Available online at www.sciencedirect.com

ScienceDirect

IFAC PapersOnLine 58-2 (2024) 162–167

Optimization of Electric Bus Charging: Integrating Discrete Event Modeling in Public Transportation Systems

Virginia Casella* Riccardo Minciardi* Luca Parodi*

** Department of Informatics, Bioengineering, Robotics and Systems Engineering (DIBRIS), University of Genoa, Genoa, Italy (Tel: 3473117314; e-mail: luca.parodi@edu.unige.it).*

Abstract The transition to electric transportation is gaining more and more importance in the last years leading to new challenges to be addressed. A key role in this framework is represented by public transportation systems. This paper introduces a Discrete Event (DE) optimization model to optimize the charging scheduling of electric buses (EBs). By accounting for time tabling constraints, energy demand satisfaction, and the capability for simultaneous multi-socket charging, our model addresses the complexities inherent in managing EB fleets. Utilizing a periodic model to capture cyclical system behavior, we incorporate a detailed battery model reflecting nonlinear charging profiles to enhance accuracy in power requirement prediction and charging duration estimation. Validation of our model is performed using real-world data, demonstrating its practical applicability.

Keywords: Electric Buses; Electric Vehicles; Optimization; Smart Charging; Discrete Events Modeling.

1. INTRODUCTION

In the last decade, electric mobility has been rapidly emerging since governments globally are investing heavily in electric vehicles (EVs) since they are considered one of the best solutions to environmental concerns, reduced dependence on fossil fuels and to combat climate change, and their adoption is crucial for a cleaner and more sustainable transportation alternative Ruggieri et al. (2021). This shift towards EVs is propelled not only by environmental considerations, but also by significant technological advancements, making EVs more practical, efficient, and accessible Mohammadi et al. (2023). Even if the benefits of electric mobility are evident, many challenges relevant to this new actor in the transportation system raised and must be carefully faced. As the number of EVs on the road increases, concerns about grid overload become more pronounced. As a matter of fact, if EVs are treated as fixed loads, simultaneous charging during peak periods could stress the electricity grid leading to increased demand and potential issues in grid reliability Venegas et al. (2019). Addressing this challenge requires advanced energy management systems and smart charging policies, which play a crucial role in maintaining grid stability during the transition to a more electrified transportation system, offering a resilient solution for grid management Casella et al. (2022). Smart charging provides significant benefits for grid management in the context of electric mobility as it enables load balancing by distributing EV charging loads over time and preventing grid overload during peak hours. At the same time, advantages of smart charging also include the integration of renewable energy sources by aligning the charging service with periods of high renewable energy generation, contributing to a more sustainable electric mobility ecosystem Sinha et al. (2023). Nevertheless, the greatest advantage of smart charging comes from exploiting EVs as mobile energy storage devices and enabling bi-directional power flows to potentially provide flexibility services and enhance overall grid resilience Wan et al. (2024). The role of mathematical programming and optimization methods becomes indispensable in managing the intricate challenges arising from the increasing penetration of EVs as these tools provide an analytical approach to solve the complex decision-making processes involved in smart charging, providing personalized schedules that considers user preferences, travel patterns, charging requirements, and grid safe operations.

Within the macro-topic of electric mobility, research often distinguishes between two distinct lines of focus: private and public mobility, as they exhibit notable differences in terms of routes, practical operations, and management, reflecting distinct considerations for individual users and broader public transportation systems. Private electric mobility, centered on individual users, emphasizes flexibility and personalized operations. In contrast, public electric mobility, mainly Electric Buses (EBs), follows predetermined schedules and routes designed around transportation hubs and key destinations. Moreover, public transportation often adheres to cyclical schedules, where the same route and timetable repeat daily. For these reasons, EB operations involve centralized management to ensure the seamless functioning of the overall transportation system, and the effective management of a fleet of EBs requires a comprehensive approach that considers both the periodicity characteristics inherent in public transit and the difficulties of time tabling constraints and energy demand satisfaction. Indeed, considering time tabling constraints becomes crucial as adherence to fixed schedules is essential for efficient service provision in terms of punctuality, overall reliability and convenience for customers. Then, the fleet energy requirement necessitates, especially during peak operation hours, strategic planning to ensure the availability of charging infrastructure and achieve sustainable operations.

In the last decades several research works have focused on defining decision problems and developing optimal strategies to face these issues; nevertheless, most of them focus on private EVs rather than on EBs, which are instead a special

10.1016/j.ifacol.2024.07.108

class of EVs with its own characteristics Perumal et al. (2022). The literature on electric buses (EBs) reveals limited attention to optimal scheduling, with few works addressing the issue. Notably, in Ferro et al. (2023), a planning problem determines optimal charging station (CS) locations and sizes, followed by an optimization problem for fleet sizing and EB assignment to lines, considering simultaneous charging of multiple EBs. Liu et al. (2021) presents a mixed-integer programming model to minimize total charging costs by optimizing charging power and time, developing a column-generation-based algorithm to decompose the problem and achieve scalability. He et al. (2020) focuses on overnight depot charging with on-route fast charging; the on-route scheduling is optimized to minimize costs while adhering to timetable requirements. Hu et al. (2022) analyzes the joint problem of locating en-route fast chargers and scheduling, considering penalty costs for delays caused by the charging service itself, and formulating a robust model for uncertainties. Zhang et al. (2021) incorporates battery degradation into the charging strategy optimization, with the aim of minimizing it together with total costs. A tailored branch-and-price approach is employed for the global optimal solution, while the optimal integer solution is guaranteed by the adoption of a branch-and-bound approach.

The work proposed in this paper deals with the optimal charging scheduling (start/end of the charging service and charging power level) of a fleet of EBs, considering time tabling constraints and energy request satisfaction. A multi-socket framework is also considered, allowing the simultaneous charge of several EBs. Since this paper focuses on public transportation, a periodic model is adopted to reflect the cyclical behavior which is typical for a system of EBs. Moreover, EB batteries are modeled via a nonlinear charging profile to simulate the real trend of power as a function of the state of charge. One of the most important features from a modeling point of view is the introduction of intermediate events, which allows to avoid constraining the system to have an EB under charge in every time interval. Indeed, the possibility of having some time frames when no EB is charging is essential to increase the degrees of freedom, for example to shift the charging process when the cost for withdrawing power from the grid is lower (Figure 1). This potentiality is exploited in this paper by introducing intermediate events in addition to actual completion time intervals. To the best of authors' knowledge, no other paper in literature adopts, in a DE contest, this strategy to have a greater range of possibilities.

From a methodological point of view, a Discrete Event (DE) approach is adopted as an alternative to the most common discrete-time approach, which however makes the problem quite hard to be computationally solved especially for a high number of variables. In previous works, the DE approach has already been adopted. In Ferro et al. (2021), authors propose a DE model for the optimal charging scheduling of some EVs.

In this paper, this model is improved to obtain a higher number of degrees of freedom and considering the non-linear characteristic curve of the batteries. Another study in Casella et al. (2023) considers a periodic DE model for EBs, but considering a linear model for the batteries and without considering additional time intervals (see next sections for detailed information) and thus reducing the degrees of freedom

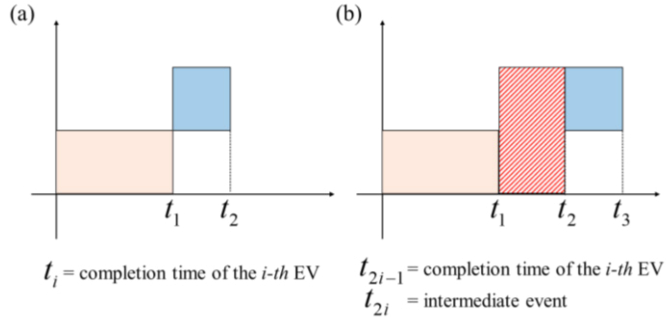

Figure 1. Intermediate events

of the system. Moreover, apart from Casella et al. (2023), none of the mentioned papers address EB charging scheduling in a periodic framework, neglecting the inherently periodic nature of public transportation. Additionally, none except for Ferro et al. (2023) and Zhang et al. (2021) consider a non-linear charging profile, and none except for He et al. (2020) considers time tabling constraints.

The main novelties introduced with this work are:

- A DE optimization model for the optimal scheduling of the EBs' charging processes in a periodic framework;
- A detailed model for the EBs' battery considering the non-linearity of the characteristic curve;
- Introduction of intermediate events to the DE model to increase the flexibility of the system.

The remaining part of this paper is divided as follows. In Section 2, the system model is presented. In Section 3 the overall optimization problem is defined. A case study is proposed in Section 4. Final conclusions are reported in Section 5.

2. SYSTEM MODEL

In this section, the formalized decision problem is outlined, detailing the mathematical models employed to describe the various devices. Figure 2 shows the system model: a charging station (CS) able to charge N vehicles at the same time is considered (i.e. it has N sockets), together with an energy storage system (ESS) and a connection to the external grid. The considered CS has to provide charging services to B electric buses; it is assumed that $B > N$, i.e. in the system, there are fewer sockets than vehicles requiring charging service. The variables in Figure 2 represent the power exchange with the grid (p_i^G), the power exchange with the storage (p_i^S), and the overall power to the charging station (p_i^{CS}), which is in turn given by the sum of the charging powers to the EBs under charge $\left(p_{i,j}^{EB},\ j \in B\right)$. For bidirectional power flows p_i^G and p_i^S, the adopted convention is to consider them positive when entering the system: buying from the grid and discharging the ESS.

Indeed, since a DE approach is adopted, time discretization is not given a priori but the optimization horizon is discretized by events (t_i), whose occurrence is a decision variable itself. Therefore, the duration of each time interval can be determined as

$$t_i - t_{i-1} = \ell_i \qquad \forall i \qquad (1)$$

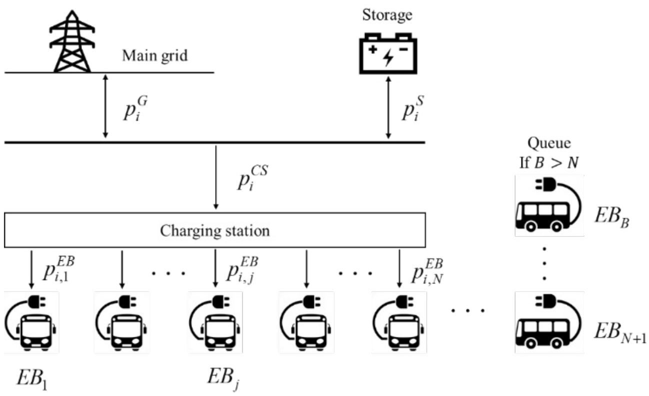

Figure 2. System architecture

Before discussing the model, it is necessary to highlight how the introduction of intermediate events affects the model itself. Indeed, the introduction of a new class of events directly affects the time discretization, entailing the number of time intervals in which the optimization horizon is discretized to be twice the number of EBs needing charge. In particular, a specific order for these two classes of events must be fixed; assuming that these two classes of events alternate and that intermediate events follow completion time intervals, completion times are identified by odd indexes, while intermediate events by even indexes.

2.1 Electric Buses and Charging Station

In the following equations all the constraints relevant to the EB characteristics and their charging power are presented.

$$SOC_{i,j}^{EB} = SOC_{i-1,j}^{EB} + \frac{\Gamma_j^{EB}}{CAP_j^{EB}} \cdot p_{i,j}^{EB}\left(t_i - t_{i-1}\right) \qquad \forall i \ \forall j \qquad (2)$$

$$\underline{SOC}_j^{EB} \le SOC_{j,i}^{EB} \le \overline{SOC}_j^{EB} \qquad \forall i \ \forall j \qquad (3)$$

$$\underline{P}_j^{EB} \le p_{i.j}^{EB} \le \hat{p}_{i,j}^{EB} \qquad \forall i \ \forall j \qquad (4)$$

$$y_{i,j}^{EB} \cdot K - p_{i,j}^{EB} \ge 0 \qquad \forall i \ \forall j \qquad (5)$$

$$\sum_{j=1}^{B} y_{i,j}^{EB} \le N \qquad \forall i \qquad (6)$$

$$\Gamma^{EB} \sum_{i=1}^{2j-1} p_{i,j}^{EB}\, \ell_i = \left(SOC_j^{EB,fin} - SOC_j^{EB,init}\right) \cdot CAP_j^{EB} \qquad \forall j \qquad (7)$$

$$p_i^{CS} = \sum_{j=1}^{B} p_{i,j}^{EB} \qquad \forall i \qquad (8)$$

$$0 \le p_i^{CS} \le \overline{P}^{CS} \qquad \forall i \qquad (9)$$

Equation (2) represents the state equation of the j-th EB, where $SOC_{i,j}^{EB}$ is the state of charge, Γ_j^{EB} the charging efficiency, while CAP_j^{EB} $[kWh]$ the capacity of the battery. The state of charge and the charging power are bounded in (3) and (4), respectively. To assign an EB to a socket, a binary variable $y_{i,j}^{EB}$ is introduced: this variable assumes value "1" if the j-th EB is under charging in time interval (t_{i-1}, t_i), "0" otherwise. To prevent the possibility of having an EB under charge when it is not connected, equation (5) is introduced. The constraint on the maximum number of simultaneous charging processes corresponds to (6). Equation (7) imposes that the total charge (up to the completion time) must be equal to the energy request (right hand side of the equation). Equation (8) defines the power to the CS, which is then bounded in (9).

2.2 Non-linear model for the EB battery

One the strengths of the work proposed in this paper is the implementation of a nonlinear model for the EB batteries to emulate the behavior of real ESSs. Indeed, empirical data show that, after a specific SOC value is reached, the maximum power that can be physically delivered to a battery pack is not the rated one $\overline{P}^{EB}$, but it is lower; a piecewise linear profile is a good approximation of this this peculiar behavior Delfino et al. (2019). Nevertheless, since in this paper it is assumed that EBs can charge in several different time intervals at different power levels, the EB state of charge at the end of each *i-th* time interval $\left(SOC_{i,j}^{EB}\right)$ is a decision variable. This makes it impossible to determine a priori which case occurs: either the whole charging process occurs before or after the knee, or charging starts before the knee and stops after it (Figure 3).

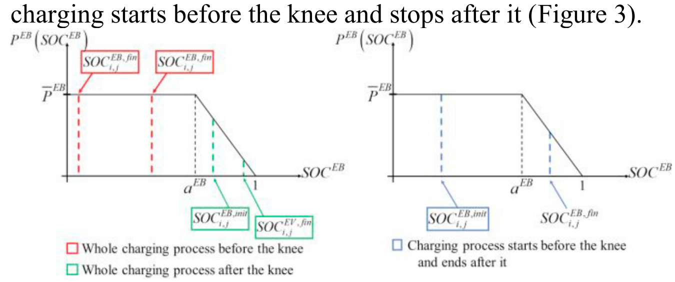

Figure 3. Possible charging profiles

This issue, given by the piecewise profile, can be solved by approximating the piecewise linear profile (black line in Figure 4) with a polynomial continuous function f (blue line in Figure 4) defined as

$$f(SOC_j) = \sum_{n=0}^{N} a_n SOC_j^n \qquad \forall j \qquad (10)$$

Indeed, approximating with a continuous polynomial function avoids the introduction of many binary variables; in fact, if piecewise profile were preserved, three different cases would have to be formulated and the computational difficulty would increase. Please note that, in any case, the adopted polynomial function is still a good approximation of empirical data.
In this paper we assume that the maximum charging power $\left(\hat{p}_{i,j}^{EB}\right)$ is given by a constant profile like the green one in Figure 4. Please note that, being a function of $SOC_{i,j}^{EB}$, the upper bound for the charging power is a decision variable itself.

$$\hat{p}_{i,j}^{EB} = f\left(SOC_{i,j}^{EB}\right) \qquad \forall j \qquad (11)$$

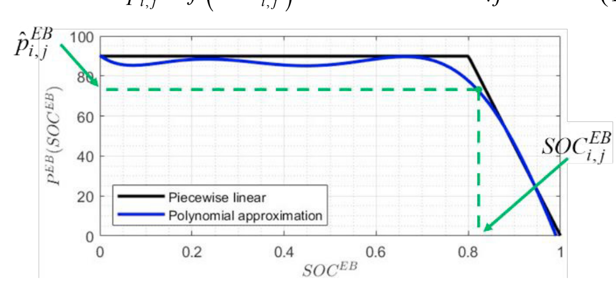

Figure 4. Polynomial approximation

2.3 ESS Model

As for the EBs, the constraints relevant to the EES are presented.

$$SOC_i^S = SOC_{i-1}^S - \frac{1}{CAP^S}\left[\Gamma^{S,dch} p_i^{S+}\left(t_i - t_{i-1}\right) - \Gamma^{S,ch} p_i^{S-}\left(t_i - t_{i-1}\right)\right] \qquad \forall i \qquad (12)$$

$$p_i^S = p_i^{S+} - p_i^{S-} \qquad \forall i \qquad (13)$$

$$p_i^{S+}, p_i^{S-} \geq 0 \qquad \forall i \qquad (14)$$

$$\underline{P}^S \leq p_i^S \leq \bar{P}^S \qquad \forall i \qquad (15)$$

$$\underline{SOC}^S \leq SOC_i^S \leq \overline{SOC}^S \qquad \forall i \qquad (16)$$

Equation (12) is the state equation where, unlike the EB case, both charging and discharging are allowed. The terms in this equation have a straightforward meaning: CAP^S $[kWh]$ is the capacity; $\Gamma^{S,dch}/\Gamma^{S,ch}$ $[kWh]$ is the discharging/charging efficiency; $p_i^{S+}/p_i^{S-}[kW]$ is the discharging/charging power. The relation between p_i^S and its components is defined as in (13); since the discharging efficiency is always higher than the charging one, it cannot happen that these two power flows are non-zero at the same time. Finally, equations (14)-(16) represent the physical bounds for ESS power and state of charge.

2.4 Power balance

Regarding the power balance the following constraints are introduced.

$$p_i^{CS} = p_i^G + p_i^S \qquad \forall i \qquad (17)$$

$$p_i^G = p_i^{G+} - p_i^{G-} \qquad \forall i \qquad (18)$$

$$p_i^{G+}, p_i^{G-} \geq 0 \qquad \forall i \qquad (19)$$

$$\underline{P}^G \leq p_i^G \leq \bar{P}^G \qquad \forall i \qquad (20)$$

The actual power balance is reported in (17). Equation (18) define the two components for the power purchased/sold from/to the grid ($p_i^{G+}/p_i^{G-}[kW]$); assuming that the buying price is always higher than the selling price ensures that both terms cannot be non-zero at the same time. Upper and lower bounds are in (19) and (20).

2.5 Time tabling constraints

The previous constraints are mostly relevant to the components operating in the system; however, it is necessary to introduce some time constraints.

$$\left(1 - y_{i,j}^{EB}\right)K - \left[T_j^{rl} - \left(t_i - \ell_i\right)\right] \geq 0 \qquad \forall i \ \forall j \qquad (21)$$

$$t_j^{TARD} \geq t_{2j-1} - T_j^{dd} \qquad \forall j \qquad (22)$$

$$t_{2j-1} \leq T_j^{dl} \qquad \forall j \qquad (23)$$

Equation (21) is necessary to impose that an EB cannot be connected before the release time T_j^{rl}. In this constraint K is a big number. Instead, in (22) the value of the tardiness term t_j^{TARD} is defined: it consists of the total charging delay of the j-th EB with respect to its due date T_j^{dd}. The deadline for the charging process T_j^{dl}, which by definition cannot be exceeded, is imposed by (23).

Moreover, some additional constraints must be added to ensure the system periodicity. In particular, the initial time t_0 and the final one t_M must differentiate by a period T, and the initial and final state of charge of the ESS must coincide.

$$t_M = t_0 + T \qquad (24)$$

$$SOC_M^S = SOC_0^S \qquad (25)$$

Last but not the least, the minimum length of each time interval is defined in (26)

$$\underline{L} \leq \ell_i \qquad \forall i \qquad (26)$$

3. THE OPTIMIZATION PROBLEM

Once the constraints for modeling the components of the system are defined, an objective function must be introduced. In particular, four main terms have been considered. The first one is used to penalize tardiness, the second one to minimize the cost for the power purchased from the grid, the third one can be identified as an occupancy cost. This particular term is necessary to avoid the connection of the EBs when they are not under charge. The last term is a penalty to the finale state of charge of the ESS, used to avoid equivalent solutions. The overall objective function is

$$\min \sum_{j=1}^{B} \Omega_j t_j^{TARD} + \sum_{i=1}^{M} c_i^G + \sum_{i=1}^{M}\sum_{j=1}^{B} \Phi \cdot y_{i,j} + \alpha \cdot SOC_M^S \qquad (27)$$

where, c_i^G is defined as:

$$c_i^G = \left\{ \left[\int_{t_{i-1}}^{t_i} C^{buy}(t)\,dt \right] p_i^{G+} - \left[\int_{t_{i-1}}^{t_i} C^{sell}(t)\,dt \right] p_i^{G-} \right\} \qquad \forall i \qquad (28)$$

To summarize, the optimization problem is (27) s.t. (2)-(26).

4. APPLICATION TO A CASE STUDY

In this section, the proposed model is applied to a case study where 8 EBs need to be charged in a CS with 2 sockets. In Table 1, the general data relevant to the optimization problem are reported, while Table 2 shows the data relevant to each EB.

Table 1. General data

B	M	N	$T[/]$
8	16	2	24
$\underline{L}[h]$	$\bar{P}^{CS}[kW]$	$\Gamma_j^{EB}[/]$	$CAP_j^{EB}[kWh]$
0.083	162	0.95	150÷180
$\overline{SOC}_j^{EB}[/]$	$\underline{SOC}_j^{EB}[/]$	$\bar{P}_j^{EB}[kW]$	$\underline{P}_j^{EB}[kW]$
1	0	90	0
$\bar{P}^G[kW]$	$\underline{P}^G[kW]$	$\bar{P}^S[kW]$	$\underline{P}^S[kW]$
162	-162	100	-100
$\Gamma^{S,ch}[/]$	$\Gamma^{S,dch}[/]$	$\overline{SOC}^S[/]$	$\underline{SOC}^S[/]$
0.9	1.1	0.9	0.1
$CAP^S[kWh]$	$K[/]$	$C^{sell}[€/kWh]$	
100	1000	0.08	

Table 2. Data relevant to the EBs

	$T_j^{rl}[h]$	$T_j^{dd}[h]$	$T_j^{dl}[h]$	$SOC_j^{EB,init}[/]$	$SOC_j^{EB,fin}[/]$
EB_1	1.25	6.25	7.25	0.3	0.9
EB_2	2	7	8	0.2	0.85
EB_3	2.5	7.5	8.5	0.3	0.9
EB_4	3.25	8.25	9.25	0.2	0.85
EB_5	4	9	10	0.4	0.85
EB_6	4.75	9.75	10.75	0.3	0.9
EB_7	5.5	10.5	11.5	0.2	0.85
EB_8	6.25	11.25	12.25	0.4	0.85

Finally, the coefficients in the objective function are set to $\Omega_i = 0.98[€/h]$, $\Phi = 1[€/h]$ and $\alpha = 1$. Then, the buying price is given by a 6th order polynomial function, used to approximate the blue piecewise-constant function in Figure 5. Please note that in Table 1 the full range for the EB batteries is considered since a nonlinear model is implemented; then, the minimum charging power is zero as Vehicle-to-Grid mode is discarded.

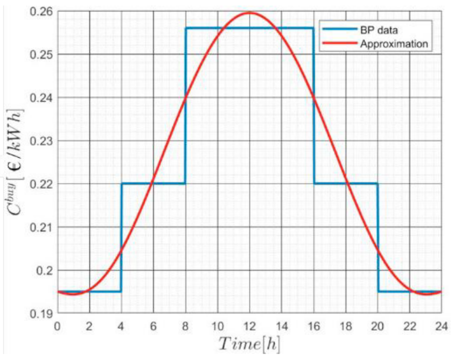

Figure 5. Buying price

The resulting problem is a MINLP and has been solved by using software LINGO™ on an Intel Core i5-8265U CPU 1.60GHz 1.80 GHz PC with 8,00 GB RAM. The runtime is about 100 seconds.

In the objective function (27) four different terms are considered; according to the results, the tardiness cost is null, the cost for buying energy from the grid is 183.91€, the occupancy cost amounts to 12€, and finally the last term is 0.1€. Of course, the largest contribution is given by the grid cost as it is the only energy source to charge the EBs; the tardiness cost is null meaning that no EBs terminates its charging process after its due date, and finally the occupancy cost simply reflects how many times EBs are globally connected to the CS. Since a DE approach is adopted, the temporal discretization is a decision variable itself and Table 3 reports its optimal values. In addition to these values, it is necessary to report the initial time $t_0[h] = 1.25$, which allows to verify that the periodicity constraint (24) is respected.

Table 3. Temporal discretization

$t_1[h]$	$t_2[h]$	$t_3[h]$	$t_4[h]$
3.73	4.76	5.09	6.07
$t_5[h]$	$t_6[h]$	$t_7[h]$	$t_8[h]$
6.22	6.3	8.21	8.75
$t_9[h]$	$t_{10}[h]$	$t_{11}[h]$	$t_{12}[h]$
8.84	8.92	9.00	9.09
$t_{13}[h]$	$t_{14}[h]$	$t_{15}[h]$	$t_{16}[h]$
9.17	9.25	10.57	25.25

The Gantt diagram in Figure 6, together with Figure 7, reports the optimal charting scheduling, in terms of timing and charging power. From these two figures, it is possible to appreciate that the introduction of intermediate event actually increases the problem degrees of freedom by allowing the system to shift the charging service where it is more convenient (see Figure 5). Moreover, at first sight one can contest that in the first interval, when the cost is at its minimum, only one bus is charged; however, this is due to the release time of the 2nd and 3rd buses (Table 2), which prevents charging from starting. Indeed, EB_2 and EB_3 start their charging process in the second time interval, which begins after their T^{rl}.

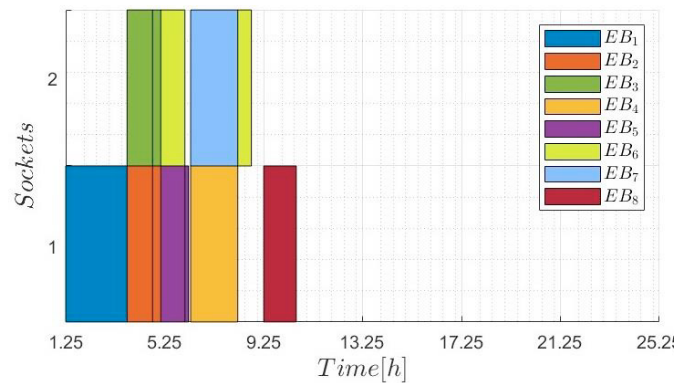

Figure 6. Gantt diagram

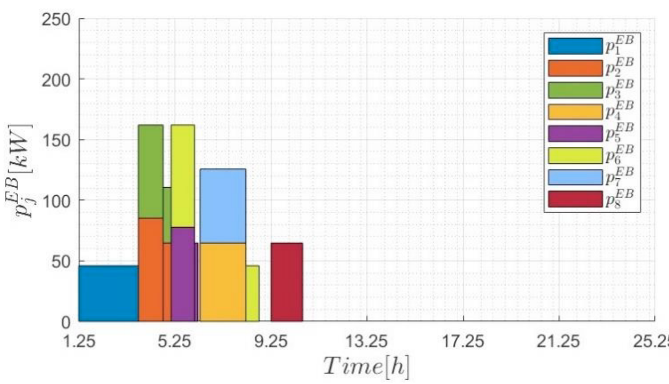

Figure 7. Charging powers

Figure 8 displays the power balance and allows to verify how the ESS is exploited: in the first time interval, when C^{buy} is the lowest possible but only EB_1 can be charged because of the constraint given by the release time of the other buses, the system withdraws power form the grid to charge the ESS. The stored energy is then used in the 15th time interval to charge EB_8; however, it is not enough, and so part of the charging power is provided by the grid.

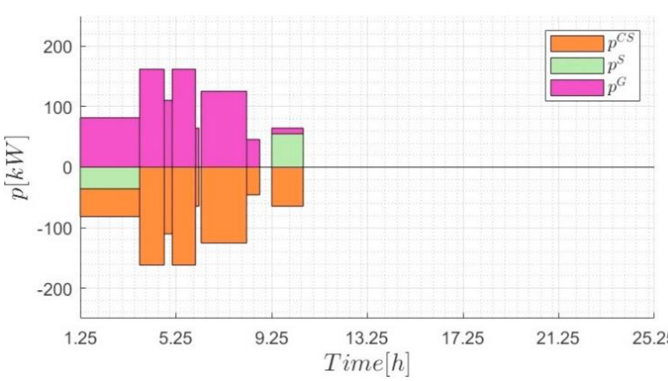

Figure 8. Power balance

Finally, Figure 9 reports the evolution over time of the state of charge of the EBs connected to the charging station in the 2nd and 3rd time intervals, and allows to verify that the energy request is satisfied; please note that an insight on these two EBs has been performed for sake of legibility. Then, from this figure one can also visualize the main consequence of adopting a DE approach: the length of time intervals is not constant.

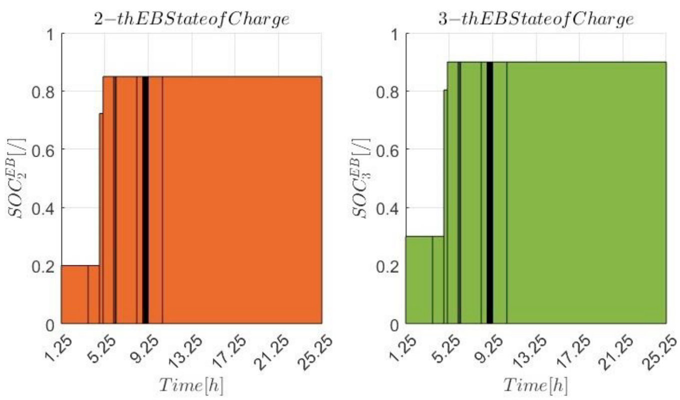

Figure 9. SOC of EBs connected in the 2nd and 3rd time intervals

5. CONCLUSIONS

In this paper, a novel approach for optimal charging scheduling of EBs in public transportation settings is presented. The model considers time tabling constraints, energy request satisfaction, and the capability for simultaneous charging of multiple EBs within a multi-socket framework, offering a comprehensive solution to the complexities of managing EB fleets. Additionally, the adoption of a periodic model accurately captures the cyclical nature of such systems. A key contribution of this work is the detailed modeling of EB batteries, incorporating their nonlinear charging profiles to better reflect real-world behavior. This enables more accurate prediction of power requirements and charging durations, leading to optimized scheduling decisions. Furthermore, the introduction of intermediate events in the DE optimization model enhances system flexibility, enabling dynamic adjustments such as shifting charging processes to periods of lower grid power costs. A potential improvement for this model includes adopting a bilevel structure to leverage the DE model and subsequently obtaining a more detailed solution by applying a DT formulation once the time schedule is obtained.

6. ACKNOWLEDGEMENTS

This work is part of the activities of the RAISE Spoke 3 project in the context of the National Resilience Recovery Plan (PNRR).

7. REFERENCES

Casella, V., Fernandez Valderrama, D., Ferro, G., Minciardi, R., Paolucci, M., Parodi, L., & Robba, M. (2022). Towards the Integration of Sustainable Transportation and Smart Grids: A Review on Electric Vehicles' Management. *Energies*, *15*(11), 4020.

Casella, V., Ferro, G., Minciardi, R., Parodi, L., & Robba, M. (2023). Optimization of electric buses charging station with multiple sockets: The case of Genoa Municipality. *IFAC-PapersOnLine*, *56*(2), 10057–10062.

Delfino, F., Ferro, G., Minciardi, R., Robba, M., Rossi, M., & Rossi, M. (2019). Identification and optimal control of an electrical storage system for microgrids with renewables. *Sustainable Energy, Grids and Networks*, *17*, 100183.

Ferro, G., Minciardi, R., Parodi, L., & Robba, M. (2021). Discrete event optimization of a vehicle charging station with multiple sockets. *Discrete Event Dynamic Systems*, *31*(2), 219–249.

Ferro, G., Minciardi, R., Parodi, L., & Robba, M. (2023). Optimal Location and Line Assignment for Electric Bus Charging Stations. *IEEE Systems Journal*, 1–12.

He, Y., Liu, Z., & Song, Z. (2020). Optimal charging scheduling and management for a fast-charging battery electric bus system. *Transportation Research Part E: Logistics and Transportation Review*, *142*, 102056.

Hu, H., Du, B., Liu, W., & Perez, P. (2022). A joint optimisation model for charger locating and electric bus charging scheduling considering opportunity fast charging and uncertainties. *Transportation Research Part C: Emerging Technologies*, *141*, 103732.

Liu, K., Gao, H., Liang, Z., Zhao, M., & Li, C. (2021). Optimal charging strategy for large-scale electric buses considering resource constraints. *Transportation Research Part D: Transport and Environment*, *99*, 103009.

Mohammadi, F., & Saif, M. (2023). A comprehensive overview of electric vehicle batteries market. *E-Prime - Advances in Electrical Engineering, Electronics and Energy*, *3*, 100127.

Perumal, S. S. G., Lusby, R. M., & Larsen, J. (2022). Electric bus planning & scheduling: A review of related problems and methodologies. *European Journal of Operational Research*, *301*(2), 395–413.

Ruggieri, R., Ruggeri, M., Vinci, G., & Poponi, S. (2021). Electric Mobility in a Smart City: European Overview. *Energies*, *14*(2), 315.

Sinha, P., Paul, K., Deb, S., & Sachan, S. (2023). Comprehensive Review Based on the Impact of Integrating Electric Vehicle and Renewable Energy Sources to the Grid. *Energies*, *16*(6), 2924.

Venegas, F. G., Petit, M., & Perez, Y. (2019). Impact of Non-Systematic Electric Vehicle Charging Behaviour on a Distribution Substation. *2019 IEEE PES Innovative Smart Grid Technologies Europe (ISGT-Europe)*, 1–5.

Wan, M., Yu, H., Huo, Y., Yu, K., Jiang, Q., & Geng, G. (2024). Feasibility and Challenges for Vehicle-to-Grid in Electricity Market: A Review. *Energies*, *17*(3), 679.

Zhang, L., Wang, S., & Qu, X. (2021). Optimal electric bus fleet scheduling considering battery degradation and non-linear charging profile. *Transportation Research Part E: Logistics and Transportation Review*, *154*, 102445.