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Unlocking the Value of Public EV Chargers: A Data-Driven Case Study from Gothenburg, Sweden

Araavind Sridhar[1], David Steen[1], Le Anh Tuan[1]
[1]*Department of Electrical Engineering, Chalmers University of Technology, Gothenburg, Sweden*
araavind.sridhar@chalmers.se, david.steen@chalmers.se, tuan.le@chalmers.se

Executive Summary

The growing adoption of electric vehicles (EVs) and the rapid expansion of public charging infrastructure pose new challenges and opportunities for energy systems, particularly in urban settings. This study presents an optimization-based evaluation of different EV charging strategies—including direct charging, average-based methods, smart charging, and vehicle-to-grid (V2G)—at public parking lots using real-world charging session data. This data-driven model is set to optimize the public EV charging of vehicles in Gothenburg, without sacrificing on the energy requirement while minimizing charging costs for the operators. Results indicate that direct charging scenarios lead to significantly higher peak loads (up to 752 kW) and costs, highlighting their inefficiency under unmanaged operation. In contrast, smart charging reduces peak loads by approximately 60% and overall costs by around 35%, showcasing its potential for cost-effective grid-friendly operation. V2G with incentives enables energy discharge back to the grid, but its benefits remain modest under current assumptions due to tight operational constraints and limited incentives. The study emphasizes the value of smart optimization and appropriate market design in enhancing the flexibility and cost efficiency of public EV charging systems.
Keywords: Vehicle to grid, energy management, parking lot operator, electric vehicle.

1 Introduction

The rapid electrification of the transportation sector has positioned electric vehicles (EVs) as a cornerstone of sustainable mobility. As EV adoption accelerates, the demand for accessible, reliable, and cost-efficient charging infrastructure becomes increasingly critical. Integrating EVs into urban infrastructure presents both challenges and opportunities for parking operators and energy systems. Public charging stations, essential for supporting EV users, are increasingly viewed not only as service points but also as potential nodes for providing grid flexibility—by modulating consumption, relieving network stress, and enabling vehicle-to-grid (V2G) technology. V2G allows bidirectional energy flow between EV batteries and the grid, positioning parked EVs as distributed energy resources [1]. In this context, public parking lots emerge as promising assets to enhance grid stability, reduce operational costs, and unlock new revenue streams.

Parking lot operators are uniquely positioned in this sustainable transition. Due to their control over the spatial and temporal availability of chargers, they can provide scalable charging services while leveraging idle vehicle time and onboard energy storage. This allows them to participate in electricity markets, reduce peak demand, and contribute to ancillary services such as frequency regulation and load balancing. However, realizing these benefits depends on understanding real-world charging behavior and the operational dynamics of public parking environments.

In literature, there has been several studies focusing on parking lot optimization. Awad et al. [2] proposed an smart parking-lot based optimization model to minimize the operational costs by determinging the optimal sizing of solar-based distributed generation along with EVs charging price by analyzing two scenarios: coordinating and uncoordinated scenario of EV demand. The results show a reduction in costs for the coordinated case without the need for any distributed generation. Zanvettor et al. [3] analyzed the problem of energy pricing under vehicle uncertainty is addressed by proposing a new energy pricing strategy where the daily profit of the parking lot is guaranteed with a given probability level. Fallah-Mehrjardi et al. [4] proposed a multi-stage stochastic programming approach using Stochastic Dual Dynamic Programming (SDDP) to optimize EV charging schedules in a public parking lot, considering admission control and uncertain future demands to minimize expected energy costs and the results showed that the method significantly reduces total energy costs and rejected charging requests compared to a myopic strategy. Jhala et al. [5] developed a centralized linear programming strategy for coordinating EV charging at renewable-powered parking lots, aimed to maximize parking lot operator profits under time-varying electricity prices while meeting customer demand and system constraints. While these studies underscore the economic viability of optimizing EV parking lots, they focus solely on grid-to-vehicle (G2V) charging.

In contrast, V2G integration offers additional flexibility and revenue potential. Sevdari et al. [6] reviewed the existing literature in terms of the flexibility potential of EV participation in different services through V2G and the potential returns of such services. Alinejad et al. [7] proposed a particle swarm optimization to maximize the returns of an parking lot utilizing V2G services while addressing the randomness of the EV owners behaviour. Chandra Mouli et al. [8] proposed a work place PV-installed parking lot optimization with V2G services based on Mixed-Integer Linear Programming (MILP) optimization, in which results show a 32% to 651% reduction in costs for EV charging. Salvatti et al. [9] proposes a dynamic programming-based Energy Management System (EMS) for microgrids integrating EV parking lots, PV generation, and dynamic loads, optimizing EV charging and discharging profiles to reduce grid dependence, enhance efficiency, and respect user preferences.

Despite extensive work in the area, the evaluation of public EV charging stations remains relatively underexplored. Furthermore, most existing models rely on assumptions about user preferences and charging acceptance, limiting real-world applicability. This study aims to fill that gap through a data-driven analysis of charging session records from public stations in Gothenburg, Sweden. By analyzing current charging patterns and evaluating multiple charging strategies—including smart charging and V2G—this paper assess both the economic and operational impacts for parking lot operators.

The findings of this research contribute to the broader discourse on sustainable urban mobility and energy systems by demonstrating how public charging infrastructure can be transformed as an active participant within the energy ecosystem. The insights presented here provide a foundation for parking operators, policymakers, and energy stakeholders to collaboratively design and implement ideal solutions in public charging stations that balance environmental, economic, and operational considerations.

2 Methodology

The proposed workflow used in this study is illustrated in Fig. 1. The analysis begins by assessing the charging demand and session duration of each EV connected to the public parking lot, specifically, the arrival and departure times, requested energy, and connection periods. This data is then used as input to the optimization model, which is designed to optimally reschedule charging and discharging activities under various scenarios. The model supports multiple objectives, including minimizing energy costs, reducing peak demand, and enabling participation in grid services. The final step involves analyzing and interpreting the results across different charging strategies.

The input data required to simulate the optimization model include:

- Arrival and departure timestamps for each EV
- Number of connected EVs at each time step
- Requested energy per EV.

Based on this data, the model schedules charging and discharging while ensuring energy requirements are fulfilled prior to departure and operational limits are respected.

2.1 Optimization model

The optimization model is based on linear programming which is used to optimize the parking lot charging of EVs on a daily basis. The model is then looped to assess a specific time period. The model

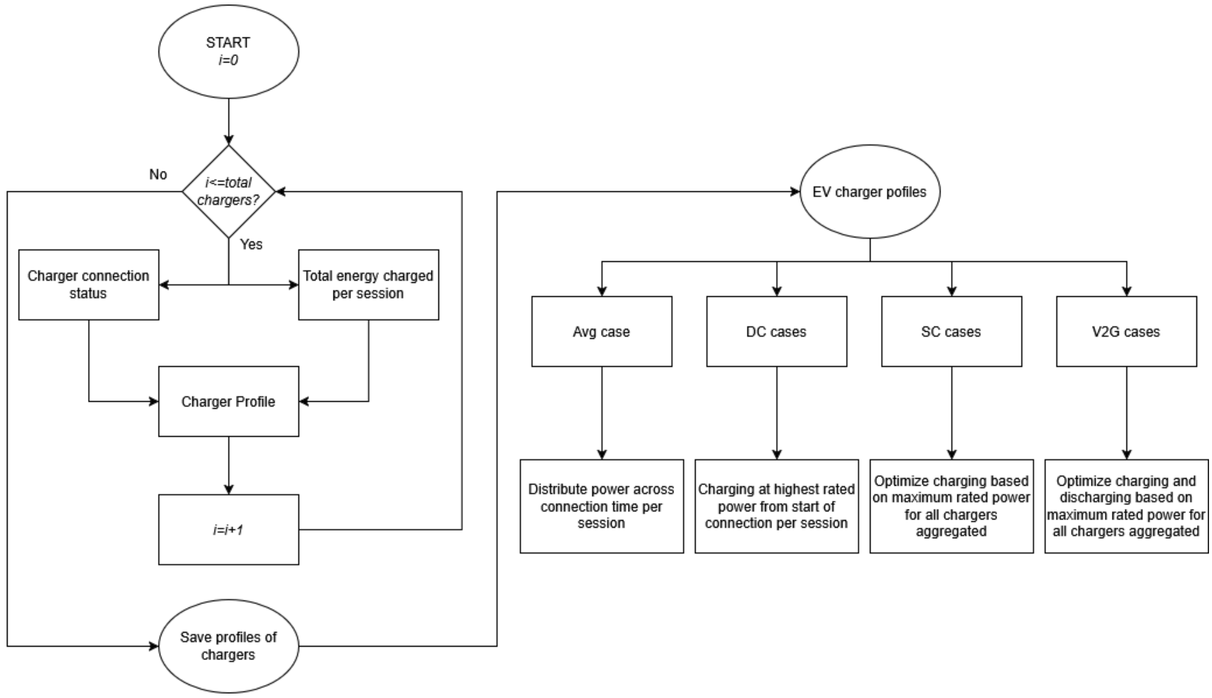

Figure 1: Workflow in this study

considers an aggregated EV fleet and not each EV individually in order to solve the model more efficiently.

2.1.1 Objective function

The objective function of the optimization model is to minimize the overall costs which is expressed as:

$$\min \left(\left[\sum_t P_t^{ch}(\lambda_t^{DA} + \lambda^T + \lambda^{EC} + \lambda^{TR}) - P_t^{ds}(\lambda_t^{DA} + \lambda^T + \lambda^I) \right] + \lambda^P P^P \right) \tag{1}$$

where P_t^{ch}, P_t^{ch}, P^P is the respective charging and discharging power at time t and peak power in that day, $\lambda_t^{DA}, \lambda^T, \lambda^{EC}, \lambda^{TR}, \lambda^I, \lambda^P$ is the respective spot-market price in SEK/kWh, energy tax price, energy certificate price, tranmission cost, incentive price for selling energy back to the grid and the peak power cost.

2.1.2 Constraints

Energy Fulfillment: Ensures that the total energy charged meets or exceeds the total requested energy for all EVs and can be observed in Eqn. 2.

$$\sum_t P_t^{ch}\eta - P_t^{ds}/\eta \geq \sum_t E_t^{req} \tag{2}$$

where η is the charging and discharging efficiency and E_t^{req} is the requested energy at time step t right before the EV departure.

Departure Requirement: Guarantees that each EV receives its requested energy before departure for all EVs and can be observed in Eqn. 3.

$$\sum_i^t P_t^{ch}\eta - P_t^{ds}/\eta \geq \sum_i^t E_t^{req} \tag{3}$$

Power Limit per Time Step: limits the charging/discharging to the installed capacity of chargers and the connected EVs to the chargers. This can be observed in Eqn. 4.

$$P_t^{ch} + P_t^{ds} \leq a_t^{EV} \bar{P} \tag{4}$$

where a_t^{EV} is the number of connected EVs at time t and $\bar{P}$ is the limit of charging/discharging power of the EV charger.

State of Energy Balance: Tracks the total energy stored in the EV fleet, accounting for departures and can be observed in Eqn. 5.

$$SOE_t = SOE_{t-1} + P_t^{ch}\eta - P_t^{ds}/\eta - SOE_t^{dep} \tag{5}$$

where SOE_t, SOE_t^{dep} is the state of energy of the entire parking-lot at time t and the state of energy of departing EVs at time t respectively.

State of Energy Bounds: Keeps the aggregated battery energy levels within operational limits and can be observed in Eqn. 6.

$$a_t^{EV} SOC_{min}^{EV} \leq SOE_t \leq a_t^{EV} SOC_{max}^{EV} \tag{6}$$

where $SOE_{min}^{EV}, SOC_{max}^{EV}$ is the minimum and maximum state of charge of an EV considered in this study.

3 Case study

3.1 Public charger data

In this paper, a dataset containing charge sessions for public chargers in the city of Gothenburg has been utilized to assess the flexibility from public EV chargers. The dataset contains data for the first six months of 2023. During this timeframe, there were 684 EV charging stations and a total of 1,298 charging outlets in Gothenburg. This can be observed in Fig. 2.
Among the installed public chargers, there are four different maximum rated output power for charging and can be seen in Table 1.

Table 1: Power levels and occurrences for charging

Rated Power (kW)	**Occurrence**
22	881
11	18
8.3	26
3.6	373
Total	**1298**

The data also includes the connection status of each charger and the total consumed energy for every day. If a charger is connected for longer duration spanning more than one day for an EV, then its consumption is provided in the day of start of the charging. For chargers with multiple charging sessions in a single day, the dataset provides only the total daily energy consumption. To address this, the total energy is proportionally distributed across sessions based on their relative durations.

The connection status of the public chargers in Gothenburg for the first six months of 2023 can be seen in Fig. 3. It can be seen that there is typically more chargers connected during the day times and the connection of chargers increases from January to July.

The requested energy before the time of departure can be observed in the Fig. 4.

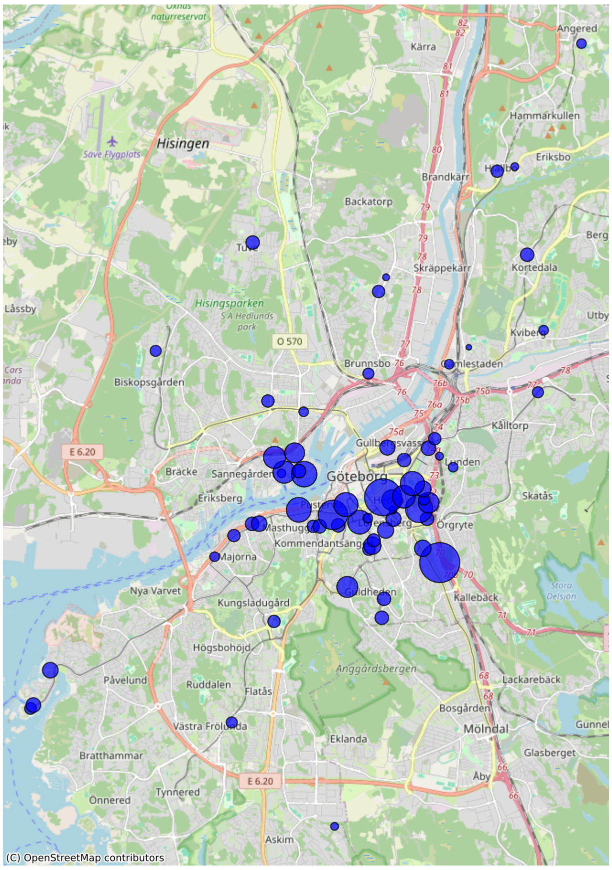

Figure 2: Public EV chargers in Gothenburg as of June 2023

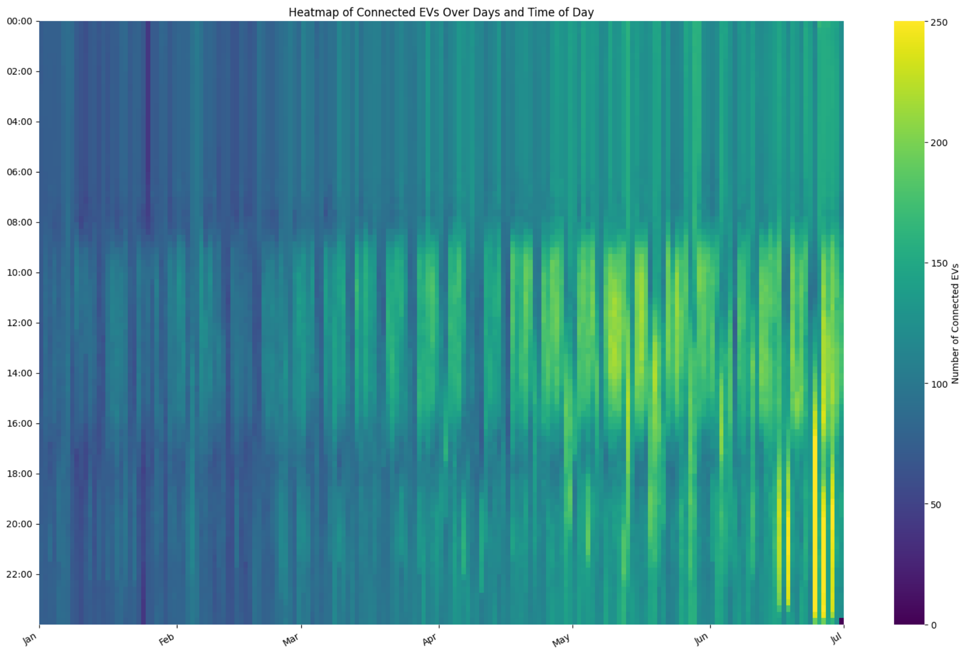

Figure 3: Connection status of public chargers

3.2 Electricity cost

Sweden's electricity market operates under the broader Nordic electricity market framework, governed by Nord Pool, the world's first international power market. The Swedish spot market plays a crucial role

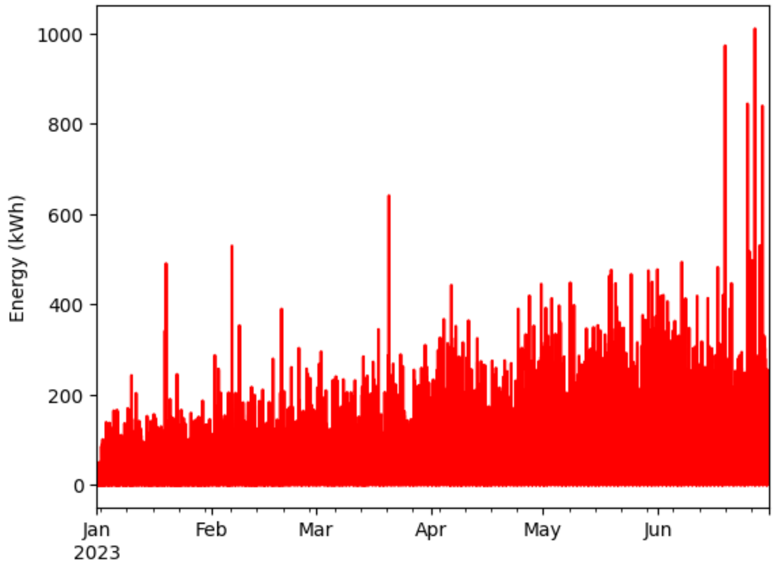

Figure 4: Requested energy before departure

in determining short-term electricity prices, reflecting the supply and demand dynamics for electricity in real-time. The market operates on an hourly basis, where electricity prices are set for each hour of the next day, with the spot price determined through competitive bidding from producers, distributors, and traders.

Gothenburg, falls under the area SE3 price zone and hence the spot price for SE3 region is used for this analysis in this paper. The SE3 prices for the first six month of 2023 can be observed in Fig. 5.

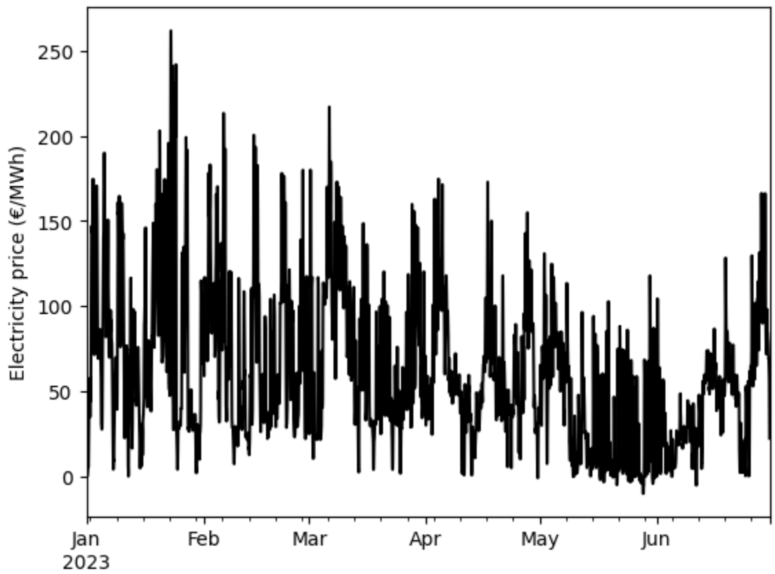

Figure 5: Spot price of SE3

The spot prices in Gothenburg during the first half of 2023 exhibited high volatility, ranging from negative prices to approximately 250 €/MWh.

In addition to the spot prices, consumers in Sweden have to pay energy tax cost, energy certificate cost, transmission cost, and peak cost. If a consumer sells electricity back to the grid, they are compensated by spot prices, energy tax and some incentive price. The values for the different cost components can be seen in Table 2. Currently in Sweden, there is no incentive for consumers to sell electricity back to the grid from EVs, but in this paper, two scenarios are analyzed: one considering current regulations with no V2G incentives, and another assuming a hypothetical incentive (0.018 €/kWh) to evaluate its potential impact on cost reduction and grid participation.

Table 2: Cost Parameters for Energy Usage (without VAT)

Parameter	Costs
Energy tax	0.03955 €/kWh
Energy certificate cost	0.00045 €/kWh
Transmission cost	0.01 €/kWh
Peak cost (monthly)	5.54 €/kW
Incentive cost	0/0.018 €/kWh

3.3 Assumptions

To ensure both the tractability and practical relevance of the proposed optimization model, several assumptions are made regarding the operation of the charging infrastructure, market dynamics, and EV user behavior. These are outlined below:

1. The optimization is conducted over an aggregated dataset of all public chargers, effectively modeling them as a single virtual power plant. As a result, the physical location of individual chargers is abstracted and not explicitly considered.
2. It is assumed that the departure time and energy demand of each EV are known at the time of connection to the charger.
3. The overall state of energy in the parking lot is determined by the aggregated state of energy of the connected EVs, taking into account their minimum and maximum allowable state of energy. For modeling consistency, each EV is assumed to have a battery capacity of 65 kWh, with operational limits set between 20% and 100% state of charge.
4. As the model aggregates all chargers into a unified system, inter-EV energy exchange is assumed to be feasible without incurring any energy losses.
5. Although the charge stations are connected to the grid at different connection points, it is considered that the peak tariff will be based on the aggregated peak demand of all EVs.
6. The conversion rate of Euro (€) to Swedish Krones (SEK) is assumed to be fixed throughout the horizon at 11.1 SEK/€.
7. The value added taxes (VAT) has been excluded in this analysis.

3.4 Scenarios

To evaluate the performance of the parking lot under various operating strategies, a range of scenarios have been developed. These scenarios differ in terms of charging profiles, control strategies, and market participation options. The defined scenarios are as follows:

1. **Avg**: For each charging session, the energy demand is averaged over its connection time. These session-level profiles are then aggregated across all chargers.
2. **DC11** (Direct Charging 11 kW): Charging begins immediately upon connection, drawing power at a constant rate of up to 11 kW until the requested energy is delivered.
3. **DC22** (Direct Charging 22 kW): Similar to DC11, but the charging power is limited to 22 kW.
4. **DC50** (Direct Charging 50 kW): Similar to DC11, but the charging power is limited to 50 kW.
5. **SC11** (Smart Charging 11 kW): Charging is optimized over the connection duration to minimize electricity costs, with a maximum power of 11 kW. The requested energy is guaranteed to be delivered before departure.
6. **SC22** (Smart Charging 22 kW): Same as SC11, but with a maximum charging power of 22 kW.
7. **SC50** (Smart Charging 50 kW): Same as SC11, but with a maximum charging power of 50 kW.

8. **V2G1** (Vehicle-to-Grid 1): Charging is optimized over the connection period with bidirectional energy flow. The charger can both charge and discharge at a maximum of 50 kW. No additional incentives are provided for energy fed back into the grid.

9. **V2G2** (Vehicle-to-Grid 2): Similar to V2G1, but with a feed-in incentive of 0.018 €/kWh for discharging energy back to the grid.

4 Results and Discussion

Based on the case study presented above, the optimization model is simulated for the different scenarios and the overall results can be observed in Table 3 and the charging power for two typical days in 2023 for selected scenarios can be seen in Fig. 6.

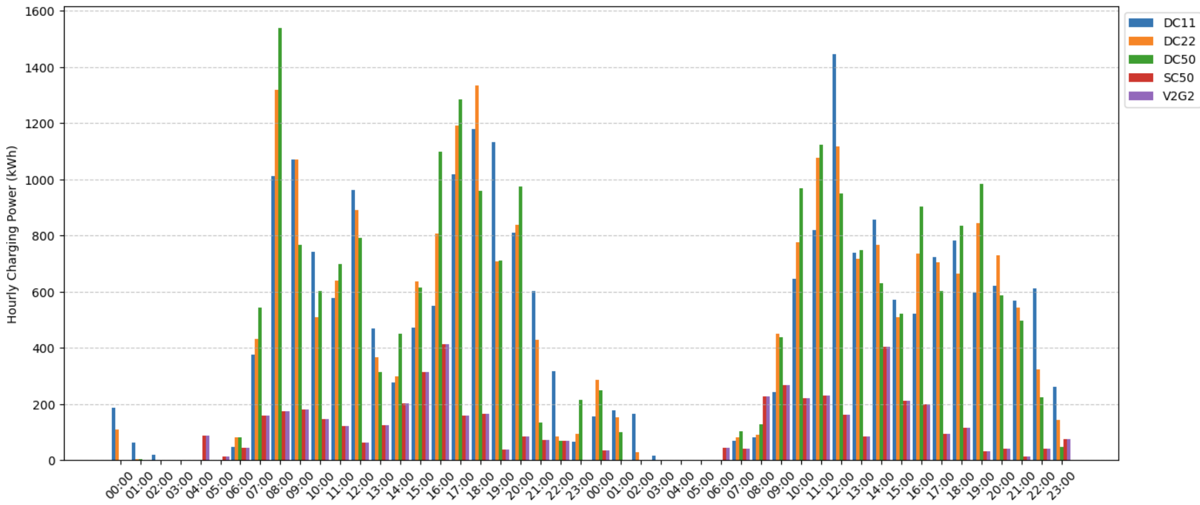

Figure 6: Charging power in a typical day for selected scenarios

From Fig. 6, it can be observed that the SC50 and V2G2 scenarios are utilizing a lower charging power in comparision to DC11, DC22 and DC50 cases in order to optimize the charging. The highest peak was oberved for DC50 at 08:00 in this specific day highlightling the higher peaks of DC50 scenario in comparsion to the other scenarios.

Table 3: Performance metrics under different charging strategies

Performance Metric	Avg	DC11	DC22	DC50	SC11	SC22	SC50	V2G1	V2G2
Overall cost (k€)	31.02	40.87	42.94	44.14	28.68	28.69	28.69	28.69	28.66
Peak cost (k€)	1.39	2.13	2.21	2.25	1.96	1.96	1.96	1.96	1.96
Maximum peak power (kW)	118.30	207.61	331.18	752.68	297.23	297.23	297.23	297.23	297.23
Total energy charged (MWh)	948.8	948.8	948.8	948.8	948.05	948.8	948.8	948.8	1,260.63
Total energy discharged (MWh)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	269.69
Total charge-discharge (MWh)	948.8	948.8	948.8	948.8	948.05	948.8	948.8	948.8	990.93
Difference in costs from DC50 (%)	-29.7	-7.4	-2.7	0	-35	-35	-35	-35	-35.1

From Table 3, the overall costs of charging electric vehicles over the first six months of 2023 are summarized for all considered scenarios. The DC50 scenario results in the highest total cost—approximately

44.14 thousand €—due to its assumption of a charging the EV directly from the time of connection at 50 kW.

The costs in direct charging scenarios increase with the maximum rated power of the charger. Since charging begins immediately upon connection without any scheduling or load optimization, these scenarios closely reflect typical real-world behavior. As a result, they experience significantly higher peak loads, with DC50 reaching a peak power of 752 kW—the highest observed.

The Avg scenario achieves lower overall costs than the direct charging scenarios. By distributing each EV's energy demand evenly across its connection period, it reduces peak loads and smooths demand profiles. This flexibility yields moderate cost savings.

Smart charging scenarios (SC11, SC22, SC50) offer even greater cost reductions compared to Avg, with SC11 slightly outperforming the others. This difference is attributed to a lower total energy charged (approximately 748 kWh less), which results from the charger's lower power limit. Notably, SC22 and SC50 yield identical outcomes, suggesting that increasing the maximum charging power from 22 kW to 50 kW offers no additional advantage under the optimization framework used.

In the V2G1 scenario, results are identical to SC22 and SC50, as no electricity is discharged back to the grid. This is due to the lack of economic incentives, making discharging unprofitable. When a selling incentive of 0.018 €/kWh is introduced in the V2G2 scenario, approximately 270 MWh is discharged, but the overall cost reduction is minimal—only around 25 €. This marginal benefit likely results from the difficulty in aligning discharging schedules with EV departure constraints, limiting the economic value of V2G operations under the given assumptions. Additionally, the total charge-discharge is higher for this scenario due to losses attributed to charging and discharging the vehicle.

4.1 Key takeaways

From the analysis of the presented results, four key takeaways emerge that are particularly relevant for parking operators, policymakers, and energy sector stakeholders:

First, the findings clearly indicate that direct charging strategies (DC11–DC50) lead to significantly high peak loads, posing challenges for both distribution system operators (DSOs) and parking infrastructure operators. For instance, the DC50 scenario resulted in a peak demand of 752.68 kW, highlighting that uncoordinated, simultaneous EV connections can cause substantial load spikes. As EV adoption continues to rise and public charging infrastructure expands, these peaks are likely to become more severe, leading to increased operational strain and higher peak tariffs. However, implementing smart charging or V2G strategies can effectively mitigate this issue—reducing peak demand by nearly 60%, down to 297.23 kW.

Second, both smart charging and V2G scenarios offer notable economic benefits, demonstrating an approximate 35% reduction in total charging costs compared to DC50. This reinforces their potential as cost-efficient strategies for optimizing public charger operations and leveraging the inherent flexibility of EVs.

Third, the results also show that V2G without additional incentives (V2G1) yields no energy discharged back to the grid, despite having the technical capability. This contrasts with existing literature, where V2G participation in electricity spot markets is shown to generate 10–70% more revenue compared to smart charging alone [10]. One reason for this could be the losses considered by the charge/discharge cycle together with the limited connection time for many of the EVs, limiting the potential revenue that could be achieved by discharging the EVs, making the smart charging strategy as effective as the V2G strategy.

Fourth, while the V2G scenario with 0.018 €/kWh incentive does enable grid discharge and minor cost reductions, the benefits appear limited. Nonetheless, V2G remains a promising long-term investment, as it opens the door to participate in ancillary service and local flexibility markets, which are generally more lucrative. This positions V2G not just as a load management tool, but as a strategic asset that can enhance revenue streams and grid stability, especially as regulatory frameworks and market mechanisms evolve.

4.2 Limitations and suggestions for future work

Despite the valuable insights generated by this study, several limitations must be acknowledged to accurately interpret the findings and their practical implications.

First, the optimization model aggregates EV charging loads across all chargers, fulfilling the requested energy requirements before each vehicle's departure. While this approach enables a tractable system-level analysis and ensures feasibility within the model (i.e., no unfulfilled charging sessions were observed), it may not capture individual-level charging failures that could arise in real-world operations. In practice, localized constraints—such as charger availability or user preferences could lead to unmet energy demands for specific vehicles, which are not reflected in this aggregated modeling approach.

Second, the treatment of peak cost estimation utilized in this optimization model acts as a simplification. In Sweden, peak charges are determined monthly based on the single highest hourly power demand and settled at the end of each month. However, in this study, the parking lot is optimized on a daily basis, which limits the ability to optimize peak loads over a longer horizon. As a workaround, the model estimates peak costs by applying a daily average peak charge based on each day's maximum power usage. While this method provides a useful approximation for comparative analysis, it likely underestimates the true monthly peak cost, as the actual billing would be based on the single highest load point within the month.

5 Conclusion

This study examined the operational performance and cost implications of various EV charging strategies at a public parking facility, using real-world data and a series of realistic charging scenarios. The results highlight key trade-offs between direct charging, average consumption methods, smart charging, and V2G integration.

The findings demonstrate that direct charging methods, while straightforward and reflective of current practice, result in significantly higher peak loads—up to 752 kW in the worst-case scenario—placing stress on the distribution network and increasing monthly peak cost burdens for parking operators. In contrast, smart charging and V2G strategies can reduce peak loads by approximately 60% and cut overall costs by around 35%, offering a strong case for their adoption in future urban charging infrastructure.

However, the effectiveness of V2G is highly dependent on the availability of market incentives. Without compensation for energy discharged back to the grid, V2G systems tend to behave similarly to smart charging alone. With incentives in place, discharging can occur, but the economic benefits are marginal under current assumptions, mainly due to the dynamic nature of EV arrivals and departures in urban parking environments.

Ultimately, while smart charging emerges as the most practical and cost-effective solution in the short term, V2G capability remains promising, particularly for participation in ancillary service markets. For parking operators and policymakers, this study underlines the importance of coordinated optimization, regulatory support, and well-designed incentives to unlock the full flexibility potential of public EV charging infrastructure.

Acknowledgments

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Presenter Biography

Araavind Sridhar received his B.Tech. degree in mechanical engineering from SRM Institute of Science and Technology, Chennai, India, in 2018, the M.Sc. degree in sustainable energy engineering from KTH Royal Institute of Technology, Stockholm, Sweden, in 2021, and the Ph.D. degree in electrical engineering from LUT University, Lappeenranta, Finland and Politecnico di Milano, Milan, Italy in 2025. He is currently a postdoc researcher with the Department of Electrical Engineering in Chalmers University of Technology. His researh interest include modelling and optimization of distributed energy resources, electricity markets and machine learning applications within the energy system.

David Steen received the M.Sc. and Ph.D. degrees in electrical engineering from the Chalmers University of Technology, Gothenburg, Sweden, in 2008 and 2014, respectively. He is currently an Associate Professor with the Department of Electrical Engineering, Chalmers University of Technology. His research interests include modeling and control of integrated energy systems and distributed energy resources, such as solar photovoltaic (PV), wind power, electric vehicles, and energy storage.

Le Anh Tuan received the B.Sc. degree in power systems from Hanoi University of Technology, Hanoi, Vietnam, in 1995, the M.Sc. degree in energy economics from Asian Institute of Technology, Bangkok, Thailand, in 1997, and the Ph.D. degree in power systems from the Chalmers University of Technology, Gothenburg, Sweden, in 2004. He is currently an Associate Professor with the Division of Electric Power Engineering, Department of Electrical Engineering, Chalmers University of Technology. His research interests include modeling, optimization, control and protection of integrated energy systems, and active distribution networks with high level of renewables and energy storage, wide-area monitoring and control of large power transmission systems, machine learning applications to power systems, modeling, and design of energy and ancillary service markets.