Energy 254 (2022) 124252

Contents lists available at ScienceDirect

Energy

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

Electric bus coordinated charging strategy considering V2G and battery degradation

Jônatas Augusto Manzolli [a, *], João Pedro F. Trovão [a, c, d], Carlos Henggeler Antunes [a, b]

[a] INESC Coimbra, University of Coimbra, DEEC, Polo II, 3030-290, Coimbra, Portugal
[b] University of Coimbra, Department of Electrical and Computer Engineering, Polo II, 3030-290, Coimbra, Portugal
[c] Polytechnic of Coimbra, IPC-ISEC, DEE, 3030-199, Coimbra, Portugal
[d] University of Sherbrooke, Department of Electrical and Computer Engineering, Sherbrooke, QC, J1K 2R1, Canada

ARTICLE INFO

Article history:
Received 31 January 2022
Received in revised form
15 April 2022
Accepted 10 May 2022
Available online 14 May 2022

Keywords:
Electric bus fleet
Optimization model
Vehicle to grid
Battery degradation
Coordinated charging

ABSTRACT

The trend for the decarbonization of the transportation sector, contributing to climate change mitigation, has driven the accelerated deployment of electric buses in cities. However, higher upfront costs, charging infrastructure deployment and operational issues are the main obstacles to their massive adoption. This work develops an optimization model to deal with the charging schedule of a fleet of battery electric buses. This approach aims to minimize the charging costs of electric bus fleets also considering the ageing of the batteries and the participation in vehicle to grid schemes. We developed a case study using real-world data from a small electric bus fleet of eleven electric buses in a medium-size Portuguese city. Further, we performed a sensitivity analysis to assess the possibilities of energy trading with the grid. The results indicate that below a battery replacement cost threshold of 100 €/kWh, it may become economically attractive for public transportation operators to sell back energy to the grid for a given remuneration scheme. Considering battery degradation and energy selling, our study indicates that operation costs could be 38% lower in 2030. The approach presented in this article provides a tool that can be employed by public transportation operators to assist decision making in the electrification of bus systems.

© 2022 Elsevier Ltd. All rights reserved.

1. Introduction

Promoting the electrification of the transportation sector contributes to energy efficiency enhancement, climate change mitigation, and air pollutants reduction in urban environments [1]. Therefore, many governments are implementing public policies to increase the utilization of electric vehicles in cities. Such policies cover purchasing subsidies, tax reduction and safety supervision [2]. As a result, some forecasts highlight that in 10 years from now, almost 70% of vehicles sales will be electric in Asia, Europe and North America [3,4]. If we consider the electrification of public transportation only, this process will be even faster with the penetration of electric bus fleets in cities that several countries are promoting. China is leading the electrification of the public transportation sector, already holding a fleet of 421,000 buses [5]. The European Union recently started the Zero Emission Urban Bus System (ZeEUS) program to finance the deployment of electric buses [6]. It is expected that, until 2025, the sales of electric buses will be greater than fossil fuel powered ones. Fig. 1 displays a forecast of electric buses sales in Europe for the next decade using data presented in Ref. [7]. In the USA, a series of financial incentives in tax credits and subsidies have been applied to stimulate research and production of electric buses [8,9]. Considering this favourable scenario, the study in Ref. [10] concludes that electric buses will displace their fossil fuels counterparts in the present decade.

However, this transition process faces many challenges caused by infrastructural and operational limitations. For instance, the significant power required to charge electric bus fleets may result in technical grid issues — e.g., voltage, frequency, congestion and peak demand violations [11]. Bidirectional charging schemes can play a role in mitigating grid issues, offering a novel alternative to ancillary services provision [12]. Lately, some pioneer projects

* Corresponding author.
E-mail addresses: j.manzolli@deec.uc.pt (J.A. Manzolli), joao.trovao@usherbrooke.ca (J.P.F. Trovão), ch@deec.uc.pt (C. Henggeler Antunes).

https://doi.org/10.1016/j.energy.2022.124252
0360-5442/© 2022 Elsevier Ltd. All rights reserved.

List of Abbreviations

DOC	Daily operating costs
DSO	Distribution system operator
MBRC	Maximum battery residual capacity
MILP	Mixed-integer linear programming
PTO	Public transportation operator
SOC	State of charge
SOH	State of health
TCO	Total cost of ownership
TSO	Transmission system operator
V2G	Vehicle to grid
ZeEUS	Zero Emission Urban Bus System

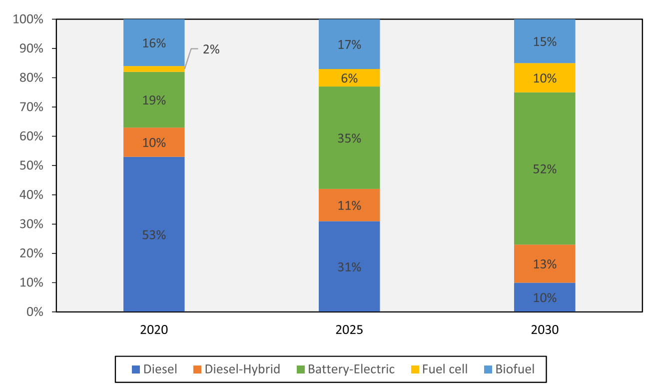

Fig. 1. European urban bus market evolution (%).

regarding vehicle to grid (V2G) hubs have been implemented worldwide [13]. The city of London recently launched a pilot project[1] aiming to become the world's largest V2G trial site. The project comprises 28 double-decker buses capable of returning over 1.1 MWh of energy to the grid. If achieving success, this project can lead to a new paradigm regarding public transportation since the electric buses will play a role as "moving" energy storage systems, thus helping to improve the grid resilience. Nevertheless, the faster battery degradation due to the additional charging cycles can be a drawback that could prevent the public transportation operator (PTO) from becoming a prosumer [14].

In this context, to develop an economical and effective electric bus system (dealing with all the issues mentioned above), smart charging strategies must be designed considering the grid operation standards while respecting the PTO's operational constraints and requirements. However, to the best of the authors' knowledge, a framework that considers electric bus charging scheduling, V2G schemes, and battery degradation has not been duly characterized in the literature. Therefore, this research aims to develop an optimization approach to address those features and contribute to fill this literature gap. The main contributions of this work are:

- We develop a mixed-integer linear programming (MILP) model to minimize the operational bus fleet costs due to charging/discharging events. As the main novelty, the model includes a battery ageing framework to evaluate degradation costs due to selling energy back to the grid, in addition to constraints related to bus assignment per route, charging thresholds and transformer capacity.
- The model evaluates the possibilities of PTOs to participate in V2G schemes considering a battery degradation scenario. Therefore, our work presents a more precise evaluation of costs associated with energy trading with the grid.
- We offer a modelling framework that assess the possibilities of energy transactions with the grid considering scenarios of battery replacement price and electricity price variations.

The article is organized as follows. Section 2 reviews the literature, presenting some works used as the basis for this research. Section 3 presents the methodology developed, describing the model formulation. Section 4 presents the case study and discusses the results. Section 5 draws the main conclusions and offers some hints for future research.

2. Literature review

There is extensive literature regarding electric bus operation management, with studies mainly focused on charging strategies, vehicle scheduling, and fleet size optimization [15–17]. Typically, the studies develop MILP models of the bus networks, considering deterministic constraints. Some studies also include stochastic variables to deal with uncertainty (e.g., weather, traffic, battery charging/discharging rates, speed) [18–21]. Regarding the scope of our article, some works have considered the optimal scheduling and charging costs of electric bus fleets. Ref. [22] presents a study that aims to minimize single-day total charging costs of a bus system while keeping the maximum battery residual capacity (MBRC) level at an operational threshold. For this purpose, the authors split the costs into single-day construction costs and single-day energy costs. Wind and solar generation, feeder load and demand response costs are also included in the model. Two different scenarios were examined: i) No consideration of renewable generation, feeder load and demand response; ii) Consideration of the features mentioned above. For the first scenario, the single-day total costs strongly influence the MBRC. For the second scenario, the results point out that demand response during the peak electricity rate hours can reduce energy consumption but at the expense of cost increase. Ref. [23] presents a coordinated charging strategy for electric bus fast-charging stations. The methodology is based on a MILP model that considers the rated capacity of the local distribution transformer and time-of-use tariffs, which is solved using a heuristic. Four different charging strategies are evaluated for the case study: optimal charging strategy, suboptimal charging strategy, uncoordinated charging scenario, and ideal charging strategy. The conclusion states that the suboptimal charging strategy improves the charging costs with much higher computational efficiency, over a slightly worst economic performance. Ref. [24] presents a MILP model to electric bus charging station planning, also considering the aggregators' participation. The model contains power grid planning constraints, including capital, maintenance, and energy costs. The outcomes indicate that increasing the number of chargers in the network has little impact on daily charging costs.

The literature unveils that coordinated charging events associated with energy management strategies are mandatory to keep the operation level of electric bus fleets at a reliable state while keeping the distribution system's security and quality of service

[1] More information at: https://www.sseenergysolutions.co.uk/news-and-insights/london-bus-garage-becomes-worlds-largest-vehicle-to-grid-site.

requirements. Furthermore, charging infrastructure upgrade (comprising distribution lines, substations, and transformers) is one of the main challenges in the electrification process of bus systems [25]. In this context, several studies have addressed the effects of energy interactions between the PTO and the grid to enable efficient charging operations and reduce costs. Ref. [26] evaluates the charging demand of battery public transportation using a heuristic vehicle scheduling tool. The study demonstrated that the impacts are most significant at the low-voltage network, attesting to the need of coordinating the charging events to avoid grid problems. Ref. [27] presents an operational feasibility and grid impact analysis of electric buses using three charging approaches: flash, opportunity and overnight. The authors developed two models: i) dealing with operational constraints of the bus system; ii) investigating the grid impacts and transformer ageing due to charging events. From an operational point of view, the flash charging approach appears to offer a better operation when compared to other charging strategies. The study indicates that overnight charging provides a better operation level regarding the grid impacts. The study demonstrates that flash and opportunity charging require a service transformer 5–6 times larger as well as increase energy daily losses. Ref. [28] presents an optimal charging strategy to minimize demand charges of a fleet of electric buses in Tallahassee, Florida. A MILP model was designed to minimize the peak demand of the charging events. The findings reveal that applying a 60–64% charging threshold contributes to total electricity cost savings. Further, the model demonstrates that frequent charging events may lead to a reduction in demand charges, contradicting the typical practice that drivers should maximize the bus driving range. Ref. [29] presents a study that evaluates grid and electric bus operators interactions regarding a dynamic market frame using locational distribution pricing for load congestion management. The authors employed bi-level optimization to model the bus-grid interaction process. The outcomes exhibit that bus fleets are capable of alleviating charging loads (reducing the power loss by 7.2%), with the trade-off of restricting their operational requirements (8.2% loss of charging demand) while increasing the battery capacity (10.6% higher). In Ref. [30], an electric bus aggregator acts as an intermediate agent for distribution system operators (DSO) and transmission system operators (TSO). The electric bus aggregator coordinates the fleet charging operations to modulate the vehicles' charging curve to keep the maximum available charging power below a feasible threshold. Further, the aggregator offers services for the DSO and the TSO to improve the grid operation. The authors present a MILP model to evaluate the effect of charging electric buses in terms of the power load. Furthermore, the sensitivity analysis demonstrated that the aggregator has more load flexibility when the number of chargers grows; however, that load flexibility does not represent a significant economic gain.

Although this literature review confirms that relevant research has been carried out concerning the optimization of electric bus scheduling and planning, in our perspective there is still a gap regarding the evaluation of electric bus fleet charging scheduling, including V2G interactions and battery ageing. Therefore, this work aims to evaluate the possibilities and impacts of grid interaction of electric bus systems, while considering a battery ageing scheme, anchoring the conclusions in the results of a MILP optimization model.

3. Model and methods

3.1. Problem formulation

The aim is to assist PTOs to minimize the daily operational costs by controlling the energy required to operate a bus fleet, including the interactions (buying/selling energy) with the grid. We consider one bus depot, where the vehicles perform the charging/discharging operations and start/finish the routes. The buses must serve multiple trips in each route, and only one bus should be assigned to each trip, meaning that a trip cannot be interrupted to switch vehicles. Further, we consider the time and the energy consumed in deadhead trips. The daily operation is discretized into time steps (1 min) to capture the evolution of the battery's energy level during the planning horizon. We describe the mathematical formulation in the following. The indices, sets, parameters and variables are presented in Table 1.

3.2. Objective function

The objective function is presented in (1), which aims to minimize the daily operating costs (DOC) of the bus fleet, allowing interactions with the grid (buying-selling energy). We also consider the battery ageing due to the charging operations as a levelized daily cost that impacts the operation.

$$Min\ DOC = \sum_{t\in\mathscr{T}} P_t w_t^{buy} - \sum_{t\in\mathscr{T}} S_t w_t^{sell} + \sum_{k\in\mathscr{K}}\sum_{t\in\mathscr{T}} d_{k,t} \tag{1}$$

The first and second terms are related to the energy bought and sold to the grid, respectively. The third term is related to bus battery degradation costs resulting from daily operation.

3.3. Constraints

The constraints are related to the vehicle's assignment per route, charging thresholds, battery ageing and transformer capacity. Buses present rigid timetables, their charging patterns differing from the ones of light electric vehicles. Therefore, the charging vs. operation scheduling trade-off is a relevant issue for system planning. Our model includes energy and schedule constraints to allow for determining the best periods to charge the buses.

Route constraints: To define the route constraints, we based our model on the Green Vehicle Routing Problem [31]. All trips must be fulfilled by one and only one vehicle. We include additional scheduling constraints, i.e., the trips must start and end at predefined times (T_i^{start}, T_i^{end}).

$$\sum_{i\in\mathscr{I}} b_{k,i,t} + c_{k,t} \le 1,\ \forall k\in\mathscr{K},\ \forall t\in\mathscr{T} \tag{2}$$

$$\sum_{k\in\mathscr{K}} b_{k,i,t} = 1,\ \forall i\in\mathscr{I},\ t\in\left[T_i^{start}, T_i^{end}\right] \tag{3}$$

$$b_{k,i,t+1} \ge b_{k,i,t},\ \forall i\in\mathscr{I}, \forall\ k\in\mathscr{K},\ t\in\left[T_i^{start}, T_i^{end}-1\right] \tag{4}$$

Constraint (2) ensures that a bus is active in only one of its possible states: charging/discharging, serving a trip, or parked. Constraint (3) guarantees that the fleet will fulfil all assigned trips. Constraint (4) ensures the continuity of a trip, meaning that a single bus will serve each trip.

Energy constraints: These constraints capture the battery's energy level at each time slot. The model also allows for selling energy to the grid via V2G schemes.

$$\sum_{k\in\mathscr{K}} x_{k,n,t} + \sum_{k\in\mathscr{K}} y_{k,n,t} \le 1, \forall n\in\mathscr{N}, \forall\ t\in\mathscr{T} \tag{5}$$

Table 1
Nomenclature.

Indices and Sets	Description	Range
i	index of a trip	[1 … I]
t	index of a time step	[0 … T]
k	index of a bus	[1 … K]
n	index of a charger	[1 … N]
$\mathscr{I}$	set of scheduled trips	$\mathscr{I} = \{1, \ldots, I\}$
$\mathscr{T}$	set of time steps	$\mathscr{T} = \{0, \ldots, T\}$
$\mathscr{N}$	set of chargers	$\mathscr{N} = \{1, \ldots, N\}$
$\mathscr{K}$	set of electric buses	$\mathscr{K} = \{1, \ldots, K\}$
Parameters	**Description**	**Unit**
T_i^{start}	start time of trip i	–
T_i^{end}	end time of trip i	–
α_n	charging power of charger n	[kW]
β_n	discharging power of charger n	[kW]
ρ_n^{ch}	charging efficiency of charger n	[%]
ρ_n^{dis}	discharging efficiency of charger n	[%]
γ_i	average energy consumption for trip i per time slot	[kWh]
P_t	electricity purchasing price in time t	[€/kWh]
S_t	electricity selling price in time t	[€/kWh]
E_k^0	initial energy level of bus k	[%]
E_k^{min}	minimum energy level allowed for bus k	[%]
E_k^{max}	maximum energy level allowed for bus k	[%]
E_k^{end}	minimum energy level after an operation day for bus k	[%]
U_t	maximum power transformer capacity at time t	[kW]
N_k^{Cy}	maximum number of cycles that the bus k battery can last	–
DoD_k	depth of discharge of the bus k battery	[%]
C_k^{bat}	total capacity of the bus k battery	[kWh]
R_k	battery replacement costs of the bus k	[€/kWh]
Variables	**Description**	**Unit**
$b_{k,i,t}$	binary variable indicating if bus k is serving trip i at time t	{0,1}
$x_{k,n,t}$	binary variable indicating if bus k is occupying charger n at time t to charge	{0,1}
$y_{k,n,t}$	binary variable indicating if bus k is occupying charger n at time t to discharge	{0,1}
$c_{k,t}$	binary variable indicating if bus k is charging/discharging at time t	{0,1}
$e_{k,t}$	energy level of bus k at time t	[kWh]
w_t^{buy}	electricity purchased from the grid at time t	[kWh]
w_t^{sell}	electricity sold to the grid at time t	[kWh]
a_k	total energy taken from a bus k battery through its lifespan	[kWh]
$d_{k,t}$	total degradation cost of the bus k battery at time t	[€]

$$\sum_{n\in\mathscr{N}} x_{k,n,t} + \sum_{n\in\mathscr{N}} y_{k,n,t} \le c_{k,t}, \ \forall k\in\mathscr{K}, \forall\ t\in\mathscr{T} \tag{6}$$

$$e_{k,t} = e_{k,t-1} + \sum_{n\in\mathscr{N}} \rho_n^{ch}.\alpha_n.x_{k,n,t} - \sum_{i\in\mathscr{I}} \gamma_i.b_{k,i,t} - \sum_{n\in\mathscr{N}} \frac{1}{\rho_n^{dis}}.\beta_n.y_{k,n,t}, \forall k\in\mathscr{K}, \forall\ t\in\mathscr{T} \tag{7}$$

$$\sum_{n\in\mathscr{N}}\sum_{k\in\mathscr{K}} \alpha_n.x_{k,n,t} = w_t^{buy}, \ \forall t\in\mathscr{T} \tag{8}$$

$$\sum_{n\in\mathscr{N}}\sum_{k\in\mathscr{K}} \beta_n.y_{k,n,t} = w_t^{sell}, \ \forall t\in\mathscr{T} \tag{9}$$

Constraint (5) ensures that a bus k occupies only one charger n, avoiding that two vehicles charge/discharge at the same time step t at the same charger. Constraint (6) guarantees that a bus k will be charging/discharging if occupying a charger n at a time step t. Constraint (7) tracks the energy level of each bus k in each time step t. Constraint (8) computes the total amount of electricity bought from the grid. Constraint (9) computes the total amount of electricity sold to the grid.

Battery threshold constraints: We define battery charge thresholds to maximize its lifespan, generally set in the literature between 20% and 80% of the battery's capacity. The energy level at the first and last time step of the day is specified, which we considered to be the same to keep the charge sustaining for daily basis operation.

$$e_{k,t} \ge C_k^{bat}.E_k^{min}, \ \forall k\in\mathscr{K}, \forall\ t\in\mathscr{T} \tag{10}$$

$$E_k^{max}.C_k^{bat} \ge e_{k,t} + \sum_{n\in\mathscr{N}} \alpha_n.x_{k,n,t}, \ \forall k\in\mathscr{K}, \ \forall t\in\mathscr{T} \tag{11}$$

$$e_{0,k} = C_k^{bat}.E_k^0, \ \forall k\in\mathscr{K} \tag{12}$$

$$e_{k,T} \ge C_k^{bat}.E_k^{end}, \ \forall k\in\mathscr{K} \tag{13}$$

Constraint (10) ensures that the energy in the battery never drops below a minimum threshold. Constraint (11) ensures that the buses will never charge above the battery's maximum capacity. Constraint (12) sets the initial energy of each bus at the time step 0. Constraint (13) guarantees a minimum energy level in the last charging of the day, ensuring that the fleets will start the next day with the expected energy level to operate.

Transformer constraints: We consider the transformer capacity since keeping the transformers at a healthy operational level is also relevant for the PTO.

$$\sum_{n\in\mathcal{N}}\sum_{k\in\mathcal{K}}\alpha_n.x_{k,n,t} + \sum_{n\in\mathcal{N}}\sum_{k\in\mathcal{K}}\beta_n.y_{k,n,t} \le U_t, \quad \forall t\in\mathcal{T} \tag{14}$$

Constraint (14) sets the transformer's capacity constraint regarding the charging power volume of simultaneous charging operations for each time step t.

Battery ageing constraints: We propose an Ah-throughput model [32,33] to assess battery loss of life and cost for each discharging event.

$$a_k = N_k^{Cy}.\, DoD_k.\, C_k^{bat}, \ \forall k\in\mathcal{K} \tag{15}$$

$$d_{k,t} = \frac{R_k.C_k^{bat}}{a_k}\sum_{n\in\mathcal{N}}\beta_n.y_{k,n,t}, \ \forall k\in\mathcal{K}, \ \forall t\in\mathcal{T} \tag{16}$$

Constraint (15) calculates the total energy taken from a bus k battery throughout its lifespan, considering the total number of cycles, depth of discharge, and total capacity. Constraint (16) defines the costs related to the battery degradation of the bus k due to discharging events. Note that, for this model, we just assumed the degradation costs associated with the selling energy discharging events. We admit that the operations regarding the battery charging are mandatory to keep the fleet's operation and should not be accounted for in the battery ageing process.

Constraint (17) and (18) establish the decision variable ranges.

$$e_{k,t},\ w_t^{buy}, w_t^{sell}, a_k,\ d_{k,t}\in\mathbb{R}_0^+, \tag{17}$$

$$b_{k,i,t},\ x_{k,n,t}, y_{k,n,t}, c_{k,t}\ \in\{0,1\} \tag{18}$$

4. Results and discussion

Firstly, this section introduces the case study and the computational results. Then, a sensitivity analysis is carried out with respect to the battery replacement and energy costs variations. Lastly, we present a total cost of ownership (TCO) study to evaluate costs variation in the long run.

4.1. Case study characteristics

We developed a case study using real-world data supplied to the mathematical model presented in Section 3. The case study refers to a bus network located in Coimbra, Portugal. We selected this case study for two main reasons: (a) the bus system is located in a medium-sized city and, therefore, has a reasonable size (total number of buses, chargers, and routes) to be solved exactly; (b) it was possible to obtain actual information from the PTO. The system is based on the "park & ride" concept, bringing together easy-parking and effective public transport. The drivers park their vehicles in specific parking lots and then board the electric buses. The parking lots are located on the main accesses to the city inner area, playing a role in improving the traffic in some areas classified as very congested. Fig. 2 presents the system's service map, including the altitude profile of each route. The figure depicts the parking lots (where the drivers can park their cars and are used as end stations) and the bus stops.

Each municipality has different bus network characteristics (e.g., time schedules, type of vehicles, user behaviours, route topologies, etc.), which makes planning an electric bus system very challenging. The model presented in Section 3 can be applied to different bus network topologies due to its generality. Planners and decision-makers need to be aware of the variety of bus system features to fit adequately the MILP model parameters.

The system runs with eleven electric buses that allow connections to different city locations and has eight chargers in the depot. The service timetable is scheduled to operate between 7:00 a.m. and 8:15 p.m. on weekdays with a frequency of 10min/15min. Table 2 shows the characteristics of the bus network.

4.2. Standard scenario

Firstly, we ran the model considering a standard scenario, which comprises the parameters closer to the specifications found in the real setting. Data were obtained from the PTO and in previous research works in the field. Table 3 presents the data used in the computational experiments.

The energy prices comprise four periods: peak, mid-peak, off-peak, and super off-peak tariffs. Table 4 presents the energy prices that apply under a contract between the PTO and an electricity retailer in 2021.

We performed all tests on a desktop computer equipped with an 80x Intel® Xeon™ Gold 6138 Processor clocked at 2 GHz with 314 GB RAM, running Linux Kubuntu 18.04. We implemented the mathematical model in the CPLEX Optimization Studio platform.[2]

4.2.1. Results

The results of the standard scenario show an optimal charging cost of 6.17 € daily. For comparison, in a "dumb-charging" scenario,[3] the costs reach 10.42 € per day (40.77% higher). Fig. 3 depicts the buses' state of charge (SOC) variation during an operation day – the red dot line denotes the energy price variation during the planning period. For the experiments, we defined a SOC lower bound of 20% to account for the batteries state of health (SOH) during their operation lifetime. As the result graph unveils, the charging events are concentrated between 02:00 a.m. to 06:00 a.m., when the energy is cheaper. No charging was made between 08:00 p.m. to 02:00 a.m., although the energy is also affordable in this period. The results indicate that not all vehicles need to be fully charged to operate daily. This aspect is relevant since it lowers the total charging cost and plays a role in improving the batteries SOH. The optimization results also indicate the buses that should be assigned to each line and at which time to help planning the overall system schedule. Lastly, the buses end the daily operation (approximately at 08:00 p.m.) with the lowest allowed battery level and keeps this energy until 02:00 a.m., when the charging operations start again on a daily basis operation scheme.

Another aspect regarding the charging events that we evaluated in the model is the transformer maximum power capacity. We considered a transformer capacity of 135 kW (based on the electric bus system's requirements) since multiple charging events could cause grid congestion. Peak demand charges can significantly impact the buses TCO [38]. Thus, limiting the maximum charging power can represent economic gains for the PTO. Fig. 4 depicts the power variation required by the operation on a daily basis.

In the standard scenario, no V2G interaction was allowed. The consideration of battery ageing in the model enabled to conclude that it is not economically attractive to sell back energy to the grid if it causes a higher battery degradation. Therefore, the price of battery replacement is crucial for increasing the adoption of V2G in the future.

[2] https://www.ibm.com/products/ilog-cplex-optimization-studio.

[3] This scenario considers that all buses would be charged from 20% to 100% SOC at the peak electricity price upon arrival to the depot after completion of the daily service.

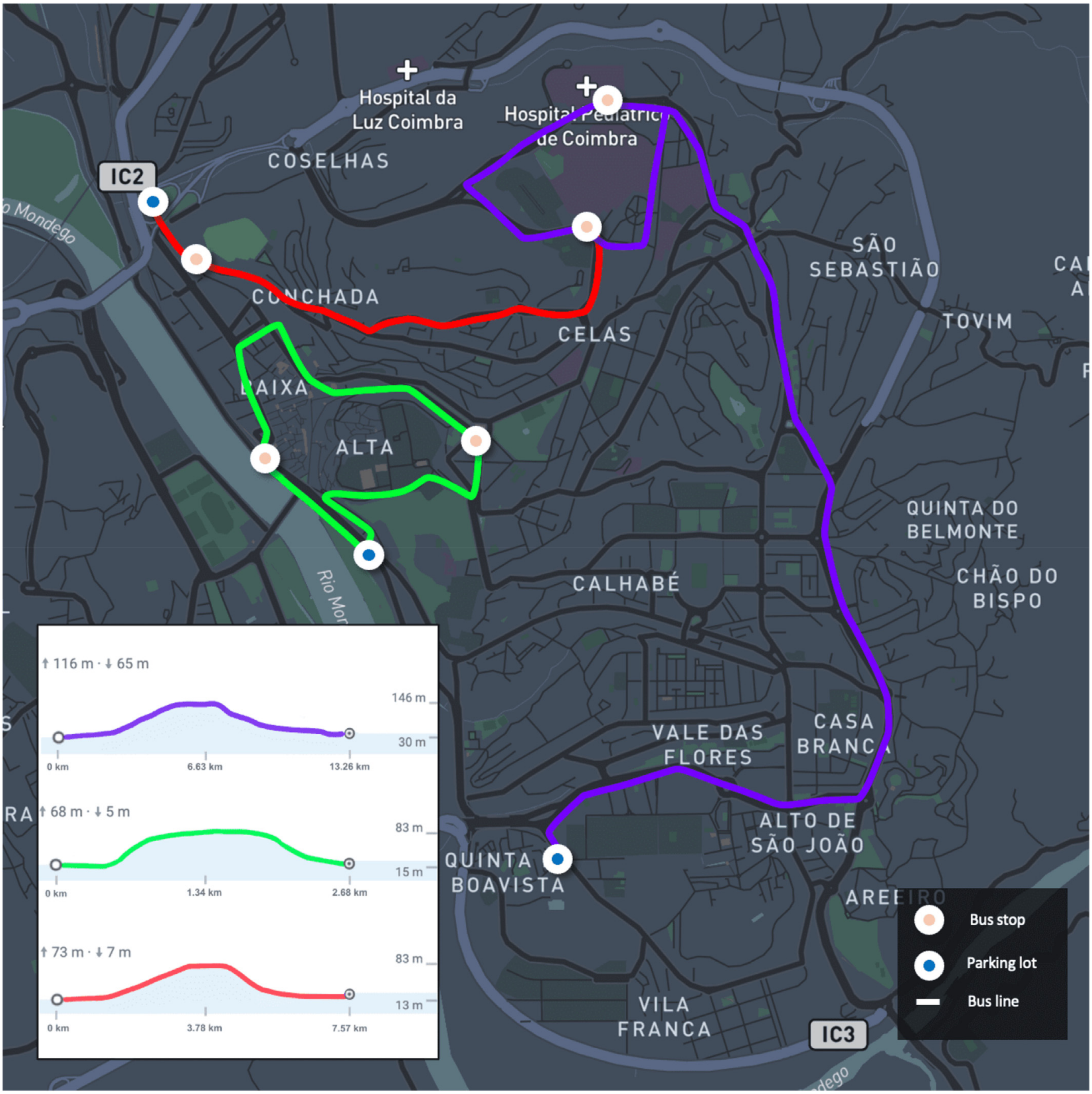

Fig. 2. The system comprises three lines (Red, Green, and Purple), which are served by eleven electric buses.

The computational effort to solve the MILP model for different time steps discretization of the planning period is displayed in Table 5.

As expected, increasing the time step discretization leads to a higher computational effort to solve the MILP model. On the other hand, a fine-grain time step discrtization gives more precise objective function values. Even in the case of 1-min discretization, the time to solve the model is still possible to be applied in a day-ahead bus network planning. Nevertheless, the case study comprises a small bus fleet. More extensive bus networks will require further computational effort to solve since the number of decision variables and constraints will increase rapidly. Thus, it is expected that for actual large-scale problems, the development of a customized meta-heuristic or hybrid approaches combining meta-heuristics with a solver could be adequate research avenues.

4.3. Sensitivity analysis

We performed a sensitivity analysis to evaluate the possibilities of energy trading with the grid. The first subsection assesses the effects that the battery price fall will have in V2G schemes. Further, we evaluated the impacts of energy buying/selling price variation.

Table 2
Case study characteristics.

Lines[a]	Per trip	
	Distance (km)	Time (min)
Green Line	2.68	7
Red Line	7.57	15
Purple Line	13.26	28
Vehicles[b]		
KARSAN Jest Electric (88 kWh)	9 units	
KARSAN Jest Electric (66 kWh)	2 units	
Chargers[c]		
Efacec EFAPOWER (22 kW)	5 units	
Efacec EFAPOWER (7.4 kW)	3 units	

[a] More information can be found in (content in Portuguese): https://www.smtuc.pt/servicos/ecovia-parkride/.
[b] Technical information: https://www.karsan.com/en/jest-electric-specs
[c] Datasheet: https://electricmobility.efacec.com/wpcontent/uploads/2016/10/CS195I1404C1_HC.pdf.

Table 3
Parameters employed in the standard scenario.

Parameter	Value
Energy consumption	1.2 kWh/km [34]
Number of cycles	3000 [35]
Maximum depth of discharge	80%
Transformer capacity	135 kW
Charging/discharging efficiency	85% [36]
Battery replacement costs	130 €/kWh [37]

Note: The maximum depth of discharge value has been defined by the authors.

Table 4
Time-of-use energy prices.

Period	Time (h)	Price (€/kWh)
Peak	09:00 a.m.–10:30 a.m.	0.0567
	06:00 p.m.–09:30 p.m.	
Mid-peak	08:00 a.m.–09:00 a.m.	0.0407
	10:30 a.m.–06:00 p.m.	
	08:30 p.m.–10:00 p.m.	
Off-peak	00:00 a.m.–02:00 a.m.	0.0146
	06:00 a.m.–08:00 a.m.	
	10:00 p.m.–00:00 a.m.	
Super off-peak	02:00 a.m.–06:00 a.m.	0.0141

The price does not include the network access components. More information at: https://mercado.ren.pt/EN/Electr/MarketInfo/MarketResults/OMIE/Pages/Prices.aspx.

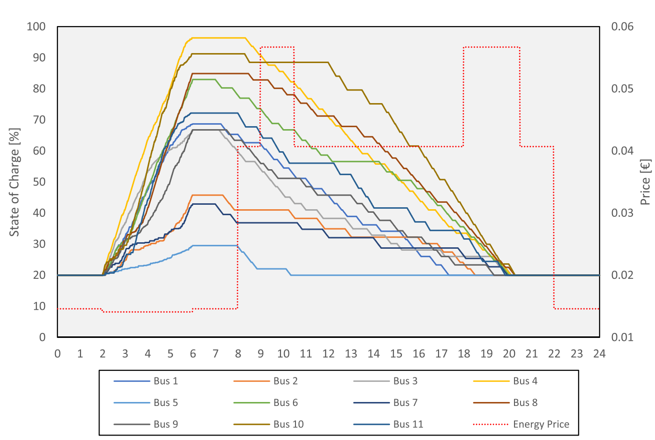

Fig. 3. SOC variation in the standard scenario.

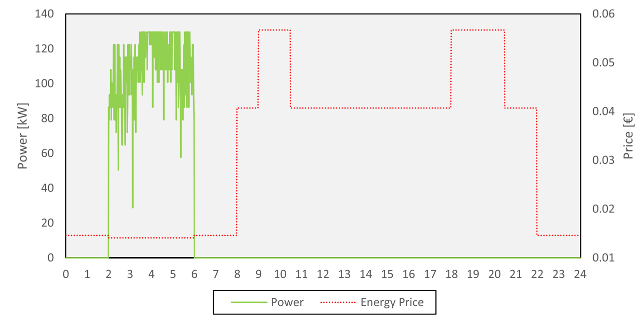

Fig. 4. Power variation required for the operation in the standard scenario.

4.3.1. Battery replacement costs

We selected different battery replacement costs to capture the possibility of grid interactions, which are based on the lithium-ion batteries price fall expected in the following years. Fig. 5 depicts the expected price decay until 2030 using data presented in Ref. [39].

This sensitivity analysis points to the interest of bidirectional charging trends in the medium-term. For the experiments, we selected six different prices of battery replacement. The first five prices are 10% (117 €/kWh), 15% (110.5 €/kWh), 23% (100 €/kWh), 25% (97.5 €/kWh) and 30% (91 €/kWh) cheaper than today's market price. The last one is a projection of the 2030 battery price, expected to be around 73 €/kWh. For the sake of space, only the charts related to the 100 €/kWh battery replacement price scenario are presented.

As Fig. 6 depicts, the charging events are between 00:00 a.m. and 08:00 a.m. when the price is lower. However, differently from the standard scenario, all vehicles must be fully charged to operate to make the most of grid interactions that may occur during the day. That is, the vehicles are extra charged when the energy is cheaper, and the energy may be sold back to the grid in the periods of peak demand, thus representing profits for the PTO at the end of the day. Since the battery replacement costs are lower, it becomes economically attractive to perform such transactions.

Regarding the energy trading events, Fig. 7 illustrates the periods where the buses must be charged and when it is feasible and favourable to sell back energy to the grid. The charging events are concentrated in the super and off-peak time window (00:00 a.m. to 08:00 a.m.) to reduce the fleet charging costs. On the other hand, the energy is sold to the grid in the peak time window (09:00 a.m. to 10:30 a.m./06:00 p.m. to 8:30 p.m.) to increase the revenues of the electricity sold to the grid.

In this scenario, the results show an optimal charging cost of 5.99 € daily, representing a price decrease of approximately 2.93% compared with the standard scenario. Differently from the standard scenario, however, the costs with energy trading are negative. That is, the PTO makes 7.27 € profits daily considering only energy transactions with the grid. The battery degradation costs play a role in keeping the total costs positive (Table 6). Since the bus network under study is of small dimension, the charging costs and savings do not represent a relevant difference in absolute values, although they are relevant percentually. Nevertheless, assuming the fleet electrification in large urban centres, such profits can deliver an attractive new revenue stream for PTOs.

In our experiments, a 100 €/kWh battery replacement cost showed to be the threshold where it becomes economically attractive to sell back energy to the grid. We carried out other experiments to forecast the possibilities of cost decrease in the bus operation in the mid-term.

As Fig. 8 indicates, the expected cost to charge the bus fleets will

Table 5
Computational effort to solve the MILP model.

Time step discretization (min)	Constraints	Variables	Objective function value (€)	Time (h:m:s)
15	9814	219996	11.23	00:18:22
10	14890	328860	10.34	00:32:34
5	29518	655452	8.34	01:03:48
1	144982	3268188	6.17	12:24:37

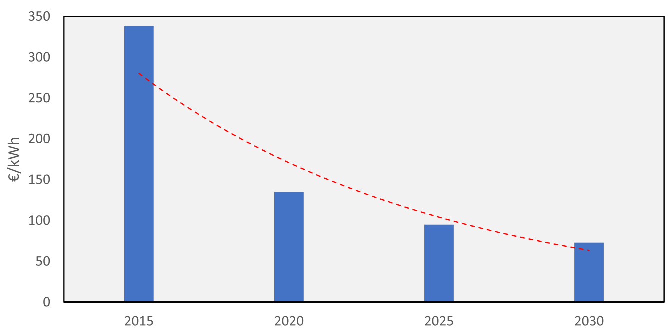

Fig. 5. Prediction of the price of a battery up to 2030.

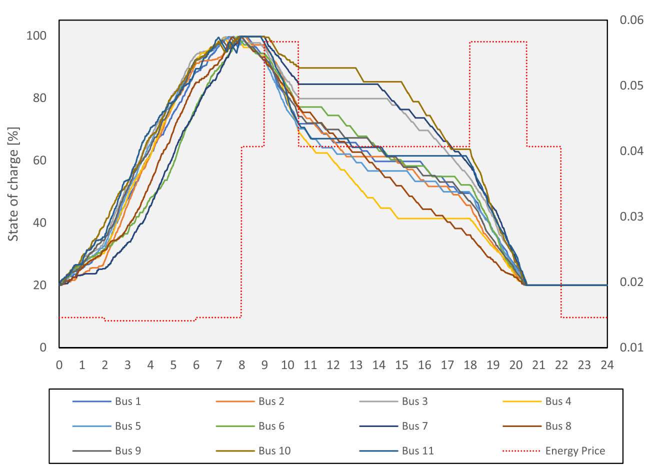

Fig. 6. SOC variation when the battery replacement cost is set at 100 €/kWh.

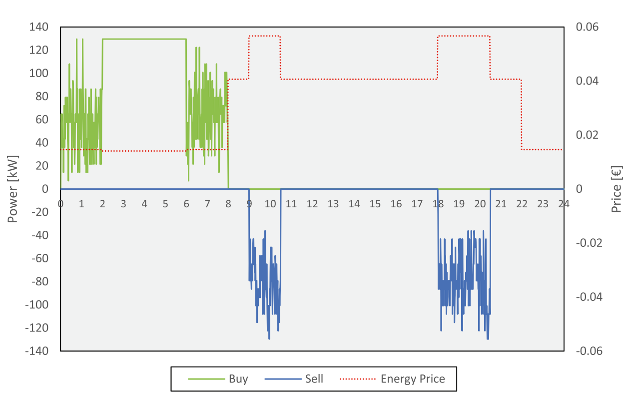

Fig. 7. Grid interaction when the battery replacement cost is set at 100 €/kWh.

decrease in the following years if two main aspects are considered: V2G interaction and battery replacement cost reduction. Regarding the energy transactions, the amounts of the energy bought from

Table 6
Battery replacement costs at 100 €/kWh results.

Costs	Values (€)
Energy cost (buy)	10.83
Energy cost (sell)	−18.10
Total energy costs	−7.27
Battery degradation cost	13.26
Total costs	5.99

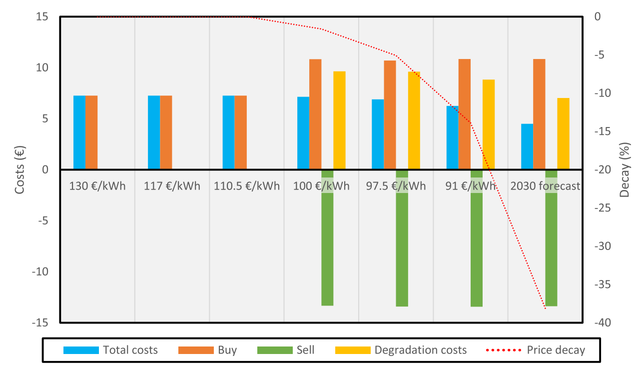

Fig. 8. Sensitivity analysis results for battery replacement cost variation.

and sold to the grid tend to keep unchanged in all experiments since the vehicles have a limited battery capacity as well as given energy requirement to operate satisfying daily demand. Of course, the amount of energy available to sell can vary during the days due to weather, traffic, driving behaviour variation, route topology. Such noise factors, leading to consumption increase, can have a significant impact on the available energy supply, even compromising the possibilities of V2G in different contexts. Furthermore, as the literature indicates [40,41], weather variation strongly impacts energy consumption. Therefore, countries with severe temperatures (high or low) would need to plan the bus scheduling and charging considering energy consumption worst-case scenarios. The stochastic behaviour of such parameters in the MILP model will be considered in further research.

4.3.2. Energy acquisition costs

The energy acquisition cost is also a model parameter that impacts the charging scheduling. Therefore, we selected different energy selling prices to evaluate the feasibility of V2G interactions. The battery replacement cost was set up as 130 €/kWh. A sensitivity analysis has been performed, with the selling prices being increased by 1% steps (until 25%). In this context, selling energy to the grid becomes economically feasible above a selling price 21% higher than the standard price. Fig. 9 depicts the results of this analysis.

As expected, bidirectional charging events become more attractive when the energy selling price increases. Further, the amount of energy sold to the grid tends to become limited by the battery capacities. Although the simulations indicate that it is

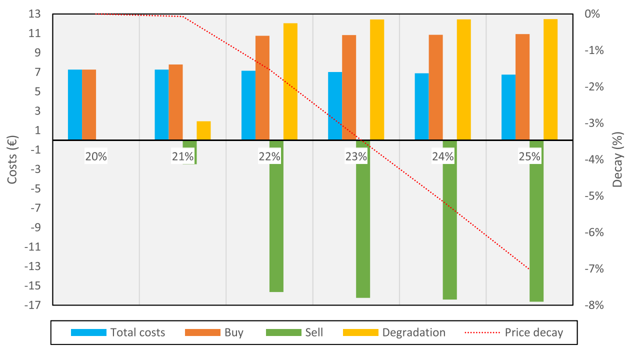

Fig. 9. Sensitivity analysis results for energy acquisition cost variation.

feasible to sell energy to the grid depending on the energy acquisition prices, in real-world situations, this outcome seems to be unlikely. In intraday energy market trading, the ratio difference between the maximum and the minimum prices tend to vary at much lower rates than 21% [42]. However, in some specific conditions, the prices can vary significantly. In this situation, PTOs could take advantage of such energy prices to sell back energy to the grid and improve revenues. Dynamic energy management strategies that consider the variation of intraday prices must be employed to achieve this goal.

The results indicate that PTO's participation in V2G schemes will be mainly driven by the battery replacement costs fall rather than energy selling price increase. Nevertheless, those two scenarios combined can push forward and accelerate the implementation of V2G schemes. In this context, electric bus fleets can contribute to grid resilience by selling energy to the grid and acting as “moving” batteries.

4.4. TCO projection

We performed a TCO analysis to evaluate the costs related to energy transactions and battery replacement. To develop the projection, we evaluate a standard and a V2G scenario. This analysis can shed light on the impacts that V2G may cause on the batteries, since the charging events become more frequent in this setting, and whether or not in the long run it makes sense to perform V2G considering economic factors.

Firstly, we evaluate the fleet battery lifetime using the Ah-throughput method. Considering equation (15), in the Standard scenario, the batteries present a 12-year lifespan. In the V2G scenario, the lifespan drops to 8 years. To be accurate regarding the battery replacement costs, we set 2020 as the initial year of the TCO analysis. Therefore, for the V2G scenario, the battery replacement would occur in 2028. The estimations point out that the battery price will be around 80 €/kWh in this year. Similarly, for the Standard scenario, the battery replacement would occur in 2032, when the battery price is forecasted to be about 73 €/kWh. Those values were used to calculate the battery replacement costs. Further, we calculate all the charging events costs expected to occur for 12 years using the prices in Table 4.

Fig. 10 depicts the costs regarding energy buying/selling events, battery replacement costs and total costs for the two scenarios.

For the time frame under evaluation, the V2G scenario presented 39.12% lower total costs (€62,054.25) than the Standard scenario (€101,938.14). This result is driven by the revenues accumulated during the years by selling back the energy to the grid; however, the fleet battery replacement time is shortened in four years.

Fig. 11 compares the TCO costs of both scenarios for a 30-year time frame over a typical bus fleet replacing period in Europe. For electric buses, battery prices around 45 €/kWh are projected for the year 2050 [37].

For the simulated time frame, the savings gap between the V2G and Standard scenarios is approximately € 50,000. Although it is necessary to replace the batteries in a shorter period, in the long run the savings made by PTOs can be enough to pay back a new battery fleet acquisition cost.

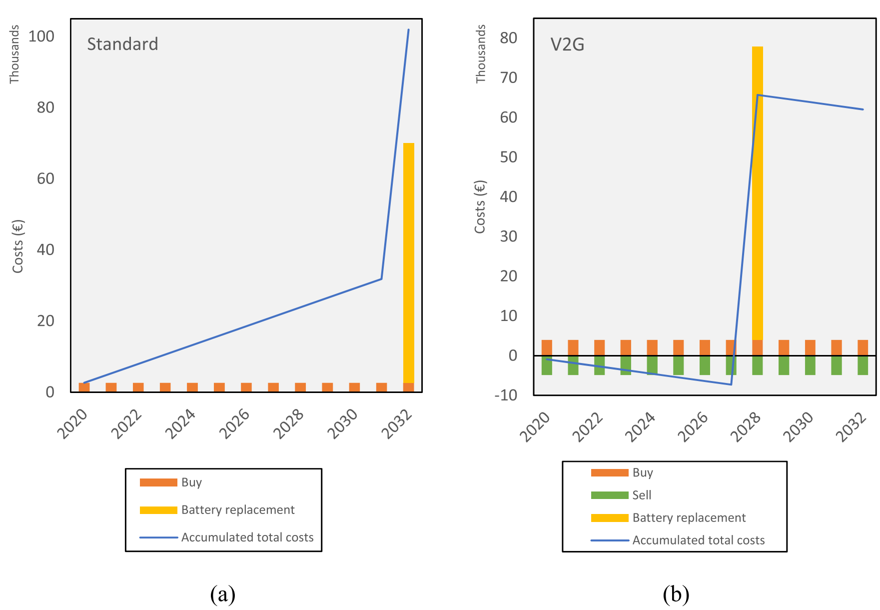

Fig. 10. TCO evaluation for: (a) the Standard scenario; (b) the V2G scenario.

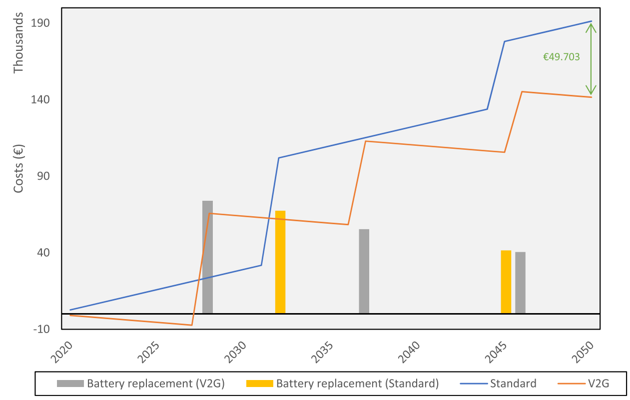

Fig. 11. TCO comparison between the Standard and V2G scenarios.

5. Conclusion

The electrification of public transportation plays an essential role in achieving more liveable cities, helping to mitigate climate change and reduce urban pollution. However, infrastructural and operational limitations are still the main barriers to adopt electric buses in our cities massively. In this setting, we presented a new optimization framework that can be instrumental in assisting the planning and operation of electric bus systems. We developed a MILP model that aims to minimize the charging costs, considering the operational constraints and requirements of the bus system, including battery degradation and participation in V2G schemes.

We analysed a case study using an 11-bus network in a medium-size Portuguese city. For the standard scenario, the experiments reveal that our approach can limit the charging power in a viable bound, representing savings for the PTO. No grid interaction was possible in this setting due to the high costs of battery degradation.

We ran a sensitivity analysis to evaluate the possibilities of energy trading between the electric bus fleet and the grid by assessing the battery replacement price decline and intraday energy price variation. The results indicate that it will be economically viable to perform bidirectional energy transactions shortly, considering the battery replacement cost reduction expected in the next years. After a threshold of 100 €/kWh, the PTO starts making profits considering energy transactions with the grid. If we assume massive electrification of a large urban centre, such profits can mean considerable savings for PTOs. In a 2030 forecast, accounting for battery degradation, the operation costs can be 38% lower than the current values. The energy acquisition cost analysis shows that it is economically feasible to sell energy to the grid; however, in intraday energy market trading, the dynamic prices tend to vary at much lower rates than those necessary to perform the transactions. Nevertheless, there is still a lack of regulation and tariff definition regarding the transactions made within V2G schemes. Therefore, this market can become more attractive in the future. The TCO analysis indicates that the V2G scenario presents 39% lower total costs than the Standard scenario. This result unveils that, in the long run, deploying V2G schemes can offer higher profits to PTOs, even with the drawback of replacing the bus batteries earlier. In summary, the results indicate a decrease in charging costs mainly driven by the reduction of battery prices; however, combining battery price fall and electricity selling price increase could accelerate the deployment of V2G. The approach developed in this work can inform decision making in the electrification of bus systems in different contexts. V2G technology is still evolving. Challenges such as bidirectional chargers technology, privacy issues and investment costs, still need to be surpassed to leverage V2G worldwide [43,44]. The focus of our work was not regarding the technical level feasibility but rather on the possibilities of trading energy with the grid regarding economic aspects, including battery degradation and energy prices.

One limitation of this study is that our model considers an average discharging rate for the vehicles. In real-world situations, energy consumption can vary due to weather, traffic, and driving behaviour variation. We aim to improve the present model by including stochastic variables (e.g., traffic conditions, delays) to deal with these types of uncertainty. As further future research, we aim to apply robust optimization techniques to determine the fleet's size, the number and power of the chargers, frequency of the vehicles, and bus battery size. Further, the model can include the DSO perspective, using bilevel optimization methods to address the hierarchical decision-making process. Such an approach could provide the requirements for the integration of the bus network operational needs and the upstream power distribution systems, contributing to avoid grid stress due to high-power charging events.

Data availability

Datasets related to this article can be found at https://data.mendeley.com/datasets/286zsdh2wy/1, an open-source online data repository hosted at Mendeley Data (Manzolli, 2022).

CRediT authorship contribution statement

Jônatas Augusto Manzolli: Investigation, Methodology, Software, Writing – original draft. **João Pedro F. Trovão:** Resources, Conceptualization, Validation, Funding acquisition, Supervision, Writing – review & editing. **Carlos Henggeler Antunes:** Resources, Conceptualization, Validation, Funding acquisition, Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The first author acknowledges the Portuguese Foundation for Science and Technology – FCT for the PhD grant no. 2021.04879.BD. This work was partially supported by projects UIBD/00308/2020 and the European Regional Development Fund through the COMPETE 2020, FCT and the Regional Operational Program of the Centre Region (CENTRO2020) within the projects MAnAGER (POCI-01-0145-FEDER-028040) and RETROSIM (POCI-01-0145-FEDER-032503), and by grant no. 950–230672 from Canada Research Chairs Program.

References

[1] Wolkinger B, et al. Evaluating health Co-benefits of climate change mitigation in urban mobility. Int J Environ Res Publ Health May 2018;15(5). https://doi.org/10.3390/ijerph15050880. Art. no. 5.
[2] Ji Z, Huang X. Plug-in electric vehicle charging infrastructure deployment of China towards 2020: policies, methodologies, and challenges. Renew Sustain Energy Rev Jul. 2018;90:710–27. https://doi.org/10.1016/j.rser.2018.04.011.
[3] Global EV outlook 2020 – analysis," IEA. https://www.iea.org/reports/global-ev-outlook-2020 (accessed Oct. 15, 2021).
[4] EVO report 2021 | BloombergNEF | bloomberg finance LP," BloombergNEF. https://about.bnef.com/electric-vehicle-outlook/(accessed Oct. 15, 2021).
[5] Du J, et al. Evaluating the technological evolution of battery electric buses:

China as a case. Energy Jun. 2019;176:309–19. https://doi.org/10.1016/j.energy.2019.03.084.

[6] Guida U, Leonard S, ZeEUS. Zero emission urban bus system. 2014. https://doi.org/10.1109/IEVC.2014.7056183.

[7] Guida U, Abdulah A. ZeEUS eBus Report #2 - an updated overview of electric buses in Europe. 2017.

[8] Jenn A, Springel K, Gopal AR. Effectiveness of electric vehicle incentives in the United States. Energy Pol Aug. 2018;119:349–56. https://doi.org/10.1016/j.enpol.2018.04.065.

[9] Shaheen S, Martin E, Totte H. Zero-emission vehicle exposure within U.S. carsharing fleets and impacts on sentiment toward electric-drive vehicles. Transport Pol Jan. 2020;85:A23–32. https://doi.org/10.1016/j.tranpol.2019.09.008.

[10] Pagliaro M, Meneguzzo F. Electric bus: a critical overview on the dawn of its widespread uptake. Advanced Sustainable Systems; Mar. 2019. p. 1800151. https://doi.org/10.1002/adsu.201800151.

[11] Tuchnitz F, Ebell N, Schlund J, Pruckner M. Development and evaluation of a smart charging strategy for an electric vehicle fleet based on reinforcement learning. Appl Energy December 2020;285:116382. https://doi.org/10.1016/j.apenergy.2020.116382. 2021.

[12] Li X, et al. A cost-benefit analysis of V2G electric vehicles supporting peak shaving in Shanghai. Elec Power Syst Res Feb. 2020;179:106058. https://doi.org/10.1016/j.epsr.2019.106058.

[13] Marinelli M, et al. Electric vehicles demonstration projects - an overview across Europe. In: 2020 55th international universities power engineering conference (UPEC); Sep. 2020. p. 1–6. https://doi.org/10.1109/UPEC49904.2020.9209862.

[14] Thingvad A, Calearo L, Andersen PB, Marinelli M. Empirical capacity measurements of electric vehicles subject to battery degradation from V2G services. IEEE Trans Veh Technol Aug. 2021;70(8):7547–57. https://doi.org/10.1109/TVT.2021.3093161.

[15] Shaobo X, Qiankun Z, Xiaosong H, Yonggang L, Xianke L. Battery sizing for plug-in hybrid electric buses considering variable route lengths. Energy Jul. 2021;226:120368. https://doi.org/10.1016/j.energy.2021.120368.

[16] Wu X, Feng Q, Bai C, Lai CS, Jia Y, Lai LL. A novel fast-charging stations locational planning model for electric bus transit system. Energy 2021;224. https://doi.org/10.1016/j.energy.2021.120106.

[17] Alwesabi Y, Liu Z, Kwon S, Wang Y. A novel integration of scheduling and dynamic wireless charging planning models of battery electric buses. Energy Sep. 2021;230:120806. https://doi.org/10.1016/j.energy.2021.120806.

[18] Liu Z, Song Z, He Y. Planning of fast-charging stations for a battery electric bus system under energy consumption uncertainty. Transport Res Rec Dec. 2018;2672(8):96–107. https://doi.org/10.1177/0361198118772953.

[19] Tang X, Lin X, He F. Robust scheduling strategies of electric buses under stochastic traffic conditions. Transport Res C Emerg Technol 2019;105: 163–82. https://doi.org/10.1016/j.trc.2019.05.032. March.

[20] He Y, Liu Z, Song Z. Optimal charging scheduling and management for a fast-charging battery electric bus system. Transport Res E Logist Transport Rev 2020;142. https://doi.org/10.1016/j.tre.2020.102056.

[21] Zhuang P, Liang H. Stochastic energy management of electric bus charging stations with renewable energy integration and B2G capabilities. IEEE Trans Sustain Energy 2020. https://doi.org/10.1109/TSTE.2020.3039758.

[22] Ke B-R, Lin Y-H, Chen H-Z, Fang S-C. Battery charging and discharging scheduling with demand response for an electric bus public transportation system. Sustain Energy Technol Assessments Aug. 2020;40:100741. https://doi.org/10.1016/j.seta.2020.100741.

[23] Chen H, et al. Coordinated charging strategies for electric bus fast charging stations. In: 2016 IEEE PES asia-pacific power and energy engineering conference (APPEEC); Oct. 2016. p. 1174–9. https://doi.org/10.1109/APPEEC.2016.7779677.

[24] Clairand J-M, González-Rodríguez M, Cedeño I, Escrivá-Escrivá G. A charging station planning model considering electric bus aggregators. Sustain Energy Grid Netw Jun. 2022;30:100638. https://doi.org/10.1016/j.segan.2022.100638.

[25] Lopez de Briñas Gorosabel O, Xylia M, Silveira S. A framework for the assessment of electric bus charging station construction: a case study for Stockholm's inner city. Sustain Cities Soc Mar. 2022;78:103610. https://doi.org/10.1016/j.scs.2021.103610.

[26] Purnell K, Bruce AG, MacGill I. Impacts of electrifying public transit on the electricity grid, from regional to state level analysis. Appl Energy Feb. 2022;307:118272. https://doi.org/10.1016/j.apenergy.2021.118272.

[27] Mohamed M, Farag H, El-Taweel N, Ferguson M. Simulation of electric buses on a full transit network: operational feasibility and grid impact analysis. Elec Power Syst Res Jan. 2017;142:163–75. https://doi.org/10.1016/j.epsr.2016.09.032.

[28] Qin N, Gusrialdi A, Paul Brooker R, T-Raissi A. Numerical analysis of electric bus fast charging strategies for demand charge reduction. Transport Res Pol Pract Dec. 2016;94:386–96. https://doi.org/10.1016/j.tra.2016.09.014.

[29] Wu Z, Guo F, Polak J, Strbac G. Evaluating grid-interactive electric bus operation and demand response with load management tariff. Appl Energy Dec. 2019;255:113798. https://doi.org/10.1016/j.apenergy.2019.113798.

[30] Clairand J-M, Gonzalez-Roriguez M, Teran PG, Cedenno I, Escriva-Escriva G. The impact of charging electric buses on the power grid. In: 2020 IEEE power & energy society general meeting (PESGM); Aug. 2020. p. 1–5. https://doi.org/10.1109/PESGM41954.2020.9282014. Montreal, QC, Canada.

[31] Erdoğan S, Miller-Hooks E. A green vehicle routing problem. Transport Res E Logist Transport Rev Jan. 2012;48(1):100–14. https://doi.org/10.1016/j.tre.2011.08.001.

[32] Sarasketa-Zabala E, Gandiaga I, Martinez-Laserna E, Rodriguez-Martinez LM, Villarreal I. Cycle ageing analysis of a LiFePO4/graphite cell with dynamic model validations: towards realistic lifetime predictions. J Power Sources Feb. 2015;275:573–87. https://doi.org/10.1016/j.jpowsour.2014.10.153.

[33] Maheshwari A, Paterakis NG, Santarelli M, Gibescu M. Optimizing the operation of energy storage using a non-linear lithium-ion battery degradation model. Appl Energy Mar. 2020;261:114360. https://doi.org/10.1016/j.apenergy.2019.114360.

[34] MARCON. Electric bus feasibility study. Edmonton; 2016.

[35] Molaeimanesh GR, Mousavi-Khoshdel SM, Nemati AB. Experimental analysis of commercial LiFePO4 battery life span used in electric vehicle under extremely cold and hot thermal conditions. J Therm Anal Calorim Feb. 2021;143(4):3137–46. https://doi.org/10.1007/s10973-020-09272-z.

[36] Kieldsen A, Thingvad A, Martinenas S, Sørensen TM. Efficiency test method for electric vehicle chargers: international battery, hybrid and fuel cell electric vehicle symposium. In: Presented at the international battery, hybrid and fuel cell electric vehicle symposium; 2016. Montreal, Québec, Canada.

[37] Mauler L, Duffner F, Zeier WG, Leker J. Battery cost forecasting: a review of methods and results with an outlook to 2050. Energy Environ Sci 2021;14(9): 4712–39. https://doi.org/10.1039/D1EE01530C.

[38] Gallo Pj-B. Peak demand charges and electric transit buses, vol. 57; 2014.

[39] Berckmans G, Messagie M, Smekens J, Omar N, Vanhaverbeke L, Van Mierlo J. Cost projection of state of the art lithium-ion batteries for electric vehicles up to 2030. Energies Sep. 2017;10(9). https://doi.org/10.3390/en10091314. Art. no. 9.

[40] Fetene GM, Kaplan S, Mabit SL, Jensen AF, Prato CG. Harnessing big data for estimating the energy consumption and driving range of electric vehicles, vol. 54. Transportation Research Part D: Transport and Environment; Jul. 2017. p. 1–11. https://doi.org/10.1016/j.trd.2017.04.013.

[41] Szumska EM, Jurecki RS. Parameters influencing on electric vehicle range. Energies 2021;14(16). https://doi.org/10.3390/en14164821.

[42] Chamandoust H, Derakhshan G, Bahramara S. Multi-objective performance of smart hybrid energy system with Multi-optimal participation of customers in day-ahead energy market. Energy Build Jun. 2020;216:109964. https://doi.org/10.1016/j.enbuild.2020.109964.

[43] Yuan J, Dorn-Gomba L, Callegaro AD, Reimers J, Emadi A. A review of bidirectional on-board chargers for electric vehicles. IEEE Access 2021;9: 51501–18. https://doi.org/10.1109/ACCESS.2021.3069448.

[44] Rajasekaran AS, Azees M, Al-Turjman F. A comprehensive survey on security issues in vehicle-to-grid networks. J Control Decis Jan. 2022:1–10. https://doi.org/10.1080/23307706.2021.2021113. vol. 0, no. 0.