Charging Management Strategy using ECO-charging for Electric Bus Fleets in Cities

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Abstract—Charging Management Strategy is a critical aspect in electric bus fleets to minimize the impact on the local electricity grid and to minimize the financial cost to the bus operators. To realize a fleet of battery electric public transport buses in a city depends on two major stakeholders, namely the city bus operator and the electricity distribution systems operator. The cost of the electric charging infrastructure, including the high powered ultrafast DC chargers for opportunity charging and lower powered depot chargers for overnight charging is a significant investment for the city bus operator in terms of capital, installation, and grid connection costs, while the distribution system operator has to contend with significant power load on the electricity grid when multiple ultrafast chargers are in operation. This paper investigates a Use Case of an electric bus fleet plying a route, and the optimal selection of chargers, charging duration, and battery State of Charge that will minimize the impact on the local grid and minimize the total cost of ownership. A Simple Optimization algorithm was utilized for this purpose. Results show that the objectives are mutually exclusive, and there need to be a tradeoff to achieve the optimal balance between grid impact and total cost of ownership. Results also show that grid impact and the total cost of ownership are both minimized when opting for low c-rate charging instead of high c-rate charging or when charging only for short durations. Finally, an ECO-charging technique based on utilizing short-duration pulsed charging followed by cool-down periods instead of charging in one continuous long-duration pulse was investigated to determine its efficacy in lowering the energy requirements of the bus by reducing the battery heat generation due to high c-rate charging. The optimum charging-to-cooldown ratio and the optimum charging pulse was found using brute force method to determine the lowest cooling energy consumption for a variety of charging rates. Results show that up to 5% reduction in grid impact can be achieved due to implementation of ECO-charging technique.

Keywords—Charging Management Strategy, Total Cost of Ownership, Grid Impact, ECO-charging, Simple Optimization, Energy Requirement

I. INTRODUCTION

According to the European Commission on Mobility and Transport, improving the mass transit system in a city leads to the reduction in the congestion in the roads, improves the health of the city residents, and improves people’s mobility [1]. Furthermore, electrification of the mass transit system has additional benefit of reducing the emissions of harmful pollutants inside metropolitan city areas due to reduction in vehicular emissions inside cities. With electric power plants typically being located outside the city, and the procurement of electricity from clean and renewable sources such as wind, solar, and hydroelectric energies, residents in the cities can enjoy cleaner air quality. To electrify the city mass transportation system requires large scale investments in a city-wide integrated charging network consisting of high voltage (HV) and medium voltage (MV) grid lines, transformer sub-stations, ultrafast charging stations, and vehicle depots. The European Union (EU) 2050 carbon neutral plan [2] forecasts a 15-fold increase in public Electric Vehicle (EV) charging points by 2030 to 3 million charging points to service a projected 44 million EVs. All these will require up to €20 billion in charging infrastructure investments over the next decade [3]. These investments will bring about a citywide ultrafast public charging network all over Europe.

Within the context of the EU 2050 carbon neutral plan, the aim of the ASSURED project [4] is to boost the electrification of urban heavy-duty vehicles, like trucks and buses. Towards that end, this paper will focus on developing a Charging Strategy (CS) based on ECO-charging in terms of charging duration, charging power, charging location, and charging efficiency. While Energy Management Strategies (EMS) and Thermal Management Strategies (TMS) are effective in reducing the energy requirement during driving [5, 6], a proper Charging Management Strategy (CMS) is required to ensure that the impact on the electricity grid is minimized, when a fleet of buses undergoes ultrafast charging. The CS will determine the charging power and the charging durations and ensure that the battery SoC limits and scheduling constraints of the bus fleet are respected.

This paper investigates a Use Case (UC) based on a fleet of twenty 12m buses plying a bus route in Barcelona city. The aim is to determine the optimal number of opportunity chargers, opportunity and depot charging power, opportunity charging duration, and initial battery State of Charge (SoC) that will minimize the Total Cost of Ownership (TCO) for the city bus operator (CBO) and also minimize the impact on the grid for the Distribution System Operator (DSO). The multi-objective optimization for this UC is carried out using the improved Simple Optimization (SOPT) Algorithm; this will lead to an optimal tradeoff between the fleet of buses and the charging infrastructure.

II. BACKGROUND

A. Charging Management Strategies

Various CMS have been implemented in literature, depending on various situations. Most employ static charging in charging stations, bus stops, or at the depots. But dynamic charging (i.e. charging while the bus is traveling) can be utilized if the Electric Bus (E-Bus) is capable of wireless inductive charging. With static charging, some CS employ charging points at every bus stop, while others opt for a charging station at the ends of a bus route. Some CS ensures that the battery SoC does not deviate too much from its highest allowed level, while others allow the SoC to fall to its lowest allowed SoC before being charged. Furthermore, some CS are geared towards minimizing battery size, while others allow for batteries having enough capacity to endure long periods before charging. Finally, some CS employ high-powered ultrafast charging, while others opt for low power charging.
A Wireless Power Transfer (WPT) system for inductive charging has been optimized for two scenarios, static and dynamic charging, using three different CMS in [7, 8, 9]. The basic CMS advocates continuous dynamic charging along the bus track to keep the battery SoC near its maximum allowed value, thus the battery size can be minimized as it is only required to supply peak power on demand. The stop CMS advocates static charging at stops bringing the battery SoC to its maximum allowed value each time, thus the battery should have enough capacity to power the vehicle in between stops, and a high-powered charger is required. The low CMS advocates a mix of dynamic and static charging optimized to find an ideal blend between charging power and battery capacity. The effects on the grid of three types of CS, flash, opportunity, and overnight, are compared in [10] for a fleet of E-Buses, in terms of the number of chargers, the average charging durations, and the frequency of charging to determine operational feasibility. Predictably, flash charging had the worst effect on the grid, but had the best operational feasibility, allowing the battery size to be minimized while using only overnight CS required the E-Bus to carry batteries storing an entire day worth of energy, but had the least impact on the grid. An event driven model predictive control architecture utilizing Mixed Integer Linear Programming (MILP) is used to manage the CS for a fleet of EVs, in [11], to find the proper trade-off between minimizing energy consumption cost, tracking a reference charging profile, and respecting driver preferences and market and grid constraints. A comprehensive solution to determining the distribution of charging infrastructure, including the number and location of the chargers, required for the bus network of Stockholm based on optimization using MILP has been presented in [12]. The paper considers the ideal distribution based on either cost or energy optimization. The research studied various factors, including the capital and operational costs which determine how many routes can become electrified. Finally, in [13], the authors assessed the energy consumed by the E-Bus based on the operating environment and determined the appropriate charging duration for the bus. The authors also conducted an economic efficiency analysis to select the most appropriate charging type, including plug-in charging, wireless charging, and battery swapping (also an appropriate CS in Asian cities). The paper is notable for utilizing actual driving conditions, route details, and battery ageing as part of the operating environment to determine the actual energy consumption of the vehicle, based on which a cost-benefit ratio and not present value of using different types of CS is considered.

The CS described in [9] is great for WPT enabled E-Buses, thus cannot be utilized for the UC considered in this paper. The research in [10] would be ideal, if not for the fact that it ignores the driving scenario completely, even omitting the energy recovered from regenerative braking, opting instead of using an average energy consumption per kilometer, and uses a non-optimal algorithm to determine the number of chargers. While the paper in [11] makes a comprehensive study and tackles a lot of the factors relating to charging and the grid, it is geared toward light-duty EVs, with very low grid impact. Furthermore, allowing the charging efficiency to be assumed while the Power Factor (PF) is taken to be unity, which is not accurate for charging systems. Elements from [12] and [13] are in fact utilized for the implementation of the UC for this paper, which will take into account the daily operating conditions including the route condition such as slope and speed profile, passenger load profile, climate profile, and the bus schedule data to create a dynamic energy utilization profile to determine charging requirements, costs, and impact on the grid.

B. ECO-charging

ECO-charging is an intelligent charging method that can improve battery longevity, minimize the peak load on the grid, and lower cost. It accomplishes this by limiting the charging c-rate, not charging a battery to full capacity, employing flexible charging behavior and scheduling, or obtaining charging energy from renewable sources when possible [14]. ECO-charging will reduce the need for expensive grid reinforcements, reduce need to invest in large Energy Storage Systems (ESS), and improve grid stability and reliability. With the proliferation of high-powered ultrafast chargers, ECO-charging has become a critical necessity; research conducted in [15] found that utilizing ESS to reinforce the grid, especially a low voltage grid, when installing a fast charging station, is not always a cost effective solution.

A CS based on ECO-charging intended to minimize the negative impacts on the grid, due to many vehicles charging simultaneously, is presented in [16]. It accomplishes this by distributing the charging over a large period and flattening the load-demand curve, thus protecting against overloads, improving the reliability of the grid, and reducing energy costs. The research considers lots of factors, including contracted power, vehicular power requirements, residential load forecast, real time energy tariffs, and renewable energy generation forecast to schedule feasible time slots for charging the EV. Similarly, to lower the energy cost in [17], a CS has been presented for a DC micro-grid composed of solar panels, ESS, EV charging station, and grid connection. A smart charging controller sources the charging energy in the following order of priority: solar panels, ESS, and grid.

In both [16] and [17], the power consumption during charging is small and driving characteristics are not considered to determine EV energy usage. The authors have not indicated if their system can be scaled up to commercial ultrafast charging. Also, there is no clear optimization, thus the effectiveness of the presented algorithm cannot be determined without comparison to other CS. This paper will present an ECO-charging based on minimization of the TCO, the energy utilization, the impact on the grid, and maximize the charging efficiency.

III. PROBLEM FORMULATION

A. Simulation Framework

In ASSURED, a simulation framework has been developed using low-fidelity models based on basic electrical, mechanical, kinematic, and thermal equations to model the transformer, the charger, and the E-Bus drivetrain. Furthermore, instead of using fixed values, Look-up Table (LuT) based maps have been used to model the efficiencies for the transformer, the charger, the DC-DC converter, the inverter, electric machine, and the gearbox. Several LuTs also model the open circuit voltage, the relative capacity degradation, the series and polarization resistance, and the time constants of the ESS. The ESS incorporates a battery ageing model whose effects need to be considered by the CS; thus, the worst-case scenario, when the ESS is at the end of its useable life, is considered when developing the CS. The
The simulation framework can accept the driving (speed) profile, the charging profile, the passenger load profile, the weather profile (temperature, humidity, solar irradiance, wind, rainfall and cloud coverage), and the road elevation profile as inputs to simulate the energy requirement of the bus and the charging impact on the local grid. The aim of the simulation framework is not to conduct detailed simulations of every parameter and situation, but to keep track of the overall energy flow within the system as the E-Bus follows a typical mission scenario.

The simulation framework has been made scalable so that it can simulate a single E-Bus or a fleet of E-Buses. The transformer has been designed so that it can interact with fleets of buses according to their charging schedules. The efficiency map of the transformer, derived from a high-fidelity simulation of a generic transformer in MATLAB/Simulink, has been generated as a function of load and PF experienced by the transformer. The efficiency map of the charger, derived from experimental data of commercial fast chargers, has been generated as a function of load experienced by the charger and voltage output of the charger. The PF map of the charger has been generated as a function of load experienced by the charger. The PF map outputs the PF experienced by the grid due to the operation of the charger. The efficiency map of the DC-DC converter, derived from a high-fidelity simulation of a SiC-based interleaved bidirectional converter [18] in MATLAB/Simulink, has been generated as a function of voltage and current output of the DC-DC converter. These efficiency maps ensure a measure of realism, by ensuring dynamic changes to efficiencies due to changing conditions. The interface of the charger allows its rated power and its dynamic changes to efficiencies due to the operation of the charger. The efficiency map of the transformer has been designed so that it can interact with chargers from each other to a charger. The interface of the charger allows its rated power and its efficiency map outputs the PF experienced by the grid due to the operation of the charger. The efficiency map of the transformer has been designed so that the charger can simulate a single E-Bus or a fleet of E-Buses. The transformer has been designed so that it can interact with buses according to their charging schedules. The efficiency map of the transformer, derived from a high-fidelity simulation of a generic transformer in MATLAB/Simulink, has been generated as a function of load and PF experienced by the transformer. The efficiency map of the charger, derived from experimental data of commercial fast chargers, has been generated as a function of load experienced by the charger and voltage output of the charger. The PF map of the charger has been generated as a function of load experienced by the charger. The PF map outputs the PF experienced by the grid due to the operation of the charger. The efficiency map of the DC-DC converter, derived from a high-fidelity simulation of a SiC-based interleaved bidirectional converter [18] in MATLAB/Simulink, has been generated as a function of voltage and current output of the DC-DC converter. These efficiency maps ensure a measure of realism, by ensuring dynamic changes to efficiencies due to changing conditions. The interface of the charger allows its rated power and its location along the route to be set.

The E-Bus makes use of bus IDs to differentiate themselves from each other to a charger. The interface of the E-Bus allows the bus to be tuned to different bus sizes, battery sizes and chemistries, the city and route, and the driving and charging scenarios. To make the simulations more realistic, the climate is defined for the selected city for an entire year, with daily variation introduced between the high and low temperatures, and variation in the solar irradiance. The road elevation, bus frequency, average driving speed, operational time of the bus, and the charging type and duration can also be defined for a route. Only the passenger load inside the bus is made randomized with peaks coinciding with peak hours.

B. Total Cost of Ownership

The TCO is one of the parameters used to select the CS, including the number and power rating of the chargers, and the charging duration for the bus. It depends on the capital cost of the vehicle, the battery, the chargers, and the operational cost based on electricity consumption. It is expressed as the cost (in €) for every kilometer travelled by the bus during its lifetime. Equations (1) through (7) describe the calculation for the TCO:

\[
\text{TCO} = \text{Capital Costs} + \text{Operational Costs} \quad (1)
\]

\[
\text{Capital Costs} = \text{Battery} + \text{Vehicle} + \text{Charger} \quad (2)
\]

\[
\text{Battery} = \frac{\text{BatteryCAPEX}}{(\text{Battery Lifetime} \times \text{Distance per year})} \quad (3)
\]

\[
\text{Vehicle} = \frac{\text{VehicleCAPEX}}{(\text{Vehicle Lifetime} \times \text{Distance per year})} \quad (4)
\]

\[
\text{Charger} = \sum \text{ChargerCAPEX} \quad (5)
\]

\[
\text{Charger Lifetime} \times \text{Distance per year} \times \text{Number of buses in fleet} \quad (5)
\]

\[
\text{Charger CAPEX} = \text{Charger capital cost} + \text{Charger installation cost} + \text{Grid connection cost} \quad (6)
\]

\[
\text{Operational costs} = \frac{\text{Energy Tariff} \times \left( \sum \text{Charging Energy} - \frac{\Delta \text{SoC}}{100} \times \text{Battery Capacity} \right) + \text{Excess Power Charge} \times \left( \text{Highest Mean Power} - \text{Power Cutoff Level} \right)}{\text{Distance travelled}} \quad (7)
\]

The charging energy, depicted in (7), is calculated as a sum of the charged energy throughout the day. In addition, the SoC is considered in order to compensate for cases where the SoC level at the end of the day differs from the level at the beginning of the day. It is assumed that all chargers have similar lifetimes, although they may vary depending on the manufacturer, power rating, and operational conditions, such as frequency or intensity of use and the average and peak power load on the charger. On the other hand, the costs of the different chargers are uniquely considered based on their rated power, installation costs, and grid connection costs. Table 1 presents the capital costs for the vehicle, battery, and charger, while Table 2 presents the installation and grid connection cost for the chargers.

<table>
<thead>
<tr>
<th>Battery</th>
<th>Vehicle</th>
<th>Charger</th>
</tr>
</thead>
<tbody>
<tr>
<td>Capital Costs</td>
<td>Capital Costs</td>
<td>Capital Costs</td>
</tr>
<tr>
<td>NCA: 350 k€/kWh</td>
<td>9m bus: €225k</td>
<td>50kW: €25,500</td>
</tr>
<tr>
<td>NMC: 420 k€/kWh</td>
<td>12m bus: €300k</td>
<td>150kW: €67,500</td>
</tr>
<tr>
<td>LFP: 580 k€/kWh</td>
<td>18m bus: €450k</td>
<td>350kW: €126,000</td>
</tr>
<tr>
<td>LTO: 1005 k€/kWh</td>
<td>6 and above 16,000€ 16,750€ 23,000€</td>
<td></td>
</tr>
</tbody>
</table>

The lifetimes for vehicles and chargers are assumed to be 15yrs, and for batteries to be 8yrs except for LTO batteries, which have a lifetime of 15yrs. Furthermore, the actual cost of the charger’s is interpolated and extrapolated based on the data provided in Table I, to get the approximate cost for a given rated power.

<table>
<thead>
<tr>
<th>Chargers / site</th>
<th>50kW Charger</th>
<th>150kW Charger</th>
<th>350kW Charger</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>41,000€</td>
<td>43,000€</td>
<td>47,250€</td>
</tr>
<tr>
<td>2</td>
<td>32,500€</td>
<td>34,250€</td>
<td>47,250€</td>
</tr>
<tr>
<td>3 – 5</td>
<td>24,250€</td>
<td>25,500€</td>
<td>35,250€</td>
</tr>
<tr>
<td>6 and above</td>
<td>16,000€</td>
<td>16,750€</td>
<td>23,000€</td>
</tr>
</tbody>
</table>

The actual charger installation costs are interpolated and extrapolated based on the data provided in Table II. The grid connection cost is assumed to be 100 k€/kW. The following electricity tariffs are used: Barcelona is 0.21 k€/kWh, Brussels is 0.15 k€/kWh, Gothenburg is 0.20 k€/kWh, Jaworzno is 0.13 k€/kWh, and Osnabruck is 0.31 k€/kWh. Finally, the operational distance for all the routes are assumed to be 45,000kms per year.

C. Use Case Scenario

The UC is described for a bus route in the city of Barcelona during the month of July. July has been selected because, the operational energy utilization is the greatest during this month.
according to [21]; therefore, a worst-case energy utilization is used to determine the optimal number and power rating of the chargers that will minimize the grid impact, TCO, and maximize the charging efficiency.

The route considered for the UC is the H16 line in Barcelona, travelling between Zona Franca and Campus Besos. The route length is 11.9kms and there are 35 bus stops along the route. The average driving time for buses traveling along the route is 75mins, which calculates to an average speed of 9.52 km/h. A SORT speed profile is used to model the driving behavior; the mean velocity of the SORT speed profile is adjusted so that it is equal to the average speed of the bus along the route. Fig. 1 shows the adjusted SORT speed profile and the road elevation profile for the entire return trip. Since the adjusted SORT profile only covers 1.5kms and the route length is 11.9kms, 8 SORT cycles are combined to describe the route, and 16 SORT cycles define 1 return trip.

![Fig. 1. Plot showing the speed and road elevation profile of the H16 route](image)

The route has a peak-time bus frequency of a bus arriving at a bus-stop every 8mins; the peak-time frequency has been considered for the simulation to account for the worst-case grid energy consumption requirements and charging scenario. Thus, each bus in a fleet will have a fast charging duration of 8mins maximum. The minimum fast charging duration has been assumed to be 3mins. The buses have a daily operational time of 17.5hrs, without considering time spent charging, and travel 165kms; this calculates to each bus making 7 return trips daily. Considering the charging duration, each bus will take between 153mins to 158mins to make return trip; thus, to maintain a bus frequency of a bus arriving every 8mins, 20 buses would need to ply this route. The information of the route has been taken from the TMB website [22] and is depicted in Fig. 2.

![Fig. 2. Route of the H16 line in Barcelona](image)

Each bus will spend 5.7hr in the depot towards the end of the day, where it will have between 1hr to 5hrs of overnight charging duration depending on the power rating of the depot charger. The weather for the city of Barcelona is described in [21]. The bus in question is a standard 12m bus, and its specifications are in Table 3.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bus Dimensions (L x W x H)</td>
<td>12m x 3.51m x 2.55m</td>
</tr>
<tr>
<td>Empty mass</td>
<td>13 tons</td>
</tr>
<tr>
<td>Maximum passenger capacity</td>
<td>80 (average mass of 75kg / person)</td>
</tr>
<tr>
<td>Electric Motor</td>
<td>Induction motor: 153kW continuous power, 2500Nm maximum torque, operational voltage of 480V to 680V</td>
</tr>
<tr>
<td>Gearbox</td>
<td>1:3 ratio, with 95% average efficiency</td>
</tr>
<tr>
<td>Battery</td>
<td>160kWh Li-NMC battery with nominal voltage of 575V, usable SoC range of 90% to 10%</td>
</tr>
</tbody>
</table>

All chargers are Combined Charging System (CCS) level 2 chargers. An opportunity charger can either be installed in one end of the route, in which case the bus will have an electric driving distance of 23.8km, or it can be installed in both ends of the route, in which case the bus has an electric driving distance of only 11.9km.

IV. OPTIMIZATION METHODOLOGY

A. Optimization Framework

The SOPT algorithm as presented in [23] will be used to minimize the cost function shown in (8), which defines the weights given to each objective towards the overall score.

\[ S_{\text{opt}} = \text{grid + energy + 2 * tco + (100 – efficiency)} \] (8)

The algorithm allocates the highest priority to TCO minimization, followed by grid impact minimization, charging efficiency maximization, and vehicle energy utilization minimization, to calculate an overall score that will be minimized. Furthermore, the algorithm gives double the weight to the TCO, which is favorable to the CBOs, while giving equal weights to the remaining parameters, which favors the DSOs. The algorithm will try to determine the optimal number of opportunity and depot chargers, their power ratings, the opportunity charging duration, and the initial starting SoC of the battery. The SOPT algorithm is slightly modified to fit in within the constraints of the allowable power rating of the opportunity charger and the depot charger and ensures that the number of chargers, whether opportunity or depot, is not a fractional value.

SOPT is a meta-heuristic algorithm, like Genetic Algorithm, which uses a random set of parameter values within the solution space to ensure that the optimization result does not get stuck in a local minimum. SOPT consists of an exploratory and an exploitation stage within each iteration, represented by the controlling parameters \( c_1 \) and \( c_2 \); the value of \( c_2 \) is set as half of the value of \( c_1 \) to lessen the dependency of the algorithm on these controlling variables, and \( c_1 \) is set to be between 1 and 2, to decrease the number of
iterations required to reach the optimum solution. Equations (9) and (10) describe the method used to calculate a new solution during each iteration, and Fig. 3 depicts a flowchart describing the algorithm.

$$x_{i,m,new} = x_{i,m,best} + c_1 \times R_{i,m} \quad (9)$$
$$x_{i,m,new} = x_{i,m,best} + c_2 \times R_{i,m} \quad (10)$$

where $x_{i,m,best}$ is the value that represents the best solution in the current iteration, $i$, for a given optimization parameter, $m$, and $R_{i,m}$ is a randomly generated number normally distributed around zero with a standard deviation of $\sigma_m$ for that parameter in the solution space. The solution space, $n$, is a set of 10 values for every optimization parameter, and the maximum number of iterations, $d$, is set to 50.

To improve the SOPT algorithm and ensure that the best solution is truly a global minimum, the best solution is replaced by a new randomly generated solution if the best solution remains unaltered for a certain number of iterations given by (11).

$$R_{count} = 0.5 \times m \times n \quad (11)$$

where $m$ is the number of optimization parameters and $n$ is the number of solutions in the population set.

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where $m$ is the number of optimization parameters and $n$ is the number of solutions in the population set.

Fig. 3. Flowchart depicting the SOPT algorithm

B. Setting up the SOPT Algorithm

The SOPT algorithm is initialized with a set of random solutions in a population set; the size of the population will remain constant throughout all the iterations. There are five optimization variables considered: number of opportunity chargers, $N_{opt}$, opportunity chargers power level, $P_{opt}$, initial SoC of ESS, $S_{int}$, opportunity charging duration, $D_{opt}$, depot chargers power level, $P_{dep}$, and initial SoC of ESS, $S_{init}$. The number of depot chargers and the charging duration of the depot chargers are dependent on other simulation factors, and thus not considered for optimization. Each optimization parameter is initialized with 10 random values, uniformly distributed within their constraints. $N_{opt}$, $P_{opt}$, and $P_{dep}$ are discrete variables and take distinct values, while $D_{opt}$ and $S_{init}$ are continuously varying variables and can take any values within their constraints.

The SOPT algorithm handles constraints by calculating two fitness scores that must be minimized, the optimization fitness score, based on the minimization of the desired output, according to (8), and a constraint fitness score that checks how well the values for each optimization variables fall within their given constraints [24]. The minimization of the constraint fitness score is prioritized above the minimization of the optimization fitness score to ensure that the optimized solution does not contain values that fall outside their parameter’s constraints. In this research, instead of calculating a separate fitness score for constraints, all newly calculated values are bound within their constraints during each iteration as shown in (12).

$$x_{i,m,new} = \begin{cases} \max_{i,m} & \text{if } x_{i,m,new} > \max_{i,m} \\ \min_{i,m} & \text{if } x_{i,m,new} < \min_{i,m} \\ x_{i,m,new} & \text{otherwise} \end{cases} \quad (12)$$

where $\max_{i,m}$ and $\min_{i,m}$ are the upper and lower bounds of the constraints. For discrete optimization parameters ($N_{opt}$, $P_{opt}$, and $P_{dep}$), the allowable parameter value that is closest to $x_{i,m,new}$ is set for that parameter. All constraint bounds and allowable discrete values are described in the next subsection.

The algorithm ends after 50 iterations, or once $\sigma_m$ for all variables stops decreasing for 5 consecutive iterations.

C. Optimization Constraints

The objective of the research is to minimize the TCO, the energy utilization of the bus, and the grid impact, and maximize the charging efficiency when simulating the UC described in the previous section for a fleet of buses. The algorithm must respect the following constraints:

- The battery SoC should not fall below 10%
- The battery should be charged to its initial SoC level by the end of the day
- There are 20 buses in the fleet
- The charging duration for opportunity charging should not exceed 8mins
- The depot charging duration should not exceed 6.2hrs

The following parameters constraints were upheld during the optimization process:

- The initial SoC at the start of day can vary between 20% and 90%
- The opportunity charging duration can vary between 1 minute and 8 minutes
- Either 1 or 2 opportunity chargers can be used
- The opportunity charger power rating could be either 290kW or 600kW
• The depot charger power rating could be 11kW (AC), 100kW, or 150kW

Based on the above points, the following two points can be found after the model has been simulated:

• The number of depot chargers can vary between 1 and 20 (since there are 20 buses in the fleet)

• The charging duration for a bus with a depot charger can vary between 17.1 mins and the entire 6.2 hrs

The constraints for the chargers are imposed by the OEM, and must be honored, even though better results could have been achieved if other charging power levels could be considered. The CBO imposes the constraint on the charging duration, which cannot exceed 8 minutes, since there is a bus every 8 minutes during peak hour.

V. RESULTS AND DISCUSSION

The result for each objective will be given before the overall result is presented. Table 4 presents the findings of the simulations in a concise format.

<table>
<thead>
<tr>
<th>Objective</th>
<th>Opportunity Charger</th>
<th>Depot Charger</th>
<th>Initial SoC</th>
<th>Optimized Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>Minimize Grid Impact</td>
<td>2 x 290kW chargers, 3-min charging</td>
<td>1 x 100kW charger, 18.6-min charging</td>
<td>90% (i.e. fully charged battery)</td>
<td>223 kWh of electricity consumed from grid</td>
</tr>
<tr>
<td>Minimize Energy Utilization</td>
<td>2 x 290kW chargers, 3-min charging</td>
<td>5 x 11kW chargers, 93-min charging</td>
<td>For initial SoC &gt; 40%</td>
<td>Energy utilization rate of 1.08 kWh/km</td>
</tr>
<tr>
<td>Minimize TCO – 1 bus</td>
<td>1 x 290kW charger, 6-min charging</td>
<td>1 x 11kW charger, 93-min charging</td>
<td>90% (i.e. fully charged battery)</td>
<td>TCO of 0.784 €/km</td>
</tr>
<tr>
<td>Minimize TCO – 20 buses</td>
<td>1 x 290kW charger, 6-min charging</td>
<td>1 x 150kW charger, 17.7-min charging</td>
<td>For initial SoC &gt; 55%</td>
<td>Average TCO of 0.524 €/km/bus</td>
</tr>
<tr>
<td>Maximize Charging Efficiency</td>
<td>1 x 290kW chargers, 3-min charging</td>
<td>5 x 100kW chargers, 93-min charging</td>
<td>For initial SoC between 85%–90%</td>
<td>Charging efficiency of 83.6%</td>
</tr>
<tr>
<td>Minimize Overall Score</td>
<td>2 x 290kW chargers, 3-min charging</td>
<td>5 x 11kW chargers, 93-min charging</td>
<td>90% (i.e. fully charged battery)</td>
<td>Overall score of 679</td>
</tr>
</tbody>
</table>

There are some trends that became evident during the optimization process:

• The power rating of the depot charger and the initial SoC of the battery do not seriously affect the overall grid impact.

• The energy utilization of the bus has a strong correlation to the grid impact.

• Results indicate that multiple short duration top-ups of the battery charge are best for energy utilization, if the battery is not too depleted initially.

• The lowest fleet TCO is achieved when priority is given to minimizing the number of chargers followed by minimizing the power rating of the chargers.

• Results indicate that the number and power rating of chargers, charging duration, and the initial battery SoC do not affect the charging efficiency.

• Results indicate that TCO minimization on one hand, and grid impact/energy utilization minimization on the other hand are mutually exclusive, thus there needs to be a tradeoff to attain the optimal solution.

Fig. 4. Multi-objective analysis of the optimal configuration having 2 x 290kW opportunity charger and 5 x 11kW depot charger
As can be seen from Table 4, minimizing the TCO for a single bus is not optimal when the depot charger selection is applied to a fleet of 20 buses. This is because the selected 11kW depot charger takes 5.9hrs to service 1 bus, thus requiring 20 depot chargers to handle the entire fleet, which is a significant investment. Simulating the entire fleet during the optimization process gives a better evaluation of the TCO; a lower fleet TCO is achieved when twenty 11kW chargers are replaced by one 150kW charger. The 150kW charger can handle 20 buses, since each bus will now take only 18 minutes to charge, thus 20 buses can be charged within 6hrs, which is within the constraint of the allowable depot charging duration.

As for the charging efficiency, simulations indicate that the highest efficiency is achieved when charging using the depot charger is maximized. Thus, the SoC of the battery should be allowed to fall to its minimum value (10%) by the end of the day by minimizing the opportunity charging duration throughout the day. At the end of the day, the depot charger will charge the almost depleted battery to its full charge (90% SoC). The charging duration for each bus is 93 minutes using the selected 100kW charger; thus, 5 depot chargers will be required to handle the entire fleet.

Finally, the selection that provides overall optimal score results in 224kWh of electricity being consumed from the grid, has an energy utilization rate of 1.09 kWh/km, a charging efficiency of 80.6%, and an average fleet TCO of 0.531 €/km/bus. The optimal selection is balanced between the grid impact and the TCO. Fig. 4 shows the multi-objective analysis for this optimal charger configuration as a function of Initial Battery SoC and charging duration.

A. Analysis of the ECO-charging Technique

The optimization results overwhelmingly tend towards a 290kW opportunity charger over the 600kW charger, and a shorter charging duration of 3 minutes. This is significant, since a higher power charger will heat up the battery significantly, due to the high charging current involved. Thus, the battery cooling system needs to expend more energy to keep the battery cool, leading to higher energy utilization, a greater impact on the grid, and a larger TCO. To compensate, the ECO-charging CS decreases the battery heat generation during charging by:

- Decreasing the total daily charging duration allocated to the opportunity charger, while increasing the that of the depot charger.
- Spreading out the 3 minutes of charging over the entire 8 minutes by charging in shorter duration pulses followed by cool-down periods.

Fig. 5 compares the energy expenditure of the battery cooling system due to different pulse charging frequencies and charging current. The total duration of the charging remains constant regardless of the number of pulses used during the charging process. It can be seen from the figure that, for the highest charging rate, using forty 15-second charging pulses followed by 35-second of cool-down periods lowers the battery cooling energy expenditure by 33% from when only a single 600-second charging pulse is used followed by a 1400-second cool-down period. At lower charging rates, charging using pulses does not have that much of an effect; however, the battery cooling energy expenditure using lower charging rate is significantly lower even without pulsed charging. These results indicate that it is preferable to maximize depot charging, but when opportunity charging is used, then it is preferable to employ pulsed rather than continuous charging.

Fig. 6 illustrates the effect of the different CSs on the battery SoC as the bus follows the driving strategy defined in the UC. During normal charging (blue line), the battery is always fully charged during every opportunity charging, thus there is minimum depot charging. The red dotted line shows the intermediate CS where the opportunity charging is minimized so that the SoC of the battery falls to its lowest allowable value by the end of the day, so that depot charging is maximized; however, as can be seen in the zoomed-in section, the charging is done as one continuous pulse. The green dashed line shows a full ECO-CS where not only the opportunity charging is minimized, but the charging is spread out over the entire 8 minutes in smaller pulses, as shown in the zoomed-in section. Finally, Table V shows the effect of the three CSs on the grid, the battery cooling energy, and the bus energy utilization after simulating the UC for one day.

![Fig. 5. Battery cooling energy expenditure as a function of pulse frequency and charging current for a total of 600s charging duration](image)

![Fig. 6. Effect of different CS on the Battery SoC](image)

<p>| TABLE V. EFFECTS OF DIFFERENT CS ON GRID AND ENERGY REQUIREMENTS OF BUS AND BATTERY COOLING SYSTEM |</p>
<table>
<thead>
<tr>
<th>Grid impact (kWh)</th>
<th>Normal CS</th>
<th>Intermediate CS</th>
<th>Full ECO CS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Energy drawn from opportunity charger (kWh)</td>
<td>201.4</td>
<td>127.3</td>
<td>126.0</td>
</tr>
<tr>
<td>Energy drawn from depot charger (kWh)</td>
<td>21.3</td>
<td>88.0</td>
<td>87.0</td>
</tr>
<tr>
<td>Energy required by battery cooling system (kWh)</td>
<td>9.1</td>
<td>7.3</td>
<td>6.8</td>
</tr>
<tr>
<td>Average energy utilization of E-Bus (kWh/km)</td>
<td>1.11</td>
<td>1.09</td>
<td>1.08</td>
</tr>
</tbody>
</table>

It is noticed that a large benefit is achieved when opportunity charging duration is minimized, and the depot charging duration is maximized; a more modest benefit is

![Image](image)
further achieved by utilizing pulsed charging, with a total of 5% reduction in grid impact from the normal CS.

VI. CONCLUSION

This paper presents a multi-objective optimization using the improved SOPT algorithm to determine the optimal number of opportunity chargers, charging power of the opportunity and depot chargers, opportunity charging duration, and initial battery SoC that will minimize the TCO for the CBO and also minimize the grid impact for the DSO, when applied to a UC based on a fleet of twenty 12m buses plying the H16 route in Barcelona city. Furthermore, the paper also presents an ECO-Charging CS based on pulsed charging and maximizing depot charging that offer further energy savings and reduction in the grid impact. The techniques used to investigate the UC of the H16 route in Barcelona city can be applied to other routes in Barcelona as well as in other cities by modifying the driving scenario and charging scenario in the simulation framework, and by modifying the constraints in the optimization algorithm. Furthermore, the simulation framework has been made scalable, to accommodate a wide range of buses, battery capacities and chemistries, electric motors, and electronic power converters for the main and auxiliary systems.

This research can be further expanded by investigating the effects of multiple routes, so that the effects of many opportunity chargers on the grid can be investigated. It is expected that if the full ECO CS is implemented in the opportunity chargers connected using a smart grid system, then three of these chargers can be run simultaneously with no extra load on the grid by shifting the charging pulses ±15 seconds to each other. Due to a 1:2 ratio in the charging pulse to the cool-down period, it is expected that a three-phase control signal can be implemented into the CMS to manage three opportunity chargers operating simultaneously. Finally, future research will also investigate the UC without the constraints in the charging duration and the power level of the chargers to determine if a better solution can be found outside of the constraints applied in this research.

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