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Sensitivity analysis of bus line electrification at different operating conditions

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Abstract

The electrification of public transport buses is getting more insights, especially in urban areas. The use of Battery electric buses (BEB) results in no tailpipe emissions, which gives BEB an advantage over diesel, hybrid and natural gas buses. However, the high capital costs and fluctuating operating costs of BEB limits their market breakthrough. Minimizing the total costs of BEB is essential to ease their deployment and this can be achieved by optimally designing the battery size and managing the charging strategy of the buses. These costs incur significant fluctuations as they are highly sensitive to electricity tariffs set by local authorities. In addition, these costs are directly driven by the battery costs, battery technology, and onboard energy management. For this sake, it is essential to evaluate the effect of the mentioned parameters on BEB optimal battery sizing and charging strategy and highlight their impact on the electricity grid.

Keywords: battery-electric bus; capital costs; operating costs; electricity tariffs; battery technology; electric grid

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1. Introduction

Low-emission zones for vehicles are evolving fast in European cities amid air quality concerns. Major European cities are banning diesel vehicles as an effective measure to reduce emissions in urban areas, after the perceived failure to effectively enforce and implement the adopted vehicle emissions regulations (Müller and Le Petit, 2018). The adoption of alternative bus technologies in public transportation helps to reduce the Green House Gas (GHG) emissions and pollutants when compared to diesel buses. Currently, there are many alternative bus technologies such as hybrid electric buses, compressed natural gas buses, fuel cell buses, and battery electric buses (Jorgensen, 2008). Many studies have confirmed the advantage of BEB in reducing carbon emissions when compared to diesel, hybrids and natural gas buses (Du et al., 2019; Pagliaro and Meneguzzo, 2019).

BEBs are the most promising solution to replace the current diesel bus fleet. BEBs incur lower well-to-wheel energy consumption per driven kilometers when compared to all other alternative technologies (Antonio et al., 2013; Torchio and Santarelli, 2010). This better energy performance is mainly due to the higher BEB powertrain efficiency. Moreover, BEBs result in the least well-to-wheel GHG emissions (Grutter, 2015; Nylund and Koponen, 2012). These emissions are highly dependant on the electricity generation mix.

Despite their superior environmental performance, BEBs still face many challenges that prevent their deployment at a massive scale (Bühne et al., 2015). First, the costs of BEBs deployment are the highest among all other alternative bus technologies (Lajunen, 2014; Mckenzie and Durango-cohen, 2012). The costs of the battery pack result in a very high bus unit price where only fuel cell buses record a higher unit price. In addition, the costs of infrastructural modification are very high in the case of BEBs. Other challenges facing BEBs are their operation features. The two main operation features for buses are their driving range and their refueling time. BEBs suffer the lowest driving range and highest refueling time among all alternative bus technologies which may disturb their operation resulting in schedule delays (Efthymiou et al., 2017; Mahmoud et al., 2016)

A proper battery sizing and charging strategy help to overcome the aforementioned challenges to ease BEBs deployment. The size of the battery directly affects the costs and the driving range. Bigger batteries result in a higher driving range, however, this yields to higher costs. On the other hand, reducing the battery size decreases the incurred costs but it reduces the driving range as well. In addition, the adopted charging strategy impacts the costs and refueling time. Utilizing fast chargers at a high power-rating shortens the refueling time, however, this comes at high chargers costs. On the other hand, using slower chargers incurs lower costs, but this yields to longer refueling time.

The choice of the optimal battery sizing and charging strategy of BEBs are highly affected by the BEBs operating conditions. Many parameters drive the total operating and capital costs of BEB and they are subject to continuous fluctuations. These parameters can be classified into three main categories:

- 1) Technology-related parameters: the price of Lithium-ion batteries and battery lifetime. the price of lithium-ion batteries has a direct impact on the BEB capital costs being the main battery technology used nowadays due to its energy and power density benefits (Schmuck et al., 2018).
- 2) Energy cost-related parameters: local electricity energy and power tariffs. Energy costs parameters directly drive the BEB operating costs. Electric energy and power tariffs are determined by local authorities depending on the local electricity generation mix and ON/OFF peak hours (Zhou et al., 2016).
- 3) Energy Management-related parameters: charging/discharging strategy of the battery including the minimum allowable battery state of charge (SOC) and the bus charging duration. These parameters manage the on-board energy/power source and affect both the capital and operating costs of BEB.

The mentioned parameters affect the optimal battery sizing and charging strategy of BEB leading to different total costs and charging infrastructure, in addition to different impacts on the electricity grid. That being said, it is essential to evaluate the impact of these parameters on BEB optimal battery sizing, charging strategy, and electricity grid, as they are widely varying across different countries or regions.

2. Methods

In order to provide an optimal battery size and charging strategy for BEB, 2 main components are necessary. First, a tool that can assess the energy consumption of BEB at all driving and weather conditions is required. Second, an optimization algorithm that will minimize the total costs of BEB by optimally sizing the battery and managing the charging strategy.

2.1. Energy Consumption Assessment

The energy consumption of BEB is assessed using a detailed bus energy model that is developed by the current author in previous work. The model considers the main energy loads encountered in BEBs covering the bus's entire energy needs. There are three main energy loads in BEBs: (1) traction energy load, (2) thermal energy load and (3) non-mechanical auxiliaries' energy load.

Concerning the traction energy load, a powertrain model is developed to evaluate this energy load. The model includes a battery, electric machine, transmission and braking systems, and a torque controller to supply the driver's acceleration and braking demands. The considered bus is a typical single deck 12-m long bus equipped with a Lithium-ion battery that has an energy density of 85 Wh/kg. A 155 kW electric machine propels the bus and recuperates the kinetic energy of the bus during braking. The transmission system is designed to meet the bus acceleration requirements.

The thermal energy load is evaluated by developing a bus cabin model and heating, ventilating and air conditioning model (HVAC). The bus cabin model estimates the thermal conditions inside the bus such as the internal temperature and humidity. The proposed model considers the different heat transfer phenomena that take place between the bus interior and external environment, internal bus components and passengers. The model is validated experimentally on an electric vehicle (Brèque and Nemer, 2017). The heat transfer due to frequent opening and closure of the bus doors is considered as well. On the other hand, an HVAC unit supplies the bus cabin with its energy needs in order to attain thermal comfort conditions inside the bus. The proposed HVAC unit is a 40 - kW reversible heat pump that operates as a heat pump and air conditioner in order to supply the bus's heating and cooling needs. The heat pump is properly sized and controlled in previous work (Al Haddad et al., 2019).

Non-mechanical auxiliaries are essential features for the bus operation. There are four main types of auxiliaries encountered in BEB: (1) Electric, (2) Pneumatic, (3) Hydraulic and (4) Thermal. Most of these auxiliaries are only found in heavy-duty vehicles and they can't be neglected. Bus doors, suspension system, and lighting are all-electric auxiliaries whereas the steering pump is a hydro-electric auxiliary. The pneumatic auxiliaries include the braking system as it operates by means of air brakes. Finally, thermal auxiliaries include Lithium-ion battery cooling and heating needs.

Fig. 1 shows the bus global energy scheme. More details on the modeling approach can be found in (Basma et al., 2019)

2.2. Optimization Algorithm

Moreover, the authors introduce an optimization methodology that aims at minimizing the total costs of BEB by controlling the battery size, charging energy and charging power during the day while respecting the bus schedule needs to ensure uninterrupted operation. The algorithm is based on the Dynamic Programming (DP) global optimization routine developed by Richard Bellman in 1954.

The cost function to be minimized is the total operating and capital costs of BEB as shown in equation (1)

$$\Omega_i = \sum_{i=0}^T \alpha(t) \cdot E_i \cdot \left(1 + \varepsilon \cdot \frac{p_i^2}{p_{max}^2} \right) + \beta \cdot k \quad (1)$$

The cost function is composed of two components: (1) energy costs representing the operating costs and (2) battery

costs representing the capital costs. The optimization algorithm minimizes the total operating and capital costs throughout the entire service life of the battery. Table 1 explains the cost function components.

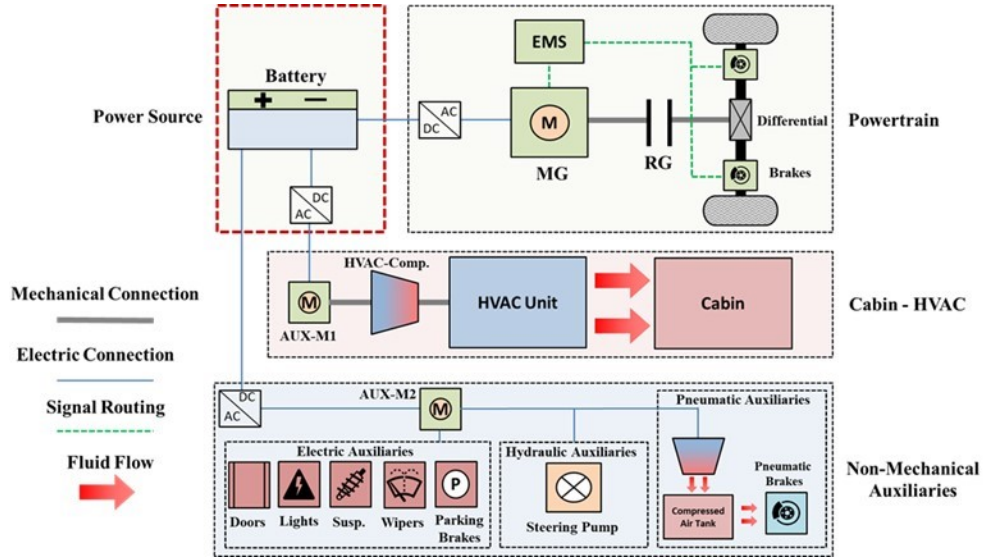


Fig. 1: BEB Global Energy Scheme

Table 1: Optimization Algorithm Cost Function Components

	Variable	Definition	Unit
Energy Costs	α	Cost of unit energy	€/kWh
	ε	Demand Charge Cost Coefficient	-
	E	Amount of Charged Energy	kWh
	p	Charging Power	kW
	p_{max}	Maximum Allowable Charging Power	kW
Battery Costs	β	Cost of Lithium-ion Batteries	€/kWh
	k	Battery Size (Capacity)	kWh

This optimization problem is a constrained problem as there exist constraints on the state and control variables. There are four main constraints to respect in this optimization problem: (1) Battery maximum charging power, (2) battery minimum and maximum state of charge (SOC), (3) bus schedule and (4) thermal comfort conditions inside the bus cabin.

The scope of the study covers stationary charging scenarios where the bus can only be charged when it is parked either at the depot, terminal station or stop station. That being said, there are 3 different stationary charging scenarios: (1) Depot Charging, (2) Terminal Station Charging and (3) Opportunity Charging at the bus stops. Fig. 2 graphically illustrates the mentioned scenarios.

The Optimization Algorithm is applied for each charging scenario providing optimal charging strategy and battery sizing. Moreover, the optimization algorithm provides the power rating of the required chargers referred to as the charging technology. Fig. 3 presents the optimization algorithm.

2.3. Framework

Fig. 4 shows the global overview of the proposed methodology. The proposed tool receives inputs such as bus line driving conditions, trajectory topography, weather conditions, and passengers flow to the bus stations, and evaluates the energy consumption of the bus during each trip. Afterward, the buses energy needs are fed to the

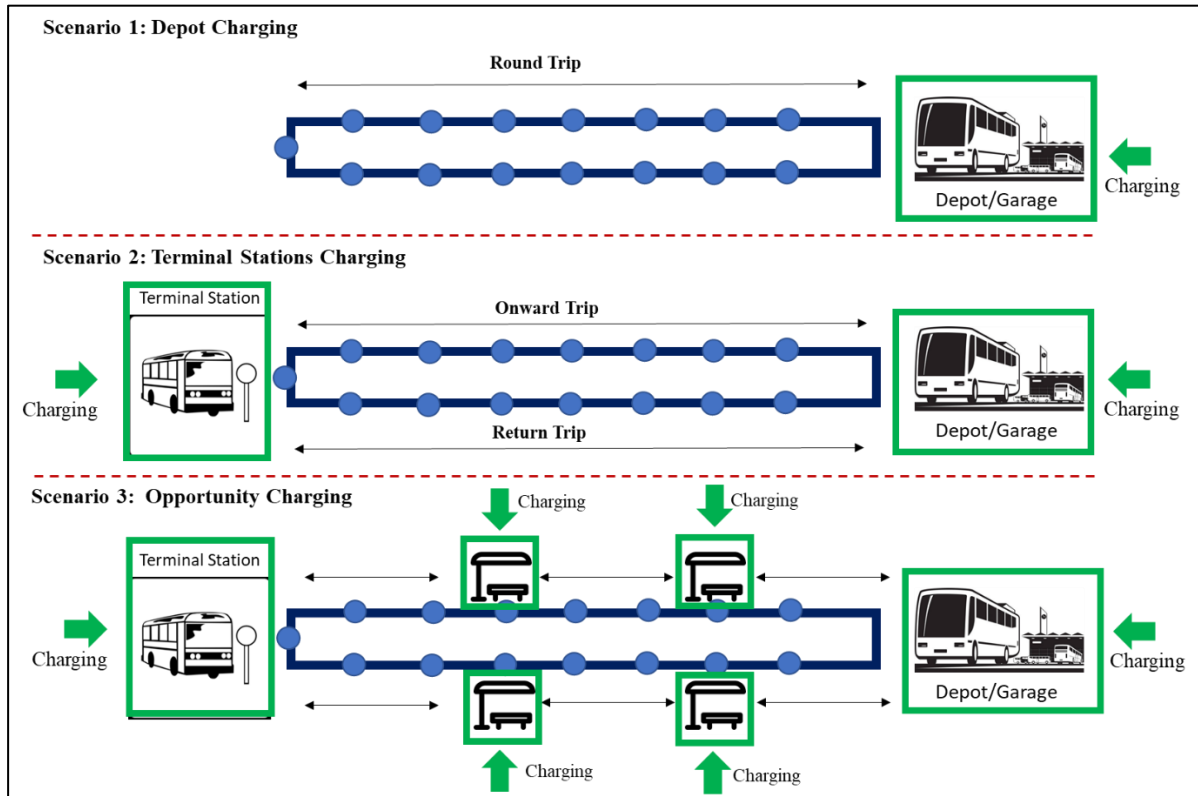


Fig. 2: Stationary Charging Scenarios

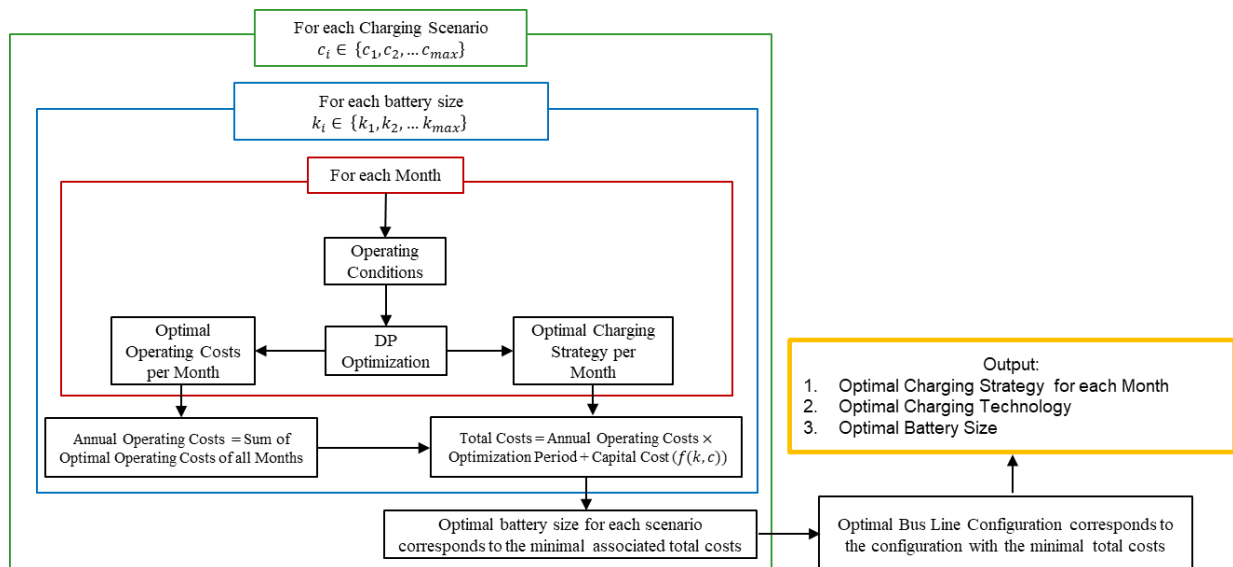


Fig. 3: Optimization Algorithm

optimization algorithm, in addition to the buses schedule, technology-related parameters, energy cost-related parameters, and energy management-related parameters, in order to optimize the bus line configuration by providing optimal battery sizing for the buses, optimal charging energy, power, duration, and location along the bus lines and the corresponding optimal charging technology.

Bus line number 21 in Paris City is considered as the case study where the data concerning the driving conditions, passengers' flow and schedule of this bus line are collected. The weather conditions and electricity tariff structure of the city of Paris are considered.

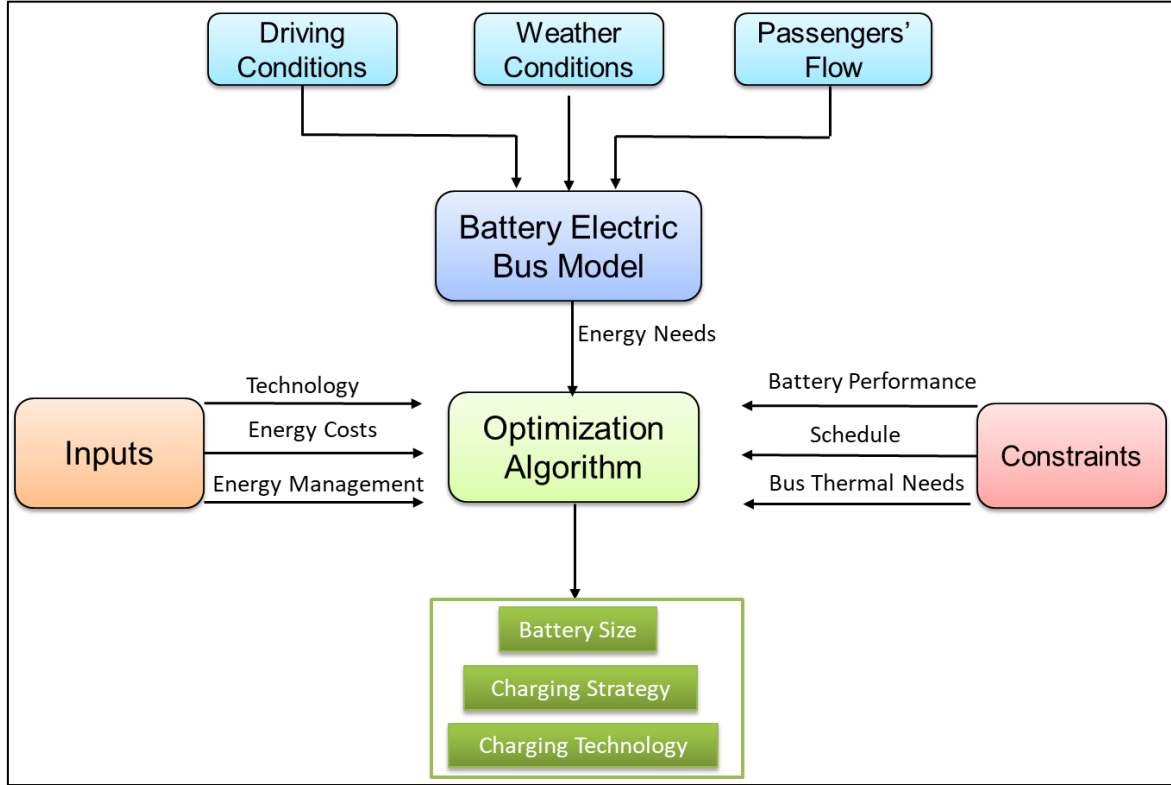


Fig. 4: Methodology Global Overview

In this study, the “Inputs” are manipulated to run a sensitivity analysis to study their impact on BEB optimal battery design, charging strategy, total costs, and the electricity grid. The energy cost parameter α is a function of time, which reflects the different electric energy tariffs imposed by local authorities during the ON/OFF peak hours. In this study, the percentile difference between the peak and Off-peak hour tariffs is manipulated. This parameter is denoted by DA and is calculated according to equation (2).

$$DA = \frac{\alpha_H - \alpha_L}{\alpha_H} \quad (2)$$

Where α_H is the high cost of electricity during peak hours and α_L is the low cost of electricity during off-peak hours. α_H is fixed and α_L is varied.

Table 2: Input Parameters

	Parameter	Definition	Range	Unit
Energy Costs	DA	Peak/Off-peak hours energy cost difference	0-0.9	-
	ε	Demand Charge Cost Coefficient	0-1	-
Technology	β	Cost of 1 kWh of Lithium-ion Batteries	50-200	€/kWh
	T	Lithium-ion Batteries service life	5-12	Years
Energy Management	SOC_{min}	Minimum Allowable Battery SOC	0.1-0.3	-
	τ	Opportunity charging duration (Scenario 3)	0.5-3	min

3. Results

This section evaluates the impact of the parameters introduced in Table 2 on the optimal battery size, power demand profile during the day, charging energy and total costs.

3.1. Impact of Energy Cost-Related Parameters

- **Peak/Off-Peak Hours Energy Cost Difference**

Fig. 5 and Fig. 6 present the variation of the optimal battery sizing and total costs function of the Peak/Off-Peak hours energy cost difference DA. As the difference between day/night electricity tariff increases, a bigger battery size is preferred. The reason is that most of the charging is done at night for bigger batteries, which reduces the operating costs despite their higher capital costs compared to smaller batteries. All 3 scenarios show a similar behavior. In addition, scenario 1 requires the biggest battery size whereas scenario 3 requires the smallest battery size, this is due to the charging frequency of the buses in each scenario. The buses can be charged once every round trip in scenario 1, twice in scenario 2 and 6 times per round trip in scenario 3. Higher charging frequency leads to smaller optimal battery size.

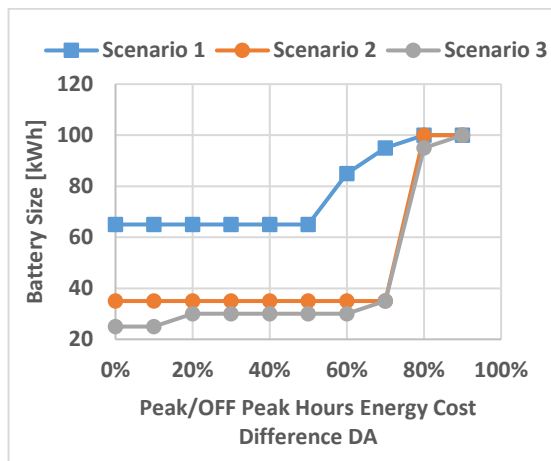


Fig. 5: Impact of Peak/Off-Peak Hours Energy Cost Difference on Optimal Battery Size

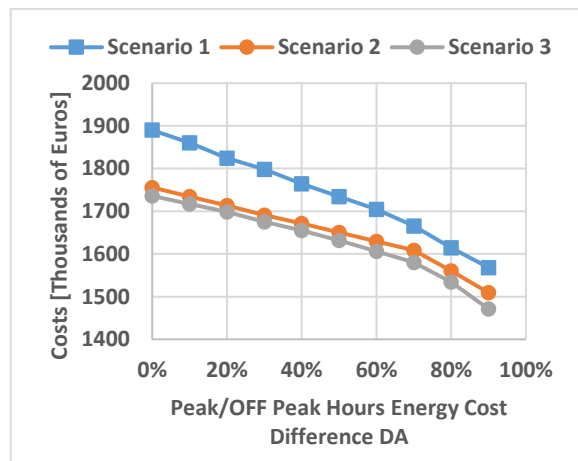


Fig. 6: Impact of Peak/Off-Peak Hours Energy Cost Difference on Total Costs

Fig. 7 and Fig. 8 show the impact of DA on the charging energy and power respectively. Higher values of DA result in lower charging during the day and more charging during the night and this is due to the following two reasons: (1) the optimal battery size increases with DA and thus more charging takes place at night for bigger batteries and (2) higher DA values imply that charging at night becomes less expensive.

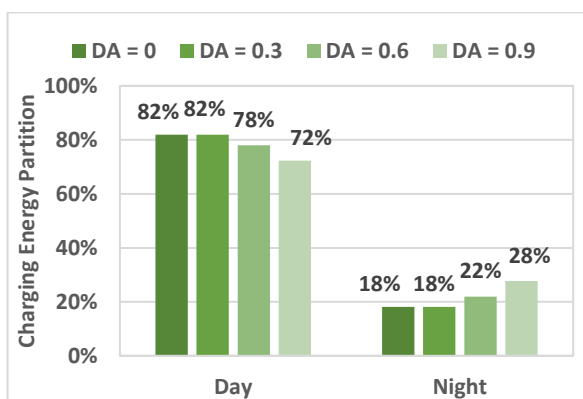


Fig. 7: Impact of Peak/Off-Peak Hours Energy Cost Difference on Charging Energy Partition

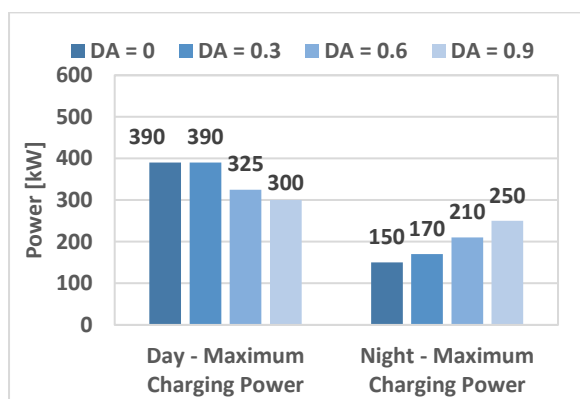


Fig. 8: Impact of Peak/Off-Peak Hours Energy Cost Difference on Daily Power Demand

- **Demand Charge Cost Coefficient**

In Fig. 9, the impact of the demand charge cost coefficient on the optimal battery size is assessed. Scenarios 1 and 2 do not show a sensitive behavior to the demand charge tariff variation. On the contrary, scenario 3 witnesses an increase in the optimal battery size as ϵ increases. Higher values of ϵ imply that the operating costs will increase

with higher power demand. Smaller batteries are charged more during the day and at higher power as their initial energy level is lower compared to bigger batteries. The sensitive behavior of scenario 3 relative to ϵ is due to the fast chargers used in opportunity charging at the bus stops where charging takes place at high power.

Fig. 10 highlights the impact of the demand charge cost coefficient on the total costs. All 3 scenarios witness an increase in total costs as ϵ increases. For scenarios 1 and 2, higher values of ϵ result in higher operating costs but no variation in capital costs as the optimal battery size is not affected by ϵ , therefore, higher total costs are obtained for these 2 scenarios. Similarly, for scenario 3, higher total costs are obtained with higher values of ϵ , however, total costs become less sensitive to ϵ for values above 0.5. This is due to the bigger optimal battery size which allows charging at a lower power rate.

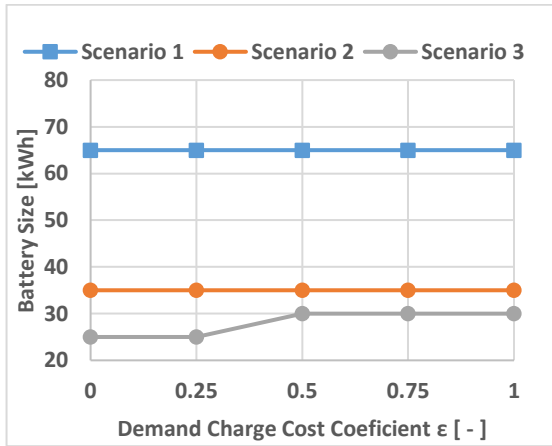


Fig. 9: Impact of Demand Charge Cost Coefficient on Optimal Battery Size

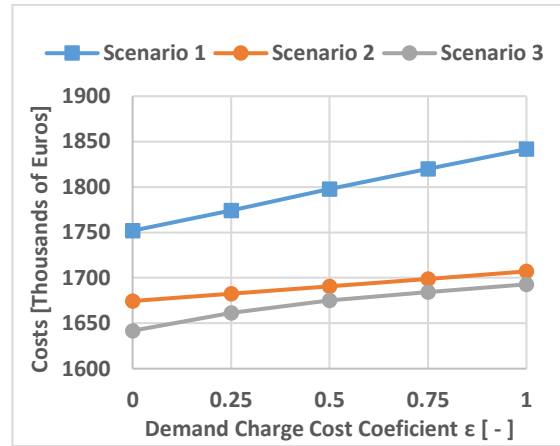


Fig. 10: Impact of Demand Charge Cost Coefficient on Total Costs

Fig. 11 and Fig. 12 show the impact of demand charge cost coefficient on the charging energy and power respectively. At higher values of ϵ , less energy is charged during the day and more energy is charged during the night as night-charging takes place at lower power rates. Concerning the power demand, reducing the demand charge tariff ($\epsilon = 0.25$) is resulting in higher power demand during the day which exceeds 500 kW whereas a high demand charge tariff limits the maximum power demand during the day to less than 400 kW.

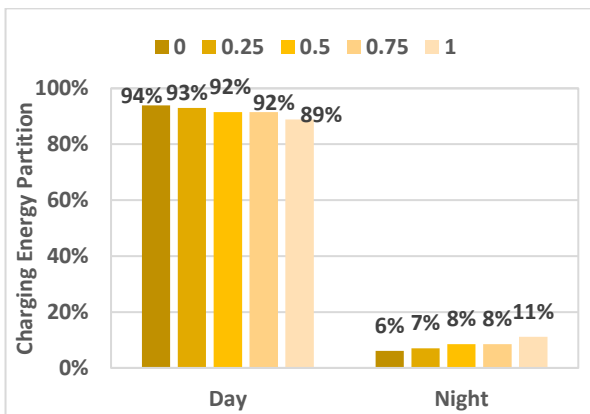


Fig. 11: Impact of Demand Charge Cost Coefficient on Charging Energy Partition

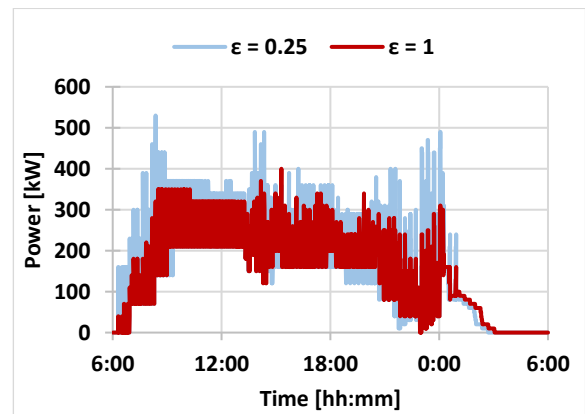


Fig. 12: Impact of Demand Charge Cost Coefficient on Daily Power Demand

3.2. Impact of Technology-Related Parameters

In this section, the presented results correspond to scenario 3, however, all other scenarios show similar behavior. Fig. 13 shows the impact of Lithium-Ion Batteries cost and service life on the total costs. At high Lithium-Ion Batteries costs, smaller batteries are preferred as they result in lower capital costs and thus lower total costs. However, when the costs of Lithium-Ion Batteries drop below a certain threshold, referred to as λ , bigger batteries incur lower total costs mainly due to their lower operating costs that compensate for the high capital costs of big

batteries.

Similar behavior is witnessed at all other values of the battery service life, however, there is a different value for the threshold λ at each battery service life. For example, the value of λ increases from 50 to 120 €/kWh as the service life increases from 5 to 12 years. This implies that with higher battery service life, bigger batteries are preferred as they incur lower total costs. The reason is that with higher battery service life, the total costs become more sensitive to the operating costs as their share in the total costs increases and therefore batteries that incur lower operating costs will be preferred.

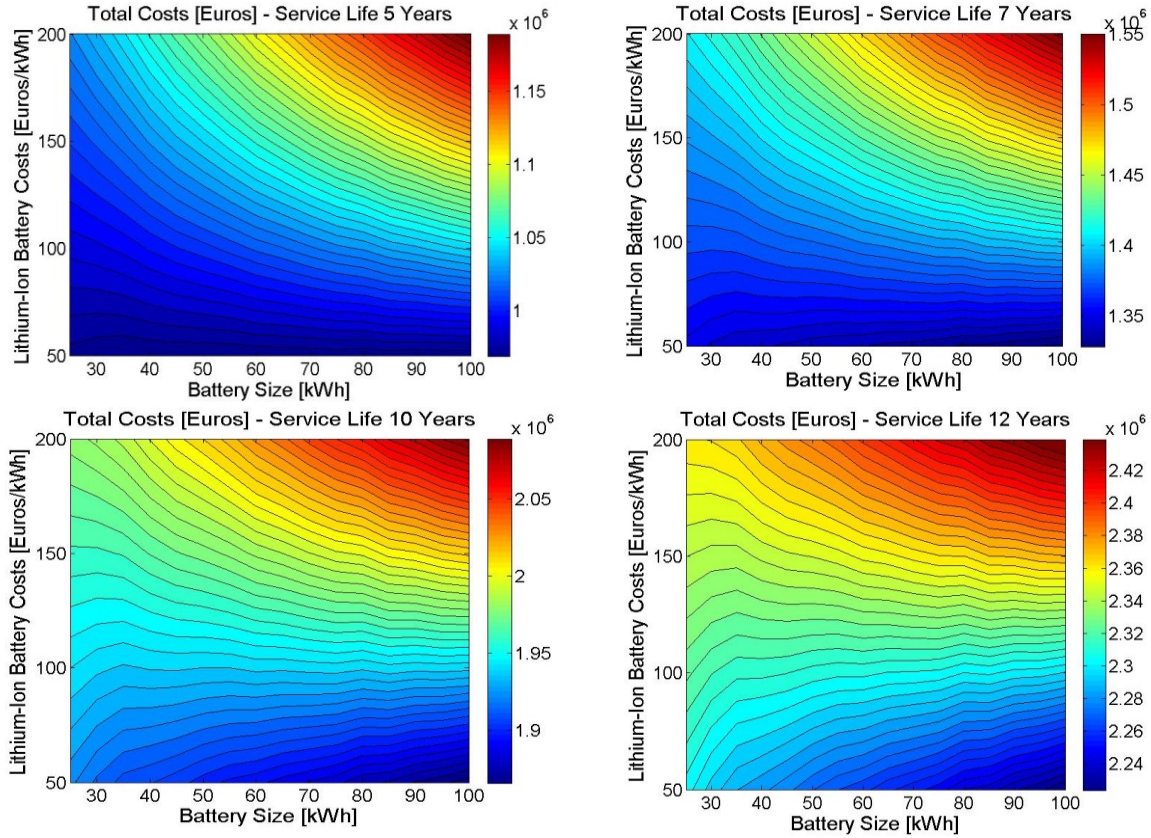


Fig. 13: Impact of Technology-Related Parameters on Total Costs

3.3. Impact of Energy Management-Related Parameters

- **Minimum Allowable Battery SOC**

Fig. 14 shows the impact of the minimum allowable battery SOC on the optimal battery sizing for the three scenarios under study. Higher values of SOC_{min} implies that the effective battery energy capacity is less, and thus bigger batteries are needed to fulfill the same energy demand resulting in higher capital costs and effectively higher total costs as shown in Fig. 15. Although higher values of SOC_{min} result in higher costs, this reduce battery aging and hence prolongs its service life.

Fig. 16 shows the impact of SOC_{min} on the power demand. The maximum power demand during the day doesn't show a sensitive behavior relative to SOC_{min} . Although the optimal battery size increases as SOC_{min} increases, the effective battery energy capacity is the same and thus the charging needs remain intact. The slight differences in the power demand during the day are due to the differences in battery size that affect the energy consumption of the bus depending on its weight. During the night, the maximum power demand is not affected by SOC_{min} because of the long charging duration that allows slow charging at a low power rate.

- **Opportunity Charging Duration**

Fig. 17 presents the impact of opportunity charging duration on optimal battery size and this is only relevant for

scenario 3. Lower durations result in higher optimal battery size as there is less time to charge the battery at the bus stop and thus the initial energy level of the battery should be higher. The need for bigger batteries at lower opportunity charging durations results in higher total costs as shown in Fig. 18.

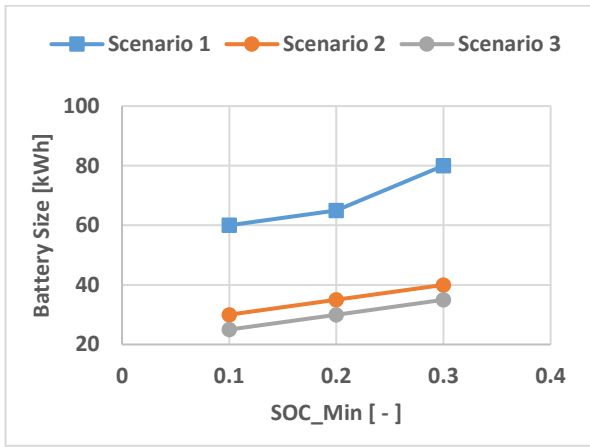


Fig. 14: Impact of Battery Minimum Allowable State of Charge on Optimal Battery Size

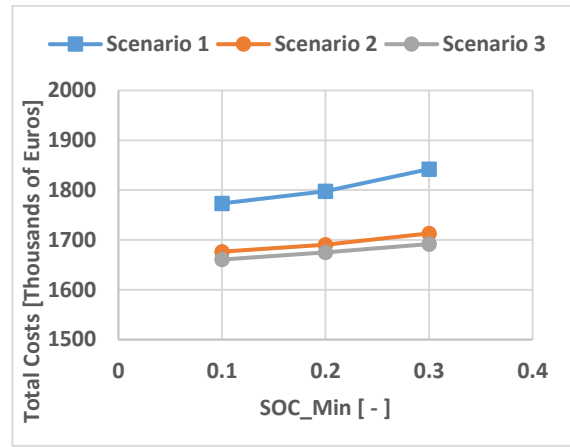


Fig. 15: Impact of Battery Minimum Allowable State of Charge on Total Costs

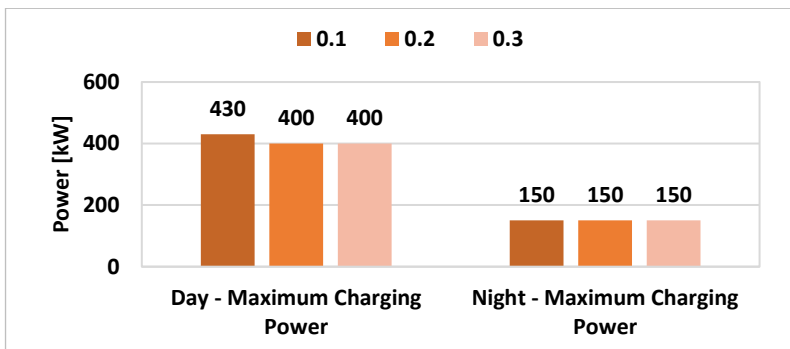


Fig. 16: Impact of Battery Minimum Allowable State of Charge on Maximum Power Demand (Scenario 3)

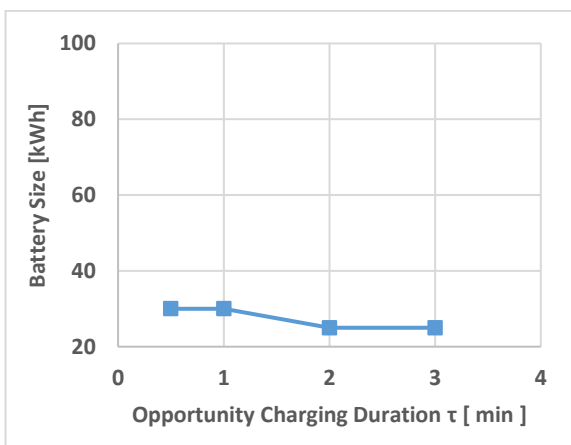


Fig. 17: Impact of Opportunity Charging Duration on Optimal Battery Size (Scenario 3)

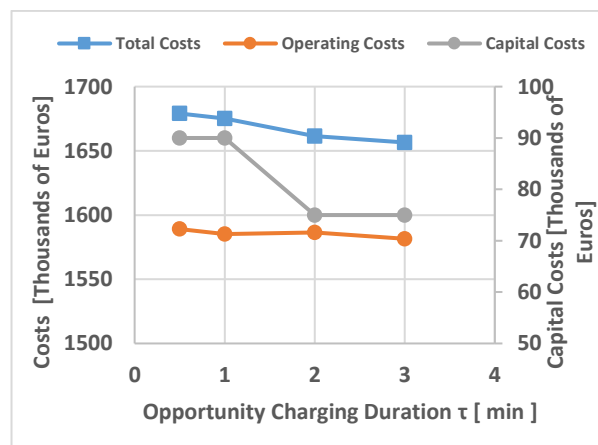


Fig. 18: Impact of Opportunity Charging Duration on Costs (Scenario 3)

Opportunity charging duration has a significant impact on the power demand as shown in Fig. 19. With higher charging durations, the charging power rate can be reduced. The maximum power demand during the day decreases from 470 – 400 kW when charging duration increases from 0.5 – 1 minute. However, at a charging duration of 2 minutes, the power demand drastically increases despite higher charging duration mainly due to the smaller

optimal battery size as shown in Fig. 17. This implies that the capital cost reduction resulting from decreasing the battery size outweighs the additional operating costs due to charging at higher power rates.

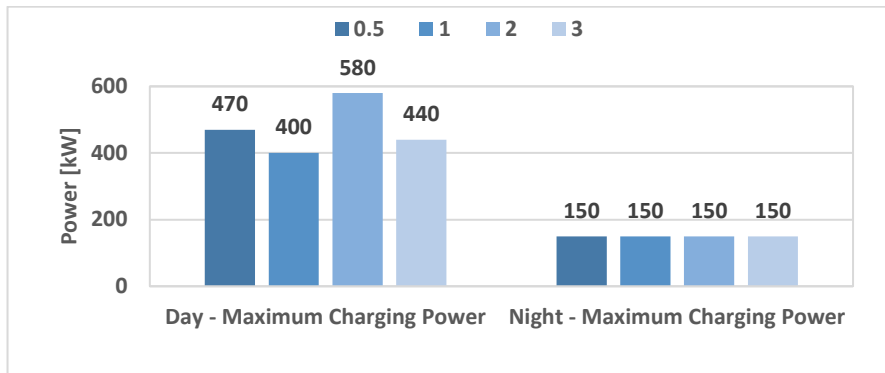


Fig. 19: Impact of Opportunity Charging Duration on Maximum Power Demand (Scenario 3)

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