A Global Optimization Framework for Orchestrating Electric Vehicles in Providing Ancillary Services

Silvia Iuliano
Dept. of Engineering
University of Sannio
Benevento, Italy
s.iuliano@studenti.unisannio.it

Hafsa Qamar
Dept. of Electrical Engineering
Lahore University of Management Sciences
Lahore, Pakistan
hafsa.qamar@lums.edu.pk

Alfredo Vaccaro
Dept. of Engineering
University of Sannio
Benevento, Italy
vaccaro@unisannio.it

***Abstract*—Exploiting the potential of electric vehicles equipped with Vehicle-to-Grid technology to supply grid ancillary services requires the development of complex optimization strategies for dynamically orchestrating the charging and discharging profiles of vehicle fleets. In this context, formalizing well-balanced objective functions, managing the nonlinear phenomena affecting the scheduling process, modeling the discrete variables and identifying a proper trade-off between promptness and accuracy requirements are some of the most challenging open problems to solve. To address these issues, we rely on the concept of electric vehicles welfare, which we modeled by combining novel utility functions quantifying the economic benefits/costs related to the charging/discharging profiles. To solve this complex optimization problem, we proposed deploying convexification procedures and decomposition methods, which allow the modeling of discrete control variables and computing the optimality gap, enabling the computation of global optimal solutions. Comprehensive simulation results are presented and discussed to demonstrate the effectiveness of the proposed methodology.**

***Index Terms*—EVs, Flexibility, Global Optimum, Scheduling, Ancillary Services.**

I. Introduction

Electric vehicles (EVs) have become increasingly popular due to their smaller carbon footprint than conventional cars. This trend is particularly evident in Europe, where the total electricity demand from EVs is expected to increase from 0.03% in 2014 to approximately 4–5% by 2030 and 9.5% by 2050 [1]. The growing penetration of EVs is expected to significantly modify the power demand profiles of distribution systems, increasing the occurrence of overload conditions caused by simultaneous vehicle charging. To try to mitigate these critical grid impacts, future EVs will be equipped with Vehicle-to-Grid (V2G) functions, which allows to connect the vehicle energy storage systems through bidirectional grid-interfaces that coordinates their charging/discharging processes properly [2]. Deploying V2G functions is one of the most promising enabling technologies to enhance the power distribution system flexibility by supplying grid ancillary services, as far as active power balancing, primary and secondary frequency regulation are concerned [3].

Achieving the full potential of these benefits requires the development of dynamic orchestration frameworks designed to schedule EV charging and discharging processes to meet the power grid requirements. These frameworks must also account for the desired state of charge of the storage systems at the end of the charging process, their actual state of charge, and the expected degradation effects associated with the charging and discharging profiles [4].

To address the challenging problem of charging and discharging EVs orchestration, various computational paradigms have been proposed in the literature [5], [6]. In particular, [7] introduced an optimization method specifically designed to provide grid ancillary services while maximizing the aggregator profit. The multi-objective characteristics of the scheduling problem were further investigated in [8], which proposed an optimization algorithm to regulate grid-injected active power flows with the aim of maximizing economic benefits and minimizing grid load fluctuations. More advanced computational paradigms have also been proposed, including blockchain-based solutions with privacy-preserving mechanisms, vehicle-to-vehicle energy trading enabled by blockchain technology, and V2G scheduling supported by federated deep learning, as reported in [9]–[11], respectively.

The methodologies proposed in these papers are mainly focused on enhancing the economic profits derived from ancillary service provision, which is a priority of the aggregators, but they lack a detailed assessment of the impacts of the charging and discharging profiles on the storage systems.

To fill this gap, the authors in [12] proposed a welfare maximization-based orchestration framework that enables ancillary service provision by scheduling the charging and discharging profiles of a fleet of grid-connected electric buses, considering simplified utility functions to model the costs and benefits associated with these profiles. In particular, to make the maximization problem tractable, it was formulated as a Mixed-Integer Linear Programming (MILP) problem under several simplifying assumptions, including the piecewise linearization of the vehicle welfare function (i.e., the objective function), the linearization of the marginal cost and benefit functions, and the use of time-invariant coefficients in the utility functions.

Although these simplified assumptions allow a prompt solution of the welfare maximization problem, they fail to capture the nonlinear phenomena affecting the orchestration process, thus preventing the computation of globally optimal solutions.

To address these open challenges, this paper proposes a framework that allows EV owners to monetize their parked

979-8-3315-8138-1

vehicles as active assets, providing ancillary grid services to balance intermittent renewable energy. Mathematically, we introduce novel utility functions that quantify the economic costs and benefits associated with charging and discharging profiles while accounting for the nonlinear phenomena affecting storage system degradation. These nonlinear cost–benefit functions enable the formulation of the welfare maximization problem as a Mixed-Integer Nonlinear Programming (MINLP) problem. To solve this complex optimization problem, convexification procedures and decomposition methods are employed to handle discrete control variables and evaluate the optimality gap, thereby enabling the computation of globally optimal solutions. Comprehensive simulation results, including scalability analyses performed on realistic vehicle fleets over multiple time horizons, are presented to demonstrate the effectiveness of the proposed methodology in computing global welfare-maximizing solutions under realistic operating conditions.

The remainder of this paper is organized as follows. Section II introduces the mathematical formulation of the orchestration problem. Section III presents the proposed welfare maximization-based methodology for EV orchestration and the solution approaches adopted to address the orchestration problem, while Section IV reports the simulation results. Finally, Section V concludes the paper with a summary of contributions and directions for future research.

II. Problem formulation

The application domain considered in this paper is a network of bidirectional charging stations connected to a common grid connection point, interfaced with a fleet of EVs equipped with V2G capabilities [13]. The key objective is to schedule the charging and discharging of each EV during every control period $\tau_k = k\Delta\tau$ over a defined time window, $\tau_k \in [0, T]$, such that the total active power exchanged at the grid connection point strictly follows a predefined power reference $P_{grid}(\tau_k)$, referred to as the grid-requested power profile, expressed as:

$$P_{grid}(\tau_k) = \sum_{j \in \mathcal{N}_{ev}(\tau_k)} [P_j^{dis}(\tau_k)\sigma_j^{dis}(\tau_k) - P_j^{chrg}(\tau_k)\sigma_j^{chrg}(\tau_k)] \quad \forall\, \tau_k \in [0, T] \tag{1}$$

Here, $\mathcal{N}_{ev}(\tau_k)$ represents the set of EVs connected to the grid at time τ_k, whereas $P_j^{chrg}(\tau_k)$ and $P_j^{dis}(\tau_k)$ denote the charging and the discharging power profile of the j^{th} EV at the same control period. The binary variables $\sigma_j^{chrg}(\tau_k)$ and $\sigma_j^{dis}(\tau_k)$ specify whether the j^{th} EV is charging or discharging at time τ_k. These decision variables must also comply with the following complementary constraints:

$$\sigma_j^{chrg}(\tau_k) + \sigma_j^{dis}(\tau_k) \leq 1 \quad \forall \tau_k \in [0, T],\ \forall j \in \mathcal{N}_{ev}(\tau_k) \tag{2}$$

Within this framework, it is assumed that the fleet operator must align the active power delivered to the common grid connection point with the power profile required by the system operator. Therefore, the grid-requested power profile is considered a known information for each control period in the total scheduling time window (i.e., $P_{grid}(\tau_k)$ for all $\tau_k \in [0, T]$). The equality constraint defined in (1) ensures that the total charging and discharging operations of the EVs collectively satisfy this reference power profile at every time step.

It is worth noting that this formulation models the grid-requested power as a deterministic input to the optimization problem, eliminating the need to explicitly model stochastic variables such as market fluctuations, operational uncertainties, or bidding interactions. In this context, the fleet operator is responsible for properly scheduling the charging and discharging operation of all connected EVs, taking into account their energy storage efficiencies, maximum power limits, current and desired state of charge at the end of the scheduling horizon.

III. A Non-Linear Welfare Maximization-based Solution Methodology

The main insight of this paper is to recast the scheduling problem introduced in Section II by a non-linear welfare maximization problem. As a starting point, the analysis focuses on evaluating the collective utility of a fleet of EVs by constructing coherent utility models that capture the trade-offs associated with their charging and discharging power profiles. These models are designed to account for both the grid power demand and the EV owners requirement for sufficient battery charge prior to departure. For these purposes, in Section III-A, we propose non-linear utility functions that quantify the incremental gain or cost resulting from injecting (or absorbing) a fixed amount of active power over a defined interval $\Delta\tau$.

A. Non-linear EVs Utility Functions

To quantify the welfare of EVs, we propose customized utility functions, combining the cost function $C_j(t)$ and the benefit function $B_j(t)$, which quantify, for the j^{th} EV, the incremental value of the power transactions with respect to the current and target state of charge:

$$C_j(\tau) = a_j(SoC(\tau_k))P_j^{dis}(\tau)^2 + b_j(SoC(\tau_k)))P_j^{dis}(\tau) + \lambda_j \tag{3}$$

$$B_j(\tau) = d_j(SoC(\tau_k))P_j^{chrg}(\tau)^2 + e_j(SoC(\tau_k))P_j^{chrg}(\tau) + \rho_j \tag{4}$$

where:

- P_j^{chrg} is the charging power;
- P_j^{dis} is the discharging power;
- a_j and b_j are the quadratic and linear coefficients of the cost function, respectively;
- d_j and e_j are the quadratic and linear coefficients of the benefit function, respectively;
- λ_j is the constant cost associated with the discharging operation;
- ρ_j is the constant benefit associated with the charging operation.

The vehicle welfare W_j is defined as the difference of costs from benefits, as expressed in Eq.(5):

$$W_j = \sum_{k=1}^{T}[B_j(\tau_k) - C_j(\tau_k)] \quad \forall j \in [1, \mathcal{N}_{ev}] \tag{5}$$

979-8-3315-8138-1

where $\mathcal{N}_{ev}$ is the total number of EVs connected.

The short-term marginal cost/benefit of discharging/charging the j^{th} EVs during can be computed as follow:

$$\begin{aligned} \frac{dC_j(\tau)}{dP_j^{dis}} &= 2a_j(SoC,\tau_k)P_j^{dis}(\tau) + b_j(SoC,\tau_k) \\ \frac{dB_i(\tau)}{dP_i^{chrg}} &= 2d_j(SoC,\tau_k)P_j^{chrg}(\tau) + e_j(SoC,\tau_k) \end{aligned} \tag{6}$$

The coefficients of these marginal utility functions, which model the impacts of the charging/discharging power profiles on the energy storage system operation, can be computed as follows:

$$\begin{aligned} a_j(SoC(\tau_k)) &= cE_j^{cap}\frac{\Delta\tau}{2\varepsilon_j^{dis}E_j^{cap}SoC_j(\tau_{k-1})} \\ b_j(SoC(\tau_k)) &= cE_j^{cap}\frac{\frac{SoC_j^{max}}{SoC_j^{min}}-1}{\frac{SoC_j(\tau_{k-1})}{SoC_j^{min}}-1}-1 \\ d_j(SoC(\tau_k)) &= \frac{cE_j^{cap}\varepsilon_j^{chrg}\Delta\tau}{2E_j^{cap}(SoC_i^{max}-SoC_i(\tau_{k-1}))} \\ e_j(SoC(\tau_k)) &= \frac{\frac{SoC_j^{max}}{SoC_j^{min}}-1}{\frac{SoC_j(\tau_{k-1})}{SoC_j^{min}}-1}-1 \end{aligned} \tag{7}$$

where:

- cE_j^{cap} is the mean monetary value of stored energy;
- ε_j^{dis} storage unit discharging efficiency;
- ε_j^{chrg} storage unit charging efficiency;
- E_j^{cap} is the rated energy capacity of the storage unit;
- $SoC_i(\tau_{k-1})$ is the state of charge at time τ_{k-1};
- SoC_j^{min} and SoC_j^{max} are the lower and upper bounds of the state of charge for j^{th} EV, respectively.

The utility functions presented in (6) are consistent with a rational charging/discharging strategy, where the incremental value of increasing the charging or discharging power of a unit depends on both its actual and expected state of charge. Notably, the benefit (or cost) decreases (or increases) as the state of charge approaches its upper (or lower) limit, and it is strictly influenced by the equivalent monetary value of the stored energy. Ongoing work by the authors focuses on enhancing the marginal utility models to more accurately model the storage system dynamics by describing the nonlinear phenomena affecting charging and discharging efficiencies, specifically by integrating functions of C-rate and State of Health. These advanced models also incorporate the cost implications of battery degradation caused by charge–discharge cycles, which, as discussed in [14], represents an important issue to address in this application context.

B. The Welfare Maximization Problem

Once the utility functions for the EV fleet have been formally defined, the welfare of the EVs fleet for each control period $\tau_k \in [0,T]$ can be expressed as follows:

$$W(\tau_k) = \sum_{j\in\mathcal{N}_{ev}(\tau_k)} \left(B_j(\tau_k)\sigma_j^{chrg}(\tau_k) - C_j(t_k)\sigma_j^{dis}(\tau_k)\right) \tag{8}$$

Based on this formulation, the EVs orchestration problem can be recasted as a multi-period MINLP welfare maximization problem, as described below:

$$\begin{aligned} \max_{\substack{P_j^{dis}(\tau_k),\,\sigma_j^{dis}(\tau_k)\\ P_j^{chrg}(\tau_k),\,\sigma_j^{chrg}(\tau_k)}} \quad & \sum_{\tau_k=0}^{T} W(\tau_k) \\ \text{s.t.} \quad & \sum_{j\in\mathcal{N}_{ev}(\tau_k)} P_j^{dis}(\tau_k) - \sum_{j\in\mathcal{N}_{ev}(\tau_k)} P_j^{chrg}(\tau_k) = P_{grid}(\tau_k) \\ & SoC_j(\tau_k{+}1) = SoC_j(\tau_k) + \frac{P_j^{chrg}(\tau_k)\varepsilon^{chrg}\Delta T}{E_j^{nom}} - \frac{P_j^{dis}(\tau_k)\Delta T}{\varepsilon^{dis}E_j^{nom}} \\ & P_j^{chrg,min}\sigma_j^{chrg}(\tau_k) \le P_j^{chrg}(\tau_k) \le P_j^{chrg,max}\sigma_j^{chrg}(\tau_k) \\ & P_j^{dis,min}\sigma_j^{dis}(\tau_k) \le P_j^{dis}(\tau_k) \le P_j^{dis,max}\sigma_j^{dis}(\tau_k) \\ & SoC_j^{min} \le SoC_j(\tau_k) \le SoC_j^{max} \\ & SoC_j(T) \ge SoC_j^{target} \\ & \sigma_j^{chrg}(\tau_k) + \sigma_j^{dis}(\tau_k) \le 1 \\ & \forall j \in \mathcal{N}_{ev}(\tau_k),\ \forall \tau_k \in [0,T]. \end{aligned} \tag{9}$$

where SOC_j^{target} is the target state of charge for the j^{th} EV at the end of the scheduling period.

Solving the welfare maximization problem formalized in (9) is a complex and computationally intensive task. The main difficulties stem from the nonlinearity of both the objective and the constraint functions, the need for modeling a large number of discrete decision variables, and the presence of a large set of inter-temporal constraints. For this purpose, we employ the solution methodology proposed in [15], which combines preprocessing, convexification, and constraint relaxation techniques to reliably estimate the feasibility region, thereby enabling the evaluation of the distance from the global optimum. Specifically, these techniques allow for the computation of the global gap, which quantifies the difference between the best integer solution Z_{BI} and the best lower bound solution Z_{BB}, as follows:

$$f(Z_{BI}, Z_{BB}) = \frac{|Z_{BI} - Z_{BB}|}{Z_{BI}} \tag{10}$$

This metric is particularly useful for assessing the effectiveness of the obtained solution. A value close to zero indicates that the best integer solution is close to the best bound solution, implying that the solution with integer variables is nearly equivalent to that obtained by relaxing the integrality constraints. Conversely, a high value suggests a significant gap, which may occur when the best integer solution is close to zero or when Z_{BB} is negative.

IV. SIMULATION RESULTS

The social welfare maximization problem formulated in (9) was solved for multiple realistic case studies considering two time horizons (i.e., one and two hours ahead) by using the FICO Xpress Mosel language [15]. A control period of 15 minutes (i.e. $\Delta\tau$ = 0.25 h) was assumed for all case studies. In modern passenger EVs, battery energy capacities typically range from approximately 30 kWh to 100 kWh or higher, depending on vehicle size and targeted driving range. Long-range EVs with driving ranges of around 300 miles commonly employ battery capacities close to 100 kWh [16]. Accordingly, in this work, the EV battery energy capacity is

979-8-3315-8138-1

selected as 100 kWh. The charging and discharging power of EVs depends on the employed charging technology and available infrastructure. Conventional AC Level 2 charging systems are typically rated up to 19.2 kW; therefore, consistent with AC Level 2 operation, the charging and discharging power is chosen as 20 kW [17]. For simplicity, all EVs are assumed to be equipped with identical energy storage systems, with charging and discharging efficiencies of 0.9.

The first case study considers a fleet ranging from 5 to 100 EVs, which are required to satisfy the grid power profile reported in Table I within a one-hour time horizon. The obtained results are summarized in Table II, which reports the optimality gap, the execution time, the objective function and the total iteration number required to solve the welfare maximization problem for all the analyzed operation scenarios. The nearly identical execution times for the 50-EV and 100-EV cases in Table II result from an imposed upper limit of 4,977 s on the solver runtime, with both simulations terminating before full convergence. The corresponding evolution of the optimality gaps is shown in Fig. 1, confirming the monotonic decrease of the gap as the number of iterations increases. The analysis of these results enables the assessment of the evolution of the optimality gap with respect to the fleet size, revealing an increasing gap as the number of EVs grows. Specifically, fleets of 5, 10, and 15 vehicles exhibit relatively low gaps, indicating that the problem remains tractable for these configurations. Conversely, larger fleets of 50 and 100 vehicles show a pronounced, and in some cases exponential, increase in the optimality gap due to the escalating computational complexity. This conclusion is further confirmed by the objective function profiles, which are not reported here due to space limitations, but exhibited an initial plateau during the first iterations followed by an approximately linear decrease.

TABLE I: Grid requested power profile - 1 hour time frame

NoEV [#]	P_{0-15} [kW]	P_{15-30} [kW]	P_{30-45} [kW]	P_{45-60} [kW]
5	-100	100	-50	100
10	-300	-150	-150	300
15	-300	-150	-150	300
50	-100	100	-50	100
100	-1000	1000	-500	1000

TABLE II: Results - 1 and 2 hour time frame. Scalability with respect to the number of EVs.

NoEV [#]	GapGO [%]	Ex. Time [s]	ObjMax [euro]	Tot. Iter. [#]
5	1.8	1.20	$6.53 \cdot 10^2$	58
10	1.0	552.33	$5.97 \cdot 10^2$	245
15	1.3	670.21	$4.66 \cdot 10^2$	126
50	5.6	4977.24	$3.28 \cdot 10^2$	236
100	76.7	4977.81	$4.09 \cdot 10^3$	230

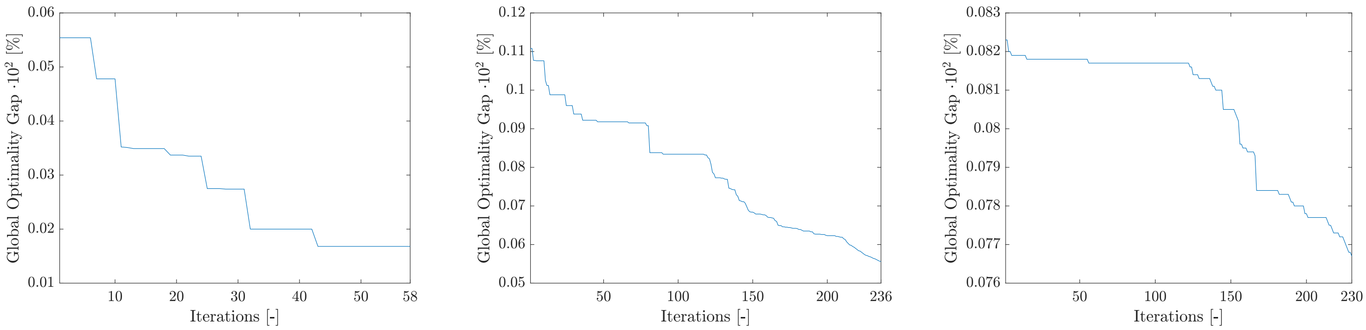
To assess the scalability of the proposed orchestration methodology with respect to the time-frame duration, the simulation were repeated using a two-hour time horizon, based on the grid power profile reported in Table III. The obtained results are summarized in Table II and illustrated in Fig. 2. The analysis of these data confirms the increased complexity of the orchestration problem, which prevents the computation of global optimal solutions within useful time-frames. Indeed, only in the simplest operational scenario (i.e., 5 EVs), does the proposed method achieve a minimum optimality gap of 1%, reached after 411 iterations and corresponding to approximately 4977 seconds of computation time. It is worth noting that the higher optimality gaps observed during the simulations may be attributed to the particularly low value of the best integer solution. As a result, the optimality gap tends to assume relatively high values even when the absolute difference between the current solution and the optimal bound is small. Finally, the scale of the scalability analysis was chosen to align with current V2G projects, ensuring the study's practical relevance.

TABLE III: Grid requested power profile - 2 hours time frame

NoEV [#]	$P_{0\text{–}15}$	$P_{15\text{–}30}$	$P_{30\text{–}45}$	$P_{45\text{–}60}$	$P_{60\text{–}75}$	$P_{75\text{–}90}$	$P_{90\text{–}105}$	$P_{105\text{–}120}$
5	-100	-50	-50	100	20	80	-40	-10
10	-100	-50	-50	100	20	80	-40	-10
15	-100	-50	-50	100	20	80	-40	-10
50	-300	-150	-150	300	60	240	-120	-300
100	-1000	-500	-500	1000	200	800	-400	-100

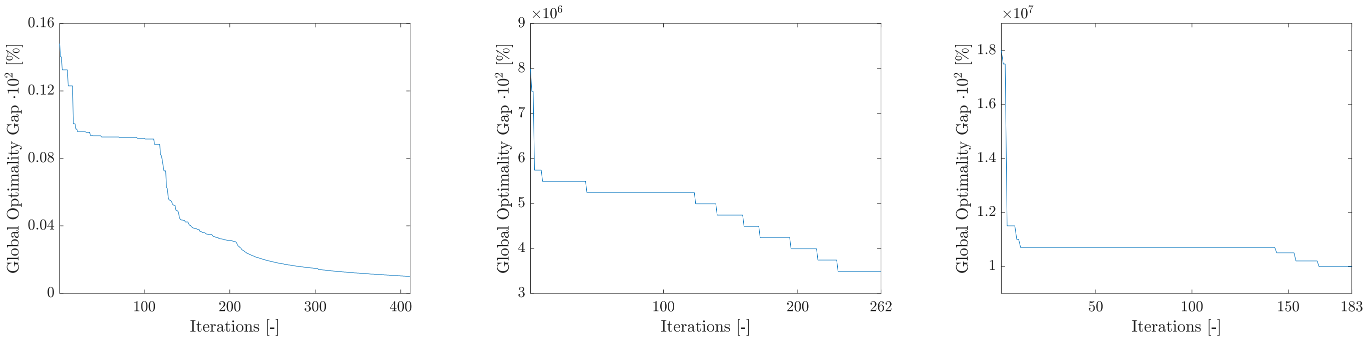
V. Concluding Remarks

This paper proposed an orchestration strategy for electric vehicles equipped with Vehicle-to-Grid technology to provide grid support services. Novel nonlinear utility functions have been defined to model the marginal costs and benefits associated with charging and discharging operations, considering their impacts on the storage system operation. These functions enabled the definition of the orchestration strategy through the solution of a welfare maximization problem, formulated as a specific instance of a Mixed-Integer Nonlinear Programming model. To handle the inherent complexity of this optimization problem, convexification and relaxation techniques are employed. These methods allow for an effective representation of discrete control variables, a reliable estimation of the feasible region, and an accurate assessment of the distance between the obtained solution and the global optimum. To achieve this, the solver first employs symbolic decomposition to approximate the convex hull of complex equations. The resulting relaxations of bilinear and quadratic terms are then tightened using McCormick envelopes and the reformulation-linearization technique. Finally, the search process is accelerated by dynamically adding global and local cutting planes, which continuously improve the lower bound and close the optimality gap. The effectiveness of the proposed methods is evaluated under multiple operational scenarios characterized by different time horizons and vehicles number. For each scenario, we analyzed the deviation from the global optimum, the evolution of the objective function, and the number of iterations required to achieve convergence to feasible solutions. The obtained results showed a significant degradation in algorithmic performance as the fleet size increases, with solutions deviating markedly from the global optimum. This effect is particularly pronounced in the 2-hour time horizon scenario, where the algorithm tends to converge to suboptimal solutions. Such inefficiencies result in a reduction of overall vehicle welfare due to the suboptimal allocation of available



(a) 5 EVs (b) 50 EVs (c) 100 EVs

Fig. 1: Evolution of the optimality gap across fleet sizes - 1 hour time frame.



(a) 5 EVs (b) 50 EVs (c) 100 EVs

Fig. 2: Evolution of the optimality gap across fleet sizes - 2 hour time frame.

resources. Ongoing research efforts are directed to overcome the computational burden of guaranteeing global optimality, especially for large-scale fleets where the required time can be excessive. Within this field, the authors' contribution is specifically focused on designing alternative mathematical formulations of the same problem to improve computational efficiency.

References

[1] European Environment Agency, "Electric vehicles and the energy sector – impacts on europe's future emissions," European Environment Agency, Luxembourg, Technical Report, Jul. 2016, eEA Report.

[2] O. Stogl, M. Miltner, C. Zanocco, M. Traverso, and O. Starý, "Electric vehicles as facilitators of grid stability and flexibility: A multidisciplinary overview," *WIREs Energy and Environment*, vol. 13, no. 5, Sep. 2024.

[3] M. Yilmaz and P. T. Krein, "Review of the impact of vehicle-to-grid technologies on distribution systems and utility interfaces," *IEEE Transactions on Power Electronics*, vol. 28, no. 12, pp. 5673–5689, 2013.

[4] A. Ali, M. F. Shaaban, A. S. Awad, M. A. Azzouz, M. Lehtonen, and K. Mahmoud, "Multi-objective allocation of ev charging stations and ress in distribution systems considering advanced control schemes," *IEEE Transactions on Vehicular Technology*, vol. 72, no. 3, pp. 3146–3160, 2022.

[5] M. Al-Saadi, M. Al-Greer, and M. Short, "Strategies for controlling microgrid networks with energy storage systems: A review," *Energies*, vol. 14, no. 21, 2021.

[6] E. Elghanam, A. Abdelfatah, M. S. Hassan, and A. H. Osman, "Optimization techniques in electric vehicle charging scheduling, routing and spatio-temporal demand coordination: A systematic review," *IEEE Open Journal of Vehicular Technology*, vol. 5, pp. 1294–1313, 2024.

[7] E. Sortomme and M. A. El-Sharkawi, "Optimal scheduling of vehicle-to-grid energy and ancillary services," *IEEE Transactions on Smart Grid*, vol. 3, no. 1, pp. 351–359, 2012.

[8] T. Zhou and W. Sun, "Research on multi-objective optimisation coordination for large-scale v2g," *IET Renewable Power Generation*, vol. 14, no. 3, pp. 445–453, Feb. 2020.

[9] X. Zhang, C. Liu, K. K. Chai, and S. Poslad, "A privacy-preserving consensus mechanism for an electric vehicle charging scheme," *Journal of Network and Computer Applications*, vol. 174, p. 102908, 2021.

[10] Y. Wang, L. Yuan, W. Jiao, Y. Qiang, J. Zhao, Q. Yang, and K. Li, "A fast and secured vehicle-to-vehicle energy trading based on blockchain consensus in the internet of electric vehicles," *IEEE Transactions on Vehicular Technology*, vol. 72, no. 6, pp. 7827–7843, 2023.

[11] Y. Shang, Z. Li, S. Li, Z. Shao, and L. Jian, "An information security solution for vehicle-to-grid scheduling by distributed edge computing and federated deep learning," *IEEE Transactions on Industry Applications*, vol. 60, no. 3, pp. 4381–4395, 2024.

[12] S. Iuliano and A. Vaccaro, "A welfare maximization-based methodology for on-line orchestration of grid-connected electric buses," *Smart Grids and Energy*, vol. 9, p. 44, 2024.

[13] A. Vaccaro, S. Iuliano, V. Galdi, V. Calderaro, and G. Graber, "Achieving consensus in self-organizing electric vehicles for implementing v2g-based ancillary services," *IEEE Access*, 2024.

[14] M. Schimpe, C. N. Truong, M. Naumann, A. Jossen, H. C. Hesse, J. M. Reniers, and D. A. Howey, "Marginal costs of battery system operation in energy arbitrage based on energy losses and cell degradation," in *2018 IEEE International Conference on Environment and Electrical Engineering*. IEEE, 2018.

[15] P. Belotti, T. Berthold, T. Gally, L. Gottwald, and I. Pólik, "Solving MINLPs to global optimality with FICO Xpress Global," Optimization Online, July 2025, https://optimization-online.org/?p=31226.

[16] M. Etxandi-Santolaya, L. Canals Casals, and C. Corchero, "Estimation of electric vehicle battery capacity requirements based on synthetic cycles," *Transportation Research Part D: Transport and Environment*, vol. 114, p. 103545, 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1361920922003716

[17] S. S. G. Acharige, M. E. Haque, M. T. Arif, N. Hosseinzadeh, K. N. Hasan, and A. M. T. Oo, "Review of electric vehicle charging technologies, standards, architectures, and converter configurations," *IEEE Access*, vol. 11, pp. 41 218–41 255, 2023.

979-8-3315-8138-1