Individual Cost Impacts of Optimized EV Charging and V2G under Dynamic Pricing and Data-Driven Mobility Patterns

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SHORT SUMMARY

This study quantifies the economic potential for individual electric vehicle (EV) owners to optimize their charging and participate in Vehicle-to-Grid (V2G) under dynamic electricity pricing and data-driven mobility patterns. Using empirically derived vehicle usage profiles from the mobiTopp model and high-resolution day-ahead price data, charging decisions are modeled from a user-optimal perspective. Three strategies are compared: uncoordinated charging, price-optimized charging, and V2G-optimized charging.
Results show that price-based optimization reduces total charging costs by up to 23.5%, while V2G further decreases average costs by over 90%, enabling negative net costs for a significant share of users. However, benefits vary considerably across vehicles. Additionally, price-driven charging leads to temporal concentration of demand and pronounced load peaks. These findings highlight both the economic potential as well as the emerging system-level challenges.

Keywords: Cost Optimization, Dynamic Electricity Pricing, Mobility Patterns, Vehicle-to-Grid (V2G)

1. INTRODUCTION

The increasing share of renewable energy sources, such as wind and solar, is fundamentally transforming modern power systems and increasing the need for flexibility. However, electricity generation from these sources is inherently weather-dependent and only partially controllable, leading to increased volatility and temporal mismatches between electricity supply and demand (IEA, 2025). As a result, flexible demand-side resources that can shift electricity consumption over time have become a key requirement for the energy transition.
Electric vehicles (EVs) are widely regarded as a promising source of such flexibility. Due to their battery capacity and typically long parking durations, EVs can shift electricity consumption and help balance supply and demand. In addition, Vehicle-to-Grid (V2G) concepts enable bidirectional energy exchange, allowing vehicles to act as distributed storage resources and participate in electricity markets (Kempton and Tomić, 2005). This flexibility can further support the integration of renewable energy by mitigating temporal mismatches between generation and demand (Lund and Kempton, 2008).
At the same time, the increasing availability of dynamic electricity tariffs provides economic incentives for flexible charging behavior. These tariffs reflect time-varying electricity prices and enable consumers to shift demand to periods with lower prices (Borenstein, 2005). In the context of EVs, such price signals can be used to reduce charging costs and generate revenue through optimized charging and V2G participation.

Previous studies have shown that optimized charging strategies can improve system efficiency (Sundstrom and Binding, 2012) and reduce overall energy costs in integrated energy systems (Cao et al., 2016). However, the actual economic benefits for individual users under realistic conditions remain poorly understood. Many existing studies focus on centralized optimization or microgrid-based applications and typically rely on simplified or stylized representations of mobility behavior (He et al., 2024; Lee et al., 2025; Mahdi et al., 2024). In practice, charging decisions are constrained by individual mobility patterns, limited charging availability, and imperfect information about future electricity prices.
This paper quantifies the magnitude and variability of individual cost savings from optimized EV charging and V2G under data-driven mobility patterns and dynamic electricity pricing. The analysis is based on empirically derived vehicle usage profiles and high-resolution price data. Charging decisions are modeled from a user-optimal perspective, assuming that each vehicle minimizes its own costs. By comparing uncoordinated charging, optimized charging, and V2G, the study isolates the economic value of flexibility and bidirectional operation.

2. DATA AND PREPARATION

Electricity Prices

Day-ahead electricity prices for Germany are obtained from the Energy-Charts platform (Spot Market Prices | Energy-Charts, 2026). The data are available at a 15-minute resolution, enabling a detailed representation of short-term price dynamics. Two representative weeks (see Figure 1) are selected to illustrate distinct price patterns.
Week 41/2025 exhibits relatively stable price levels, with most values ranging between approximately 80 and 160 €/MWh. At the beginning of the week, prices drop close to zero. During periods of peak demand, however, prices increase sharply, reaching levels above 160 €/MWh and peaking at 300 €/MWh on several occasions.
In contrast, Week 10/2026 is characterized by high renewable generation and pronounced intraday price volatility. Prices fluctuate strongly within a single day, ranging from near-zero values during periods of high renewable availability and low demand to peaks exceeding 200 €/MWh during periods of high demand.

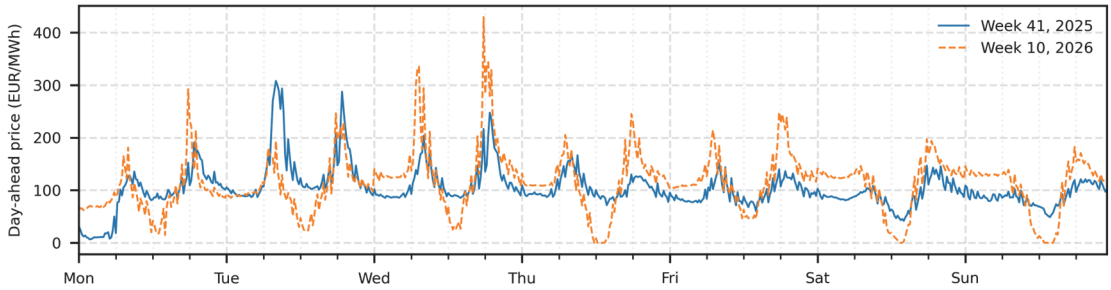


Figure 1: Day-ahead electricity price for two representative weeks

Day-ahead prices in €/kWh serve as the basis for dynamic electricity tariffs. Suppliers add grid charges, taxes, levies, and surcharges to these wholesale prices (Häseler and Wulf, 2024). In this study, grid charges of 0.093 €/kWh and taxes and levies of 0.126 €/kWh are assumed, based on BDEW (2026). The resulting values represent end-user electricity prices and serve as input to the optimization models. Prices are treated as fixed input data and are not affected by individual EV charging behavior.

Mobility Data and Vehicle Usage Patterns

The mobility data used in this study are based on the agent-based transport model mobiTopp, developed at the Karlsruhe Institute of Technology (Mallig et al., 2013). The dataset represents detailed travel behavior over a full week, including trip purposes, start and end times, origins and destinations, and transport modes. In addition, the dataset contains comprehensive information on households, individuals, and vehicles, enabling a consistent linkage between mobility behavior and vehicle ownership.

The analysis focuses on trips performed with private vehicles in the urban district of Durlach in Karlsruhe (Germany), which comprises 15,562 such vehicles. Vehicles without recorded trips during the observation period are assumed to remain parked at home throughout the week. Based on the trip data, individual vehicle usage profiles are reconstructed as continuous time series over one week at 15-minute resolution (672 time steps). Each time step is assigned one of four discrete states: D – driving, H – at home, W – at work, and O – other locations. This representation ensures a temporally consistent and computationally efficient description of vehicle availability and energy demand.

An analysis of vehicle usage patterns shows that, on weekdays, vehicles are parked at home for an average of 19.53 hours per day, while driving accounts for only 0.95 hours. On weekends, time spent at home increases to 22.90 hours per day, while driving time declines further to just 0.31 hours. These results highlight the substantial temporal availability of vehicles, indicating significant potential for flexible charging and V2G applications.

3. CHARGING MODELS

Model Assumptions, Parameters, and Constraints

All vehicles are assumed to be battery electric and equipped with bidirectional home charging infrastructure. Charging and discharging are only possible when the vehicle is located at home. The models are driven by dynamic electricity prices and vehicle profiles, which determine both driving-related energy consumption and charging availability. Electricity purchase and feed-in are assumed to occur at the same price. To reduce complexity, no explicit state of charge is modeled; cumulative driving consumption constraints and a bounded V2G energy balance ensure energy feasibility.

The models use parameters summarized in Table 1. A maximum charging and discharging rate of 2.6 kWh per 15-minute interval (equivalent to an 11 kW wall box) is assumed. Driving consumption is set to 0.75 kWh per 15-minute interval, reflecting typical urban conditions (approximately 15–20 kWh/100 km). In addition, a weekly V2G throughput limit of 20 kWh per vehicle is imposed to account for battery degradation and technical constraints, as discussed in the literature (e.g., Uddin et al., 2018). Furthermore, V2G operation is constrained by a ±10 kWh energy balance at any time, limiting the share of the battery capacity used.

Table 1: Parameters for the models

Parameter	Value	Unit	Description
Charging/discharging rate	2.6	kWh/15 min	Corresponds to 11 kW wall box
Driving consumption	0.75	kWh/15 min	Urban driving conditions
V2G throughput limit	20	kWh/week	Total V2G energy per vehicle
V2G energy balance limit	±10	kWh	Max. V2G energy at any time
Grid charges	0.093	€/kWh	Fixed component
Taxes & levies	0.126	€/kWh	Fixed component

The model ensures that no pre-charging beyond cumulative driving consumption is permitted, charging and discharging cannot occur simultaneously.
To reflect the limited availability of information in real-world electricity markets, a rolling-horizon approach is used. The planning horizon defines the time window over which the optimization is performed and corresponds to the period for which electricity prices are known, i.e., the upcoming day. Electricity prices are updated daily at 2 p.m. in line with day-ahead market clearing. At each update step, the optimization is re-solved over the remaining horizon using the latest available price information, while previously executed decisions remain fixed.
Driving demand is satisfied within each optimization horizon whenever the vehicle is at home. V2G operation is constrained by an energy balance over time, ensuring a net-zero V2G balance.
Figure 2 illustrates the temporal availability of day-ahead price information used in the rolling-horizon approach.

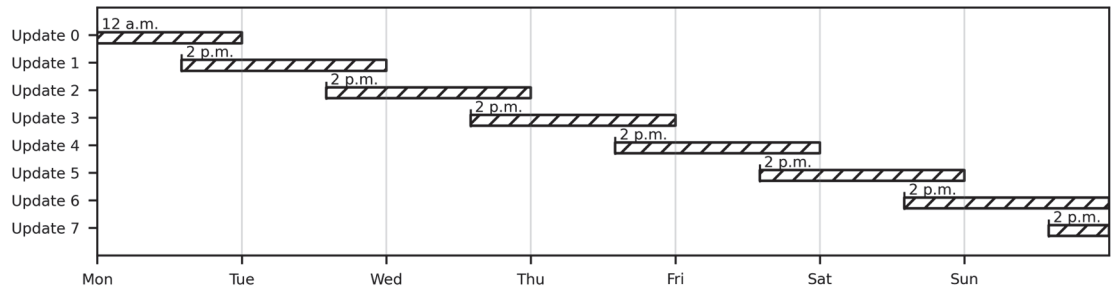


Figure 2: Illustration of electricity price updates and rolling horizon optimization

Baseline Model (M1: Uncoordinated Charging)

The baseline model represents uncoordinated charging behavior. Vehicles start charging immediately whenever charging is possible, and a charging demand exists.
Charging decisions are independent of electricity prices. However, costs are evaluated based on time-varying electricity prices. This model allows isolating the effect of dynamic pricing without behavioral adaptation. V2G functionality is not considered in this model.

Optimized Charging Model (M2: Price-Optimized Charging)

The second model introduces cost-optimal charging behavior. To ensure realistic decision-making under limited foresight of future electricity prices, the optimization is embedded in a rolling-horizon framework, as described in Figure 2. Within this framework, charging decisions are determined by solving an optimization problem that minimizes electricity costs over the planning horizon, accounting for time-varying electricity prices, vehicle availability constraints, and driving energy requirements.
Vehicles are optimized independently without coordination, i.e., no interaction or competition for electricity is modeled. This approach reflects rational user behavior under dynamic pricing, in which charging shifts to periods with lower electricity prices.
The optimization problem is formulated as a mixed-integer linear program and solved using Gurobi (Gurobi Optimization, 2026). For each vehicle i, the objective (1) is to minimize total charging costs:

$$\min \sum_t p_t \cdot x_{i,t} \tag{1}$$

where $x_{i,t}$ denotes the charging energy of vehicle i in time step t (kWh) and p_t the corresponding electricity price. The model ensures that each vehicle's driving-related energy demand is met while exploiting temporal price variations.

Optimized Charging Model with V2G (M3: Price-Optimized Charging with V2G)

The third model extends M2's optimized charging approach to enable V2G. As in M2, a mixed-integer linear program is formulated and solved with Gurobi for each vehicle and planning horizon.
To represent bidirectional operation, two additional decision variables are introduced: $v_{i,t}^{+}$ for charging energy from the grid to the vehicle and $v_{i,t}^{-}$ for discharging energy from the vehicle to the grid. The objective function (2) then becomes

$$\min \sum_t p_t \cdot \left(x_{i,t} + v_{i,t}^{+} - v_{i,t}^{-}\right) \tag{2}$$

where $x_{i,t}$ denotes the charging energy required to satisfy driving demand, $v_{i,t}^{+}$ the additional charging energy for V2G-related operation, $v_{i,t}^{-}$ the discharged energy fed back to the grid, and p_t the dynamic electricity price in time step t.
This formulation enables each vehicle to exploit temporal price differences by charging during low-price periods and discharging during high-price periods.
The comparison between M2 and M3 isolates the additional economic value of V2G, thereby enabling a clear assessment of the benefits of V2G operation beyond optimized unidirectional charging.

4. RESULTS

Optimized charging (M2) reduces total charging costs compared to the baseline (M1) in both analyzed weeks (see Figure 3). In week 41, costs decreased by 13.1% (from €84,897 to €73,795), while in week 10, a larger reduction of 23.5% is observed (from €87,196 to €66,708). This indicates that the achievable savings depend on the underlying price dynamics.
Allowing V2G operation (M3) further reduces total costs to below €70,000, highlighting the additional economic potential of V2G. This indicates that V2G captures a substantial share of the available temporal price arbitrage potential.

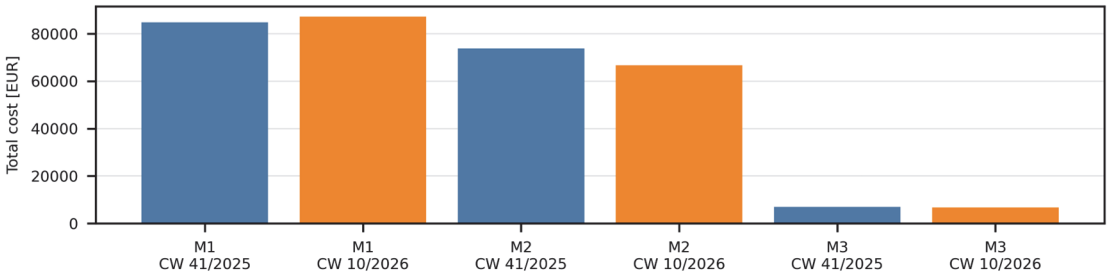


Figure 3: Total system costs under different charging strategies

Table 2 reports the mean costs per vehicle. With V2G (M3), mean costs decrease to €0.45 and €0.43, corresponding to reductions of over 90% compared to the baseline (M1). In contrast, M2 yields only moderate savings (reductions of €0.72 in CW 41/2025 and €1.31 in CW 10/2026). Results are consistent across both weeks despite differing price conditions.

Table 2: Mean costs of all vehicles per model and calendar week

	M1 [€]	M2 [€]	M3 [€]
CW 41/2025	5.46	4.74	0.45
CW 10/2026	5.60	4.29	0.43

Figure 4 shows the distribution of individual charging costs. The median values of M1 and M2 are similar, indicating that optimized charging alone has a limited impact on typical user costs. However, the upper cost range is reduced in M2, suggesting that optimization mainly lowers high-cost cases. With V2G (M3), the distribution shifts significantly: the median approaches zero in week 41 and becomes negative in week 10, indicating that a substantial share of users achieves net revenues.

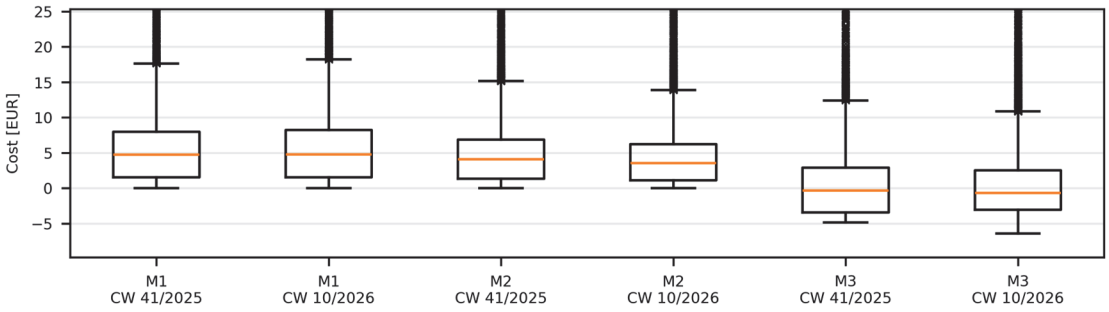


Figure 4: Distribution of individual charging costs by model and week

The following analysis focuses on calendar week 41/2025.
Figure 5 shows the distribution cost for this week. From M1 to M3, the distribution shifts to lower values. While M1 and M2 exhibit a peak around zero (indicating low or no charging demand), M3 shows a pronounced peak in the negative range, reflecting V2G revenues for a large share of users.

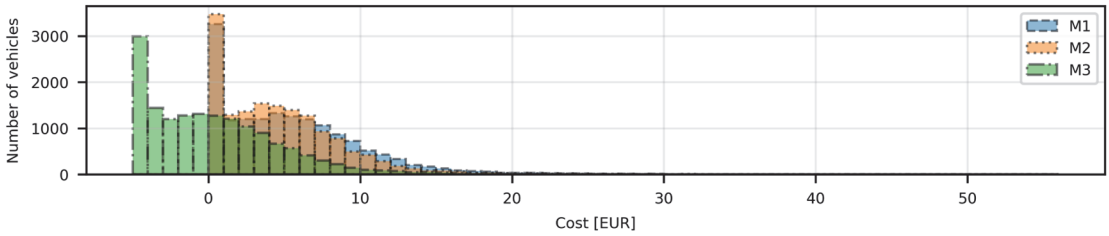


Figure 5: Shift in cost distribution across charging strategies (CW 41/2025)

Figure 6 illustrates aggregated consumption and charging/discharging behavior. In M1, charging closely follows consumption. In M2, charging shifts to low-price periods, leading to pronounced load peaks. With V2G (M3), both charging and discharging occur, resulting in stronger fluctuations with positive and negative peaks. This result indicates increased responsiveness to price signals but also higher temporal concentration of load.

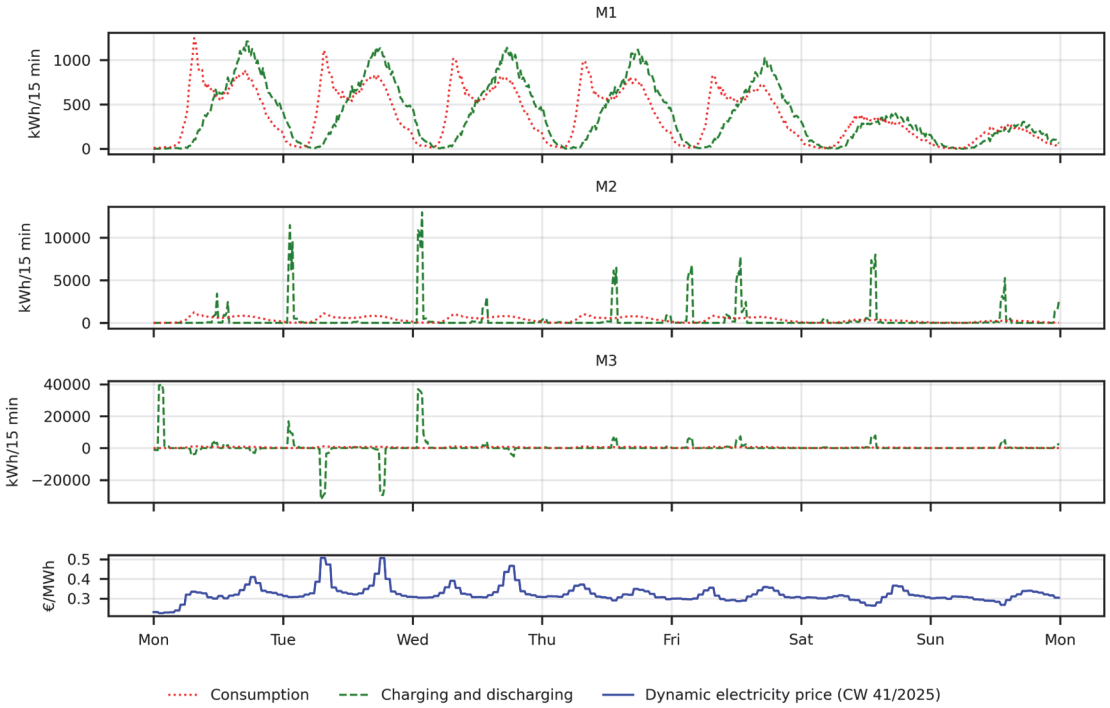


Figure 6: Temporal charging and discharging patterns across models (CW 41/2025)

5. CONCLUSIONS AND OUTLOOK

This study quantifies the economic potential of optimized electric vehicle charging and Vehicle-to-Grid under data-driven mobility patterns and dynamic pricing. The results confirm substantial cost reductions compared to uncoordinated charging through optimized charging and V2G operation.

However, benefits are unevenly distributed and depend strongly on individual flexibility, indicating that not all users can exploit these opportunities to the same extent.

At the system level, price-driven charging leads to temporal concentration of demand and pronounced load peaks. This suggests that individually optimal behavior may lead to suboptimal system outcomes, highlighting the need for coordination mechanisms beyond purely decentralized optimization.

Future research should incorporate grid constraints, endogenous price formation, and interactions between large numbers of agents to better assess system-level impacts.

Overall, while dynamic pricing and V2G offer significant economic potential, their large-scale integration requires careful system design to ensure efficient and stable grid operation.

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