEB as a means to reduce local air pollution, rather than carbon emissions [4].

According to an international survey on local bus operators [3], more than 40% of the respondents want to move towards more electric vehicles, 28% want to change in favour of more CNG, and 13% towards more biogas. Obviously, each of these choices has different economic and environmental implications, and some of them are not explicitly evaluated by local governments or by managers, whose perceptions have been demonstrated to be different from reality in many cases [3]. To enable informed decision making for public transport, decision support tools may be of help, particularly when the transition to ZEB has to be complemented with the development of appropriate but capital cost intensive charging infrastructure, and multiple technology options should be considered.

To compare different technology options, several approaches are adopted in literature.

Life cycle assessment, mainly in the form of fuel cycle or well-to-wheel (WTW) analysis [5], is one of the earliest and most commonly applied methods to evaluate the environmental impact of alternative fuels and powertrains for buses [6]. The WTW analysis of a vehicle/fuel system covers all stages of the fuel cycle—from energy feedstock recovery (wells) to energy delivered at vehicle wheels (wheels). For recent reviews one can refer to [7] for WTW analysis and to [6] for more comprehensive LCA approaches.

Well-to-wheel analysis has usually been complemented by life cycle costing to obtain more comprehensive cost-benefit analyses [8]. The performance indicators calculated with these approaches are sometimes incorporated in more comprehensive frameworks, such as external cost frameworks [9], multicriteria frameworks [10], fuzzy models [11], probabilistic models [12], and optimization approaches [13]. Among the latter, Durango-Cohen and McKenzie, [13] 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 NOx emissions, on the other hand. As observed in [12] in most cost-benefit analyses individual routes or driving cycles are taken as reference (see e.g. [9][10]); often, also one reference vehicle at time is considered. [12] 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 [13], fleets are considered, rather than individual reference vehicles, but it is assumed that fuelling issues, including cost and impacts of fuelling infrastructure, do not affect the fleeting problem. We agree that this is definitely true for traditional fuels, or anyway for fuels and technologies compatible with existing fuelling stations, e.g. biodiesel. However, this may not be the case for alternative fuels, e.g. hydrogen or biogas, which need dedicated, capital intensive infrastructure to be installed by bus companies.

In line with [12], we argue that recharging issues should be considered in cost-benefits analyses and handled at a fleet level particularly for battery electric buses, which were actually not examined in [13]. In fact, for electric buses, and for electric vehicles in general, the need to install new, capital intensive charging infrastructure is exacerbated by the cost and the limited range of batteries, range anxiety [14] and by the uncertainty about the cost effectiveness of alternative or complementary charging technologies (e.g. inductive, conductive, battery swapping [15]). Indeed, on this background, and envisioning a rapid development of battery electric vehicles and an increasing maturity of fast charging technologies in the near future, a large body of literature has been devoted to investigating the optimal deployment plans of battery charging infrastructure, particularly to serve commercial EVs such as buses. One should refer to [16] for a recent comprehensive review about EVs in general and [17] for a recent review about buses, in particular. From those reviews, it can be inferred that most infrastructure optimization models aim at deploying systems so that total costs are minimized, but only a few [18] [19] take environmental impact, particularly emissions, into account at the same time, allowing a spatially explicit cost-benefit analysis of fleet and infrastructure development.

Moreover, models are generally focused on electric technologies alone. To the best of the authors' knowledge, the model developed in [19] 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 to different routes of the same network. Such model is applied to the development of the electric buses in the city of Stockholm, particularly the inner city. The model is hence oriented to urban bus transport, as most electric bus network development models are, e.g. [20] for four German cities, [21] for the city of Münster, Germany, [22] for the city of Berlin, [23] for the city of Davis, US.

The present study was motivated by the need of an Italian regional bus transport company to evaluate the feasibility of improving environmental performance by introducing alternative bus technologies, including battery electric vehicles, in their intercity regional bus transport networks. As the region served is relatively small, 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. This could make the problem challenging in terms of range anxiety, infrastructure development, and feasibility: the company target was thus to identify in which routes and under what circumstances electrification could be viable, and how it would affect the composition and costs of their fleet. For this purpose, the model presented by [19] seemed the most promising, but it needed to be adapted to the features of regional bus transport, and to the technologies and emission settings typical of Italy, taking also a fleet optimization view. How this was performed is discussed in the following methodological section, which also addresses the environmental assessment framework developed here. The case study and data are presented in more detail in the corresponding section, which is followed by the discussion of the results.

METHODOLOGY

In view of the practical goal of this study, our objective was to consider immediate choices of regional bus companies rather than technologies available in the long term, and we hence focused on fuels and vehicle types currently considered for purchasing by company managers. Thus, unlike [19], who target a Scandinavian context aimed at 100% carbon emission abatement and considered 100% biodiesel as a fuel for conventional engines and battery electric vehicles powered by a Nordic electric mix, this study is focused on the fuels commonly used to date in regional bus companies in Italy and on general emission reduction targets limited to 50%.

CNG as a vehicle fuel generally boasts a high market penetration in Italy [24] and has been broadly used at urban level by municipal bus transport companies for more than twenty years [25], with the main aim of reducing local pollutant emissions. It may thus well be considered as a short term option by company managers and local authorities who have a long lasting perception of natural gas as a clean fuel.
The immediate alternative is the purchase of new buses with the most recent conventional technology (Diesel Euro VI). The current diesel mix entails a 9% biofuel mandatory quota on the overall market (DM MISE 13.12.2017), but a blending wall of 7% biodiesel was considered here as a maximum proportion of FAME in conventional diesel [26]). 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 [27], as well as about the high uncertainty about actual biodiesel emission factors discussed in literature [26], especially if one considers the impact of induced land use change [28].
Based on WTW carbon emission performance and on the absence of tailpipe airborne emissions, many authors in Europe [29], South America ([7] and Asia [30] call for a take up 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 [7]. Given the geographic morphology of Italy and the local bus company organization in Italy, such trip ranges are in line with the needs of regional intercity transport. In this context, it is clear that, as argued by Nie and Ghamami [14], the transition to electric vehicles faces two major barriers, i.e. that EV batteries are still expensive and limited by range, on one hand, and that the underdeveloped supporting infrastructure, particularly the lack of fast refuelling facilities, can still make EVs unsuitable for medium and long distance travel.
Indeed, such typical chicken-and-egg-dilemma arises in regional bus transport both for BEV and for CNG buses, which could need additional refuelling stations across the network.
In addition, for BEV the key research question is to evaluate wether super-fast charging and smaller energy storage with several charging stations along the network are preferable to larger energy storage in vehicles with less charging cycles [26].
As observed in [12], a fleet analysis approach is more helpful than the comparison of single vehicles in that it allows a more faithful comparison, particularly for commercial vehicles. In fact, it allows to predict the fleet and infrastructure size needed to fulfil the same function as a conventional diesel rather than just assuming driving ranges [7] or mileages [9].
In order to optimize infrastructure development and fleet composition at a regional bus transport level to meet targets of environmental impact improvement, the equations discussed in the following section “Location and capacity optimization model” have been added to the model proposed in [19], whose main elements are also briefly reported here, while the “Emission assessment framework” is presented in the section with this name.

Location and capacity optimization model

As in [19], the objective function of the model is to minimize annualized system costs. In our version of the model, costs are expressed by equation 1:

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

As more completely specified in the nomenclature, 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*.
a is the annualization factor, calculated according to equation 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.
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

Energy balance equations are the same as described in the original model [19], to which reference should be made also for details about the handling of exceptions at start and end stops.
The main differences from the original model include:

- 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 straightforwardly given by the binary decision variable *US(l,s,t)* is, which equals 1 if vehicles with technology *t* assigned to route *l* are due to be recharged at stop *s*, while here is represented by the integer decision variable *NP*, calculated as detailed below.

Number of buses

The underlying assumption in the original model was that the service level on a route was maintained if the number of buses currently operating on the route was maintained. However, Harris et al. [12] 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 e.g. to better exploit a lower 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 [23] to ensure that current schedule is maintained without any delays or charging station congestion, however the level of detail and computational effort of such approach is compatible with the operational level addressed in [23] rather than with the long term network planning perspective considering several technologies as decision variables as in our case. For this reason, a simplified approach was taken by calculating the number of buses according to equation (3):

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

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*, $t_{charge}(s,t)$ 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 depends on stops too. 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 [12], where peak and off-peak period are treated differently. Nevertheless, it helps to optimize network capacity (including recharging) and fleet composition at the same time, reducing the risk of underestimating the number of vehicles to be purchased for the new fleet to meet at least average service requirements.

<u>*Number of charging stations.*</u>

Overestimation is, on the other hand, the risk incurred by applying the same approach as in the original model [19] 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:

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

That means that charging stations, even located at junction stops, cannot be shared by vehicles assigned to different routes, as each should be dedicated to the corresponding route *l*. This may be reasonable in an urban context with a high number of trips and a high risk of congestion, but 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 to solve a simultaneous charging location and scheduling problem using the actual timetable, as exemplified by Wang et al. [23] for the city of Davis. 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 operational planning than with the strategic planning stage we are considering here, where not just electric recharging but several alternative technologies are evaluated at the same time. 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, should be shared among vehicles assigned to different routes. For CNG, the number of stations *NP* is thus determined according to equation 5 as:

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

For power charge, we considered that sharing a single charging station between all routes would be too risky, and that if several electrified routes would imply recharging at the same stop and, based on the timetable, there generally was high probability of simultaneous arrivals at that stop, two or three charging stations should be installed at that stop. For this purpose, first a simultaneity coefficient *c(s)* was calculated, with an external procedure implemented in Matlab, for each stop based on the timetable. *c(s)* was set to 1 if at least three vehicles from different routes would meet on that stop at least once a day, zero otherwise. Then, *NP* was 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, see [32]) and ε (fixed arbitrary small number) according to equations 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, γ_2 and γ_k are used as flags, and according to equations 7-12 they indicate if the total number of routes requiring recharging at the same stop is equal to zero (all flags at 1), at 1 ((γ_1=0, all other flags at 1), between 2 and *k-1* (γ_1 and γ_2 at 0 and γ_k=*1*), or larger or equal to *k* (all flags at 0). According to equations 6 and 13-18, the number of charging stations at each stop is set at zero, if no charging is performed on any route, at 1 if charging is performed for one route, or for at least two routes but with zero risk of simultaneity, at 2 if charging is performed for 2 to *k-1* routes with some risk of simultaneity and at 3 if charging is performed for *k* or more routes with some risk of simultaneity. In our implementation, *k* was set at 5.

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 equation 19 for tank to wheel CO_2 equivalent emissions

$$CO_2eq_{TTW}(t) = \sum_{l} n_{trip}(l) \cdot L_{trip}(l) \cdot co2eqTTW(t) \cdot TUS(t,l) \cdot dy \tag{19}$$

Emission factors for NOx, PM10 and carbon equivalent emissions for the technologies of concern are derived from literature, in particular from the references reported in Table 1, and expressed in g/km. Carbon equivalent emissions are based on 100 years GWP. NOx are dangerous for human health in urban environments, but are also responsible for acid rain. The Euro VI standard imposes a drastic abatement of NOx 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 Figure 1, which represents the system boundaries considered for emission assessment for WTT carbon equivalent emissions and for TTW emissions. Besides NOx, also particulate matter PM10 is considered because of its impact on smog and human health [33].

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*	-	-	-	65111	[34]
	Charging /fueling station manufacturing	g/€**	-	-	2671	524	[35]
	Urea supply chain	g/kWh	-	-	-	25	[36]
	Fuel /electricity supply chain	g/kWh	50	50	80	430	[26, 37]
Tank-to-wheel emission factors	CO2eq from fuel combustion	g/km	1207	1033	1055	-	[26]
	NOx from fuel combustion	g/km	6.83	0.475	0.310	-	[36]
	PM10 from fuel combustion	g/km	0.126	0.076	0.001	-	[36]

*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

For coherence with the context of application, Italian [33, 36, 37] and European [26, 38] data sources were preferred wherever available, in particular for the electricity mix [33, 37] and more generally for assessing WTT emissions. Such reference studies are mainly based on the JRC WTW emission calculation approach [39] and on the RED methodology [40], particularly for the assessment of emissions from biofuel quotas. We have nevertheless integrated these data with American data sources [34][35], which use the GREET methodology [41] and a hybrid approach [35], in order to derive parametric data about the impact of the manufacturing and replacement of batteries and charging stations. Our choice is mainly due to the scarcity of data about the environmental impact of manufacturing charging stations, and to our desire to enable a comparison at least in terms of relative orders of size. On the other hand, emissions from vehicle construction were not included in the analysis as they are assumed to be independent of the technology implemented.

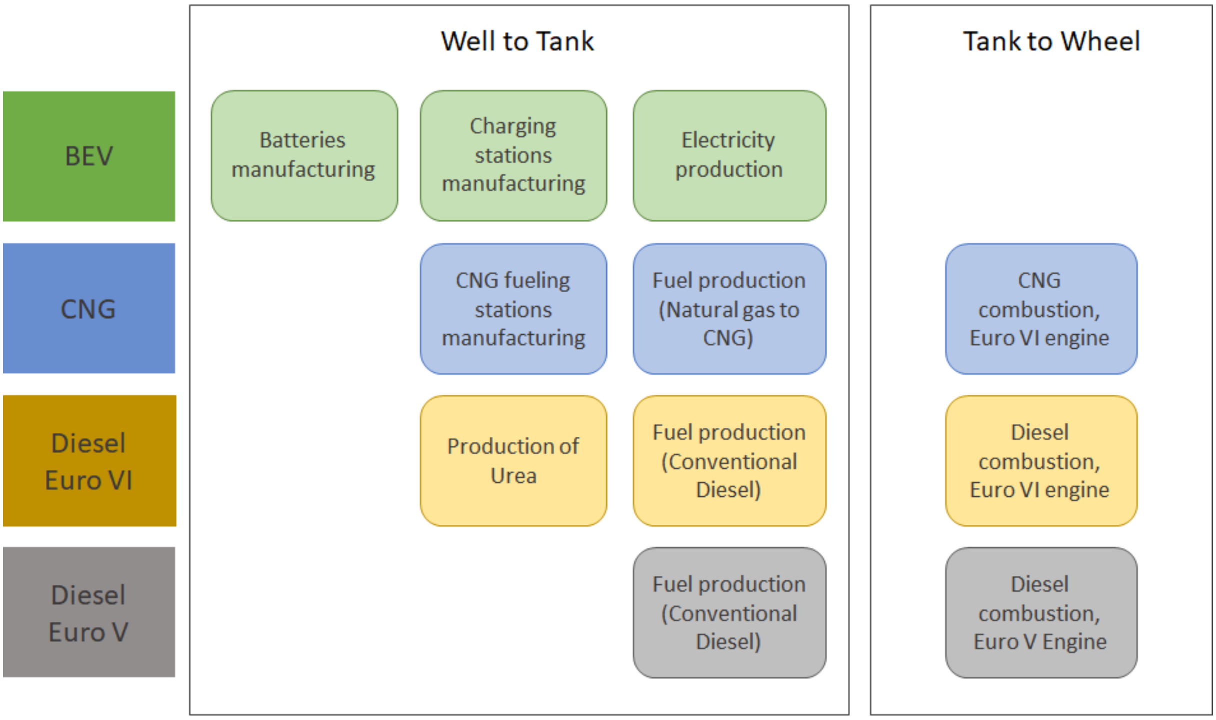

Figure 1. Activities included in calculation of WTT (CO2eq) and TTW (CO2eq, NOx, PM10) emissions

As a result, the assessment of WTT carbon equivalent emissions is performed e.g. for battery electric buses according to equation 20:

$$CO_2eq_{WTT}(el) = NB(el) \cdot \frac{co2eqWTTbatt(el)}{durationbatt(el)} + \sum_l n_{trip}(l) \cdot t_{trip}(l) \cdot TUS(l,el) \cdot cons(el) \cdot co2eqWTTfuel(el) \cdot dy + \sum_s \frac{co2eqWTTstat(el)}{durationstat(el)} \cdot NP(s,el) \tag{20}$$

CASE STUDY AND DATA

The case study involves a regional bus transport company, which at the time of the research was operating regional transport in the South Eastern part of Friuli Venezia Giulia, an Italian region close to the Slovenian boundary. As shown in Figure 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 hours a day and 280 days a year, with an total average distance travelled of about 4,2 millions km/year.

As shown in Table 2, routes are very diverse: they vary in length between some 20 and some 80 km, and travel frequencies between different routes may be very different, ranging between as little as 1 round trip per day to more than 50 round trips per day. Stops at end stations last on average 25 minutes, whereas two minutes are generally scheduled for each intermediate stop.

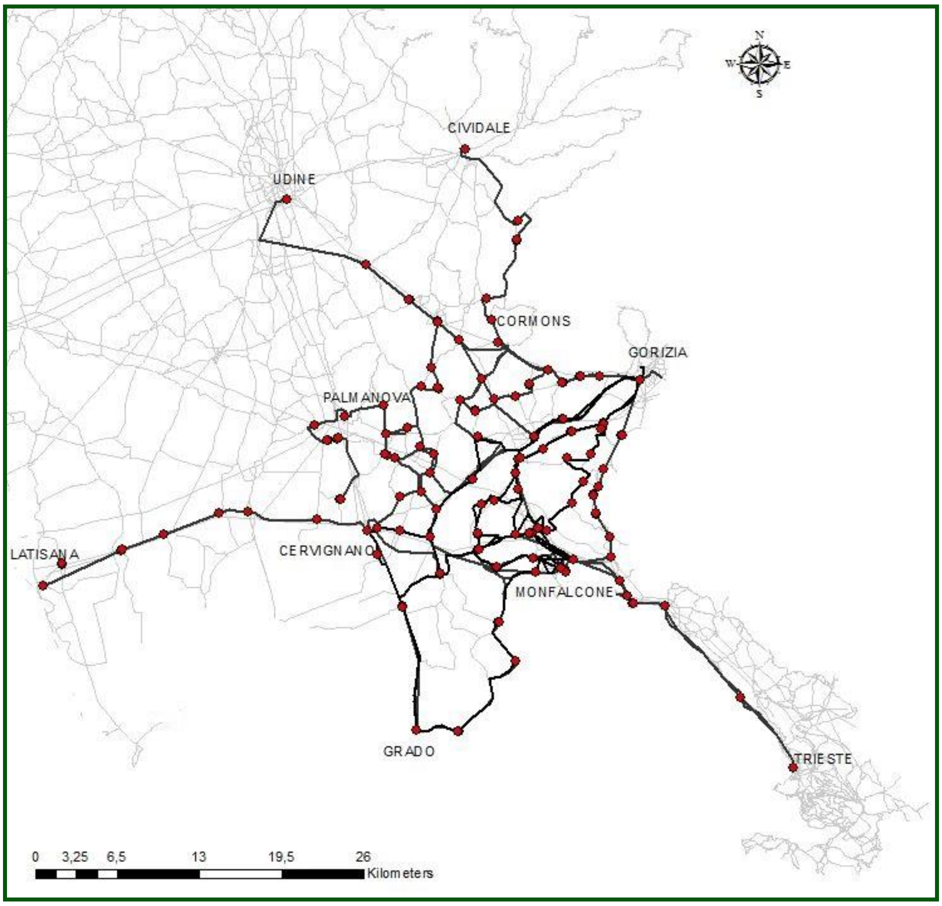

Figure 2. Map of extra urban bus network and stops

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

Total fuel consumption [MWh/year]		19262	
Total WTW CO2eq emissions [t/year]		6012	
Total NOx 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

The current fleet is varied, but relatively recent. It was agreed with the technical staff of the company that the current fleet could be approximately represented, as to fuel economy and emissions, as a Euro V fleet, and 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, thus manufacturing and two replacements are included in the analysis of battery electric vehicles based options. The technical and economic data used for the analysis are summarized in Table 3. It can be noted that the capital cost of electric buses is about 50% higher than that of CNG buses, not considering batteries cost, whereas CNG fuelling stations are about 50% more expensive than electric fast charging stations. Based on previous studies [11] the cost of CNG filling stations is assumed to be substantially lower if high pressure natural gas transport pipelines exist in proximity of possible locations, as one can avoid the additional compression of natural gas, which is required to obtain CNG from low pressure natural gas distribution networks existing in all the towns in the area of concern.

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	[19][42-44]
Vehicle energy capacity	kWh	3195	3195	3060	60 -120	[19][38][44]
Urea consumption	l/km	-	0.02	-	-	[26]
Minimum state of charge (SOCmin) for batteries	-	-	-	-	15%	[45]
Capacity of charging station	kNm3/year (CNG) kW (electricity)	-	-	700	300	[19][46]
Capital cost of charging station	€	-	-	358802 *(HP*)* 433719 *(LP*)*	211500	[19][46]
O&M costs of charging station	€/yr	-	-	26831	4230	[43][46,47]
Rate of charging	kWh/min	898	898	222	5	[19][48][49]
Capital cost of bus	€	-	240000	260000	390000	[8][19][31][34][35]
Capital cost of battery	€/ kWh	-	-	-	1000	[19][50]
Maintenance cost of bus	€/ km	0.13	0.15	0.17	0.14	[26][31]
Fuel/Energy cost	€/ kWh	0.12	0.12	0.07	0.15	[51][52]
Cost of urea	€/l	-	0.5	-	-	[26][44]

*for CNG, *HP* indicates that the station is served by a high pressure natural gas network, *LP* that there is only a low pressure gas distribution network

Scenario definition

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

<u>*Business as Usual*</u> (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 may operate for fifteen years at the maintenance costs indicated, and that engine performance do not

vary over time. It is assumed that existing fuelling stations are used for the whole period, and their capital costs, as well as those of the fleet, are thus treated as sunk costs and set to zero. The scenario is developed only for reference and comparison: maintaining current Diesel Euro V buses or purchasing used vehicles are not considered as feasible option for any of the following environmental optimization scenarios.

50% CO2 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 CO2 emissions: in this scenario, WTW carbon equivalent emissions are minimized.

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

RESULTS AND DISCUSSION

The model was implemented in GAMS using solver CPLEX 12.7 [53], while maps and timetables were elaborated with ArcGIS and Matlab to preliminarily obtain model data like e.g. distances between stops or location of high pressure gas transport pipelines. Computational times on a i7 PC were reasonable, reaching about two hours for the most complex scenarios.

Optimal system configurations under different scenarios

Table 4 shows the fleet composition and the mix of technologies used along the routes in the developed optimization scenarios. One can observe that, under the constraint of reducing NOx emissions alone, the use of Euro VI vehicles instead of the current fleet is largely enough to achieve emission reduction targets. The *50% NOx* scenario thus correspond to a full Euro VI scenario without any other technologies.

When targeting a *50% PM10* emission reduction, the use of new Euro VI buses is not sufficient, and CNG buses are introduced, which, even accounting for new refuelling stations, are less expensive than battery electric technologies on the network of concern.

Figure 3 shows the CNG gas network in blue, whereas in the remaining routes (in black) Diesel engines are used. Three CNG fuelling stations (red dots in Figure 3) are introduced at three end stops, and that the six routes to which CNG is allocated are relatively short routes with a high number of junctions. They also have an average or above average travel frequency: having set an emission constraint with a cost minimization objective, the optimization identifies a restricted number of routes where the need for refuelling stations is minimum and the fuel consumption is particularly high.

In Table 1 it can be seen that the TTW carbon emission performance of CNG Euro VI buses in terms of carbon equivalent emissions may be lower than that of corresponding Diesel Engines, mainly due to the GWP associated with leaps of CH_4.

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

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

	Propulsion system	Scenarios				
		BAU	**- 50% CO2eq**	**Min CO2eq**	**- 50% NOx**	**- 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	-	-

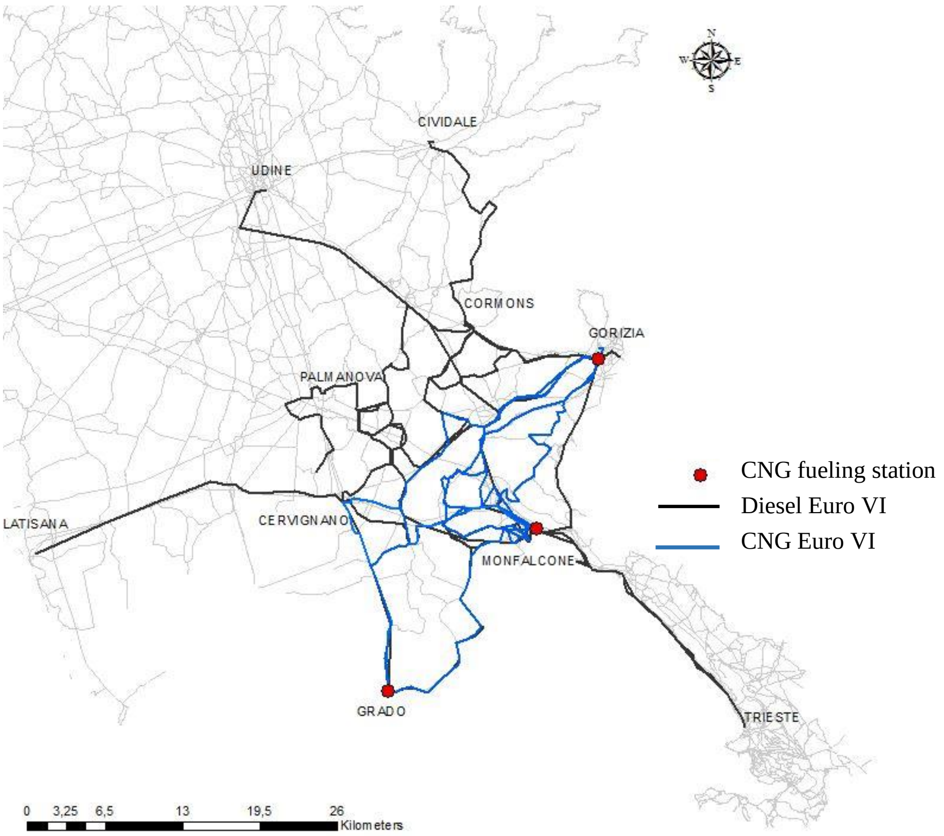

Figure 3. Map of optimal system configuration for - 50% PM10 scenario

Since the current Italian electricity generation mix includes a majority of fossil fuel sources [33], more routes need to be electrified to achieve a 50% carbon emission reduction target: in Table 4 and Figure 4 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 travel frequency than in the *50% PM10* scenario, in order to keep the number of highly expensive vehicles to a minimum. Longer routes are generally preferred for electrification in the *-50% CO2* scenario, even if this requires 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 Figure 4), to which ten 120 kWh BE buses and seven charging stations are assigned.

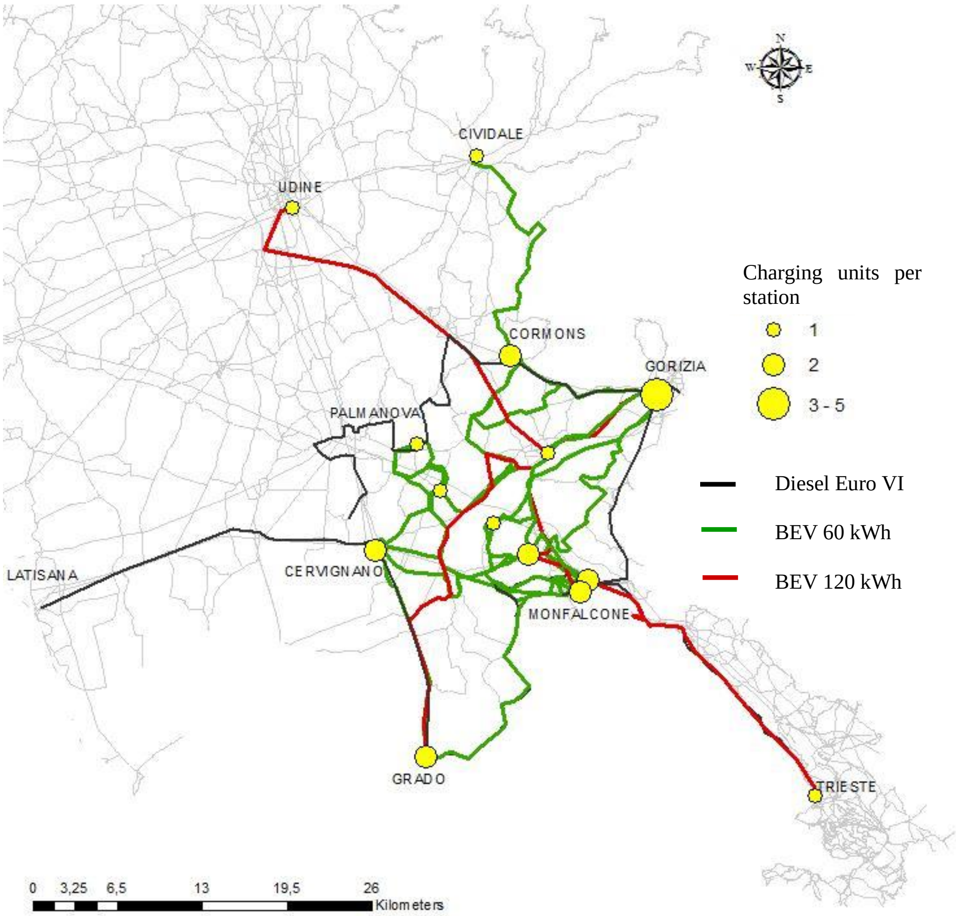

Figure 4. Map of optimal system configuration for - 50% CO2eq scenario.

Smaller electric storage is generally preferred due to the high cost of batteries, but in the CO2eq minimization scenario, in which all routes are electrified, only 120 kWh batteries are selected. In fact, energy consumption being equal, the use of larger storage systems allows to emit less greenhouse gases on a WTW basis by enabling to introduce less charging systems, whose contribution to WTW emissions is not negligible.

Economic performance

That batteries are a main cost component is confirmed by the economic results displayed in Figure 5, where annual equivalent systems cost for each scenario are compared. The investment required for batteries is larger than that required for charging stations, particularly more than twice as much in the carbon emission minimization scenario. Together with the high cost of battery electric vehicles, which represent the main cost component in the *50% CO2 emissions* scenario, this makes electric vehicle based systems between 25% and 50% more expensive than an entirely new Euro VI bus fleet, depending on scenario. While the price of electricity (see Table 3) may be deemed relatively high, and corresponding cost share figures are significant, Figure 5 shows that even if they were null electrified systems would be hardly competitive with Euro VI or CNG based scenarios.

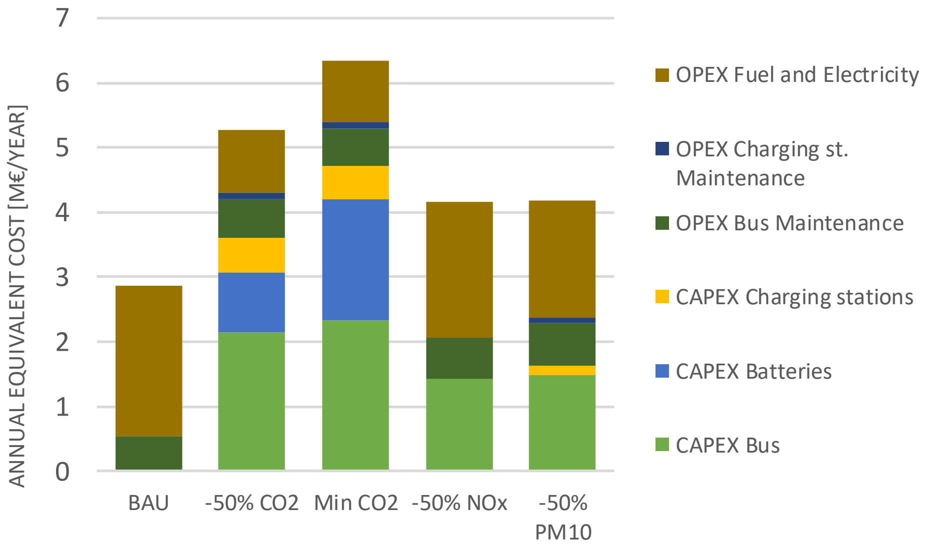

Figure 5. Annual equivalent system cost for BAU and emission reduction scenarios

Environmental performance

In terms of CO_2 emissions, even fleet renewal with Euro VI vehicles alone brings about some reduction, as can be seen in Figure 6.

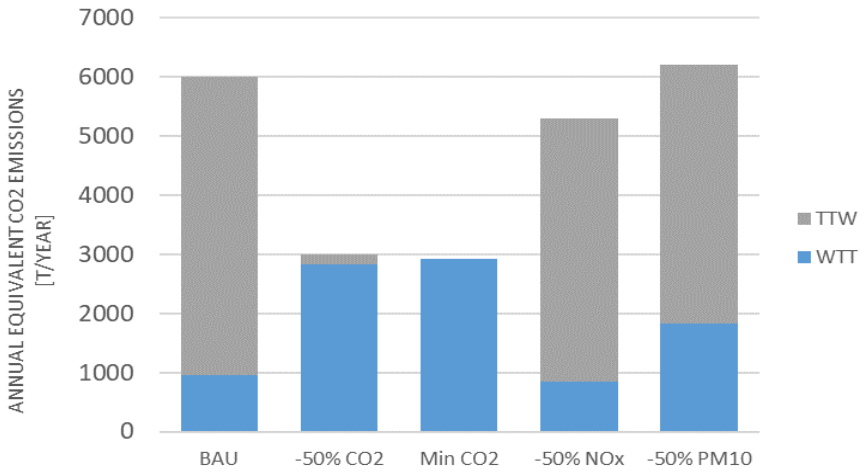

Figure 6. Annual CO_2 equivalent for BAU and emission reduction scenarios

Figure 7 shows that the emissions of other pollutants in the *50% NOx* (Diesel only) and in the *50% PM10* (with CNG) are actually very similar, while they are assumed to be null in pure electric vehicle based scenarios (*Min CO2*). On the other hand, Figure 6 also shows that the use of CNG causes an increase in the emissions of greenhouse gases even compared with the *BAU* scenario. This is evident if the whole WTW pathway is considered, mainly because of WTT emissions, mainly along the natural gas supply chain, and from the construction of fuelling stations. May the impact of the latter well be uncertain due to lack of data, as discussed above, the result nevertheless confirms that they should at least be investigated for system requiring new additional infrastructure to operate.

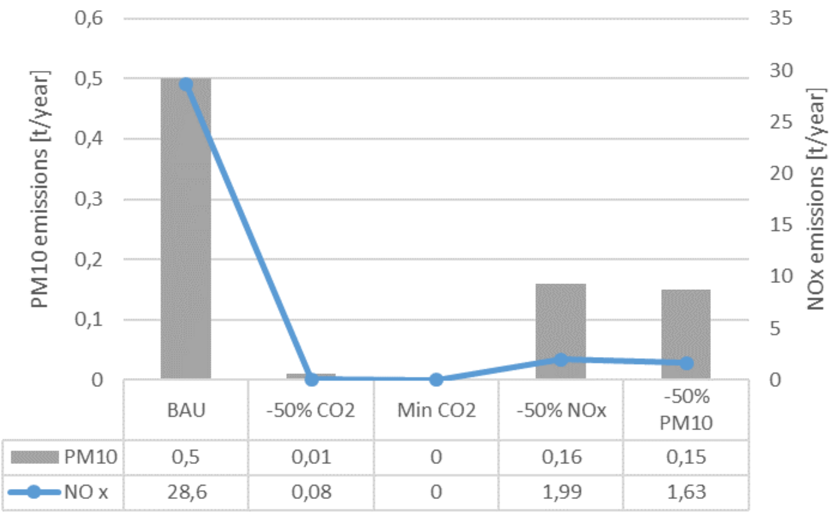

Figure 7. Annual NOx and PM10 emissions for BAU and emission reduction scenarios

In Figure 8, the environmental benefits of greenhouse gas emission reductions in the system studied are related to their costs by performing a parametric analysis.

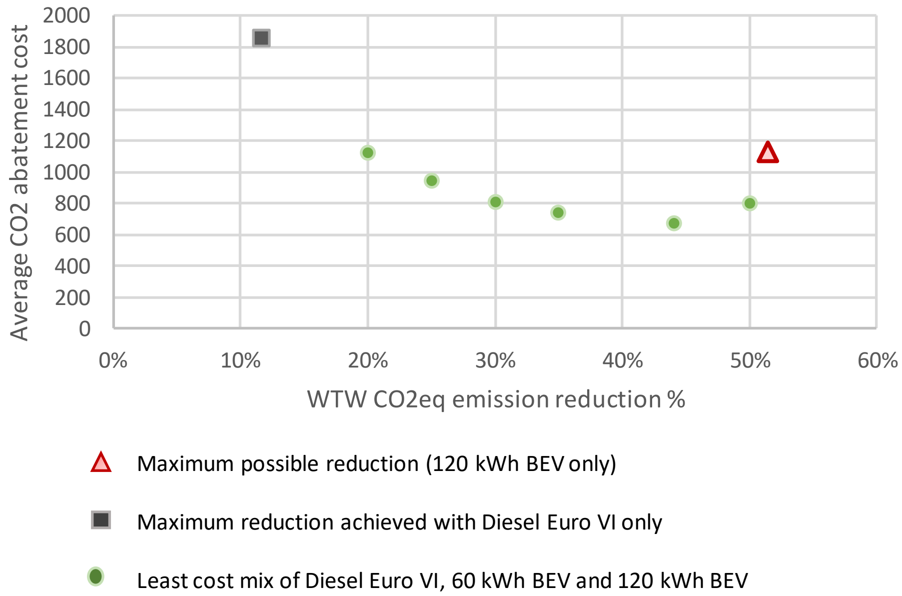

Figure 8. System average cost of CO_2 equivalent emission abatement depending on achieved reduction percentage.

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 Figure 8), and 51%, which is the maximum reduction, achieved with full network electrification in the CO2eq emission minimization scenario (red triangle in Figure 8). All the intermediate scenarios thus obtained (green dots in Figure 8) 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 obtaining the average costs of CO2eq reduction through optimization of the inter urban regional network of concern. Such costs range between 670 and 1920 €/tonCO2eq, which is quite high compared with e.g. the implicit carbon price of some renewable energy sources [54] or even with carbon capture costs (see e.g. [55] for an industrial application). Nevertheless, the overall analysis of the scenarios has confirmed that electrification is technically feasible even at the interurban, regional scale examined in the present study.
Figure 8 highlights that the average cost of CO_2 abatement for the transportation system of concern is maximum for Euro VI fleet renewal, due to the small reduction it allows, and has a minimum point at about 44% CO_2eq emission reduction, which can be actually achieved by electrifying the four routes with maximum emissions. As it is also shown in Figure 6, full electrification brings about limited benefits at very high additional costs. For a rational planning of fleet and infrastructure deployment, spatially explicit optimization models with an environmental perspective can thus be very useful to direct resources on most beneficial routes.

CONCLUSION

There are several environmental and economic factors that need to be evaluated in the strategic planning of alternative propulsion systems for local transport. In this paper, it has been shown how the economic optimization model, introduced in [19] to support the electrification planning of the urban bus network in Stockholm, can be easily adapted to the needs of different contexts, in particular to the design of intercity bus transport in less intensely served rural areas, and expanded, by treating the number of vehicles as a decision variable, in order to address bus fleet optimization issues at the same time.
Compared with the multitude of electric charging station planning models emerged in recent years, the peculiarity in this approach lies in the simultaneous evaluation of several alternative technologies, both electric and fuel based, conventional or not, which makes the model particularly suitable for strategic network planning. In this work, the model was applied to the deployment of CNG fuelling stations, of electric conductive charging stations and to the identification of the least cost fleet composition, considering two battery size classes for electric buses as well as last generation conventional diesel buses. It is nevertheless clear that alternative electric options such as battery swapping or hybrid electric buses, and alternative fuels such as first and second generation biofuels for conventional internal combustion engines or hydrogen to drive fuel cells could be easily incorporated into the model, the only limitations being problem size and complexity, and computational times depending on bus network sizes.
Being directed to the integrative assessment of several alternative technologies in a long term perspective, environmental impact indicators should naturally be incorporated in the model as well, as in [56]: in the model version developed in our study, a well-to-wheel carbon dioxide equivalent emission assessment based on Italian conditions has also been included, as well as tailpipe emissions of NOx and PM10, whose impact on local air pollution is of special concern for local authorities.

Based on case specific results, obtained here from the model application to a regional bus company managing 18 intercity routes in North Eastern Italy, one can conclude that:

- A simultaneous assessment of several emissions, as well as of economic performance, is a particularly desirable model feature, in that trade-offs may come up: here this was e.g. the case of CNG, which, even accounting for the costs of dedicated refuelling stations, proved to be an economically attractive option for reducing air particulate, but performs worse than state of the art conventional diesel buses as to emissions of greenhouse gases. Based on such 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 future development.
- The environmental impact of manufacturing charging or refuelling stations may be limited, but not negligible, and should be investigated more in detail, particularly to compare alternative options like e.g. battery swapping.
- 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 high cost of 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 by increasing the use of high capacity batteries.

The analysis of carbon emission reduction cost trends has also confirmed that the potentials of electric propulsion as a decarbonisation option for bus transport are great, reaching about 50% in the case of concern. Such potentials are, however limited, in terms of environmental benefits, by the share of fossil fuels in the electricity generation mix, and, in terms of economic performance, by the high capital costs of electric systems, which at current 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 analyzed). If the transition of regional transport to low-carbon systems is desired, significant incentives would then be needed, and the model proposed in this paper could be also used to support local policy makers in devising efficacious support schemes for their territories.

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NOMENCLATURE

Acronyms	Definition
BAU	Business As Usual
BE	Battery Electric
BEB	Battery Electric Bus
BEV	Battery Electric Vehicle
CNG	Compressed Natural Gas
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
NOx	Nitrogen Oxides relevant for air pollution
PM10	Particulate Matter 10 μm or less in diameter
TTW	Tank to Wheels
WTT	Well to Tank
WTW	Well to Wheels
ZEB	Zero Emission Bus

Indices	Definition
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 including CNG technology only

Variables	Type	Definition
US(ls,t)	binary	[0,1] variable, equals 1 if charging of technology t for line l is required at stop s
TUS(l,t)	binary	[0,1] variable, equals 1 if technology t is assigned to line l
$\gamma_1, \gamma_2, \gamma_k$ (s,el)	binary	[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)
δ1, δ2, δ3 (s,el)	binary	[0,1] variables to determine the total number of charging stations to be installed at stop s
NB(l,t)	integer	Number of buses of technology t assigned to route l
NP(s,t)	integer	Number of charging stations of technology t installed at stop s
CO2eqTTW(t)	positive	Total annual equivalent CO2 emissions from Tank to Wheels
CO2eqWTT(t)	positive	Total annual equivalent CO2 emissions from Well to Tank
C_0	continuous	Annual equivalent system costs

Parameters	Unit	Definition
$s_{cost}(t)$	€	Charging/Fuelling station capital cost
$s_{main}(t)$	€/yr	Charging/Fuelling station annual O&M cost
$b_{cost}(t)$	€	Bus capital cost
$b_{main}(t)$	€/km	Bus maintenance annual cost
bat_{cost}	€/kWh	Batteries capital cost coefficient
f(t)	€/kWh	Fuel cost
cons(t)	kWh/km	Fuel economy

$cap_{bat}(el)$	kWh	Battery storage capacity
$durationbatt(el)$	years	Expected lifetime of batteries
$durationstat(t)$	years	Expected lifetime of charging station
$L_{trip}(l)$	km	Route length
$n_{trip}(l)$	-	Number of trips per day for each route
$c(s)$	-	[0,1] scalar, is 1 if two or more trips from different routes are scheduled to stop at *s* at the same time
$D(l,s, s+1)$	km	Distance between stop s and successive stop s+1 on route l
SOC_{min}	-	Minimum state of charge for batteries
$t_{charge}(s,t)$	min	Charging time allowed for each technology and stop
$t_{trip}(l)$	min	Travel duration on route l
t_{op}	min/yr	Average total time available for bus operation, in minutes per year
dy	day/yr	Average total time available for bus operation, in days per year
n	yr	Project life in years
a	-	Annualization factor

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