Impact of Vehicle Integrated Photovoltaics on Urban Electric Vehicle Charging Demand and Public Charging Infrastructure Planning

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Short summary

This study assesses how vehicle integrated photovoltaics (VIPV) affect urban electric vehicle (EV) charging demand and public charging infrastructure planning. It combines an activity-based MATSim model of cost aware and adaptive charging behavior with a separate mixed-integer optimization model for planning public chargers, stationary photovoltaics, and battery storage. A case study for Gothenburg, Sweden compares a baseline without VIPV to a scenario in which 50% of EVs have onboard solar generation. VIPV reduces annual grid electricity demand by about 6.0% and total charging demand by about 5–6%, with the largest effects during high-solar periods. The optimization results imply an average annual reduction in public charging expenditure of about 1,300 SEK per VIPV. VIPV therefore lowers grid dependence and user charging costs, while highlighting trade-offs between decentralized energy provision and charging-network revenues.
Keywords: Activity-based modeling; Charging demand prediction; Electric vehicles; Public charging infrastructure; Renewable energy integration; Vehicle integrated photovoltaics

1 Introduction

Rapid urban transport electrification has intensified interactions between mobility systems and electricity markets, emphasizing the need to manage renewable energy integration in charging systems. This matters because the transport sector still accounts for close to one quarter of greenhouse gas emissions in Europe (Commault et al., 2021). At the same time, recent VIPV studies suggest that onboard solar generation is no longer a negligible effect. For passenger cars, a typical roof area of about 1.7 to 2.5 m^2 can provide about 1900 to 3400 km of solar driving distance per year under favorable conditions (Heinrich, 2020). Other case studies have reported that onboard PV can supply up to 41% of required vehicle energy, or about 5617 km per year, depending on the vehicle use, location, and charging strategy (Carr et al., 2020). These results indicate that VIPVs are pertinent for near future urban charging demand estimation and public charging planning.

Recent advances in activity-based and agent-based modeling have made it possible to represent charging demand as an outcome of travel behavior, charging access, electricity tariffs, and user decision making. In particular, MATSim based charging demand models have shown that charging outcomes emerge endogenously from daily activity schedules, route and mode choice, charger access, dynamic pricing, and adaptive charging behavior rather than from fixed charging assumptions (Horni et al., 2016). This behavioral realism is important for planning because relatively small changes in charging timing and charging location can affect local charger utilization and aggregate charging peaks. In parallel, charging infrastructure planning has moved beyond charger siting alone toward integrated models that also consider local PV, stationary battery storage, and spatial demand redirection. Recent work has shown that the optimal design of public charging systems depends strongly on the temporal structure of charging demand and on the trade off between grid electricity, local renewable generation, battery storage, and user redirection (Parishwad et al., 2025). Unlike stationary PV at charging sites, VIPV generates electricity directly on the vehicle during driving and parking. This changes battery state of charge (SoC) before plug in charging decisions are made. The effect of VIPV is therefore not limited to a reduction in total electricity demand. It may also change when charging becomes necessary, how often users charge, and which charging options they use. This is especially important in urban systems, where charging demand is shaped by short trips, diverse parking conditions, and strong spatial variation in

charging access. While VIPV has been studied from the perspective of vehicle design, solar yield, and technical feasibility, its implications for large scale charging demand prediction and public charging infrastructure planning are still underexplored (Commault et al., 2021; Heinrich, 2020). This study addresses that gap by extending a MATSim-based near-future charging demand framework with a VIPV module and then using the resulting scenario-specific demand as input to a mixed-integer optimization model for public charging and local energy planning. The case study focuses on an assumed 50% EV adoption scenario in Gothenburg, Sweden. It compares a baseline scenario without VIPV with a scenario in which 50% of EVs are equipped with onboard PV generation. Seasonal solar variability, time-of-use (ToU) electricity prices, and cost-aware adaptive charging behavior are represented explicitly. The resulting spatiotemporal charging demand is annualized and supplied to a planning model that optimizes public chargers, stationary PV, battery storage, and short-distance user redirection. The study makes three contributions. It introduces VIPV as a vehicle-level energy source in an activity-based charging demand model. Second, it evaluates how the resulting demand changes affect separate planning decisions for charging and local energy supply. Also, it provides evidence on how VIPV changes charging demand, infrastructure needs, energy flows, and economic outcomes in an urban EV system.

2 Methodology

The methodological framework has two sequential stages. Initially, near-future spatiotemporal charging demands are simulated seasonally. For the second stage, these scenario-specific demand outputs are used as exogenous inputs to a mixed-integer linear program for infrastructure planning. This workflow makes it possible to trace how VIPV-induced changes in charging demand affect charger deployment, local renewable energy use, storage requirements, and planning outcomes.

Simulating the charging demand with VIPV

The simulation stage builds on the agent-based MATSim framework and extends the cost-aware and adaptive smart-rescheduling charging model developed in (Parishwad et al., 2026), which itself builds on earlier UrbanEV charging behavior logic (Adenaw & Lienkamp, 2021). Charging demand is generated endogenously from daily activity schedules, route and mode choice, charger access, and charging decisions. The present study adds VIPV modules that contribute onboard solar generation directly to the vehicle energy balance[1]. VIPV therefore affects charging through the same agent-based decision process that determines when and where charging takes place.
The simulation uses synthetic population and activity-travel data for Sweden together with EV fleet specifications, charger inventories, and private charging access attributes (Tozluoğlu, 2023). Following a published study by Parishwad et al. (2026), a share of users is assumed to be aware of ToU tariffs and can postpone flexible charging to lower-price periods when feasible. Charging decisions depend on charger availability, charging context, electricity prices, and user behavior. This preserves the behavioral realism as VIPV affects charging demand through varying SoC levels, which in turn affects the timing of charging decisions. Two scenarios are evaluated. The baseline scenario assumes an EV fleet without VIPV. The VIPV scenario assumes that 50% of EVs are equipped with rooftop photovoltaics, where onboard generation occurs during driving and during eligible parking periods. Seasonal solar availability is represented using PVGIS based profiles for Gothenburg, Sweden (Huld et al., 2012). While parking, VIPV charging is assumed to occur during 50% of parked duration, reflecting exposure to open sky conditions. Vehicles can gain energy between plug in charging events, which may delay charging, shorten charging sessions, or remove some charging events altogether. The result is not only lower aggregate charging demand, but also a changed temporal and spatial charging pattern. The simulation is run for representative seasons to capture variation in solar yield and charging demand over the year. For each scenario and season, charging sessions are converted into half-hourly demand profiles and aggregated to analysis zones by charging context (home, work, and public). These profiles are annualized for the optimization stage, which uses the same zonal system for charger, PV, battery, home-charging, and redirection inputs.

[1]The implemented VIPV extension and associated data for the simulation are available online at `https://github.com/parishwadomkar/UrbanEV-v2/tree/VIPVmain`.

MILP planning of charging, PV, storage, and user redirection

The scenario specific charging demand from MATSim is then used as exogenous input to a mixed-integer linear optimization model for public charging infrastructure and local energy supply. The formulation follows the joint planning approach developed in (Parishwad et al., 2025). The model determines the number of chargers by type, local PV capacity, and battery capacity in each zone. It also decides how demand is served over time through direct charging, local PV use, battery charging and discharging, grid purchases, and limited user redirection to nearby zones. The objective is to maximize annual net profit for the charger operator:

$$\max \sum_{m} \left(\text{Revenue}_m - \text{Cost}_m^{\text{grid}} - \text{Cost}_m^{\text{incentive}} - \text{Cost}_m^{\text{slack}} \right) - \text{CapEx}^{\text{chargers}} - \text{CapEx}^{\text{PV}} - \text{CapEx}^{\text{batt}}. \tag{1}$$

Here, the operating terms are evaluated over representative months and weighted to annual values. The optimization defines the optimal charger mix, local renewable energy use, storage deployment, and the spatial allocation of demand. Demand balance is enforced for each zone, time interval, month, and charging category. Simulated charging demand must therefore be met by local service, redirected service, or penalized slack. Redirection is allowed only along feasible arcs within a maximum distance. All siting decisions are constrained by local infrastructure limits. This stage assesses how VIPV-related changes in charging demand affect infrastructure planning. Scenario-specific demand profiles affect charger utilization, local PV use, battery operation, and economic outcomes across zones. By comparing the optimized baseline and VIPV scenarios, the analysis shows how onboard solar generation changes public charger needs, stationary renewable requirements, grid dependence, and economic performance. VIPV is therefore treated as a behavioral modifier of charging demand whose effects are passed forward to the planning model.

3 Results and discussion

Figure 1 shows how VIPV and ToU awareness interact in the system. The plotted SoC trajectories compare representative EV agents in the VIPV scenario, together with their no VIPV reference trajectories. Here, the ToU aware agents shift charging more consistently toward lower-price periods, mainly during overnight home charging. Also, VIPVs gain energy during driving and during eligible parking periods. This produces a smoother recovery of battery SoC and reduces the need for immediate plug in charging. The onboard PV not only reduces electricity demand. It changes when VIPVs reach charging thresholds, which then affects the timing, location, and frequency of charging. This effect is most visible for the ToU aware agent. In that case, VIPV helps the battery remain above the critical threshold long enough for charging to be postponed to a lower-price period. This means that VIPV changes both the amount of charging and the behavioral pathway through which charging demand is initiated.

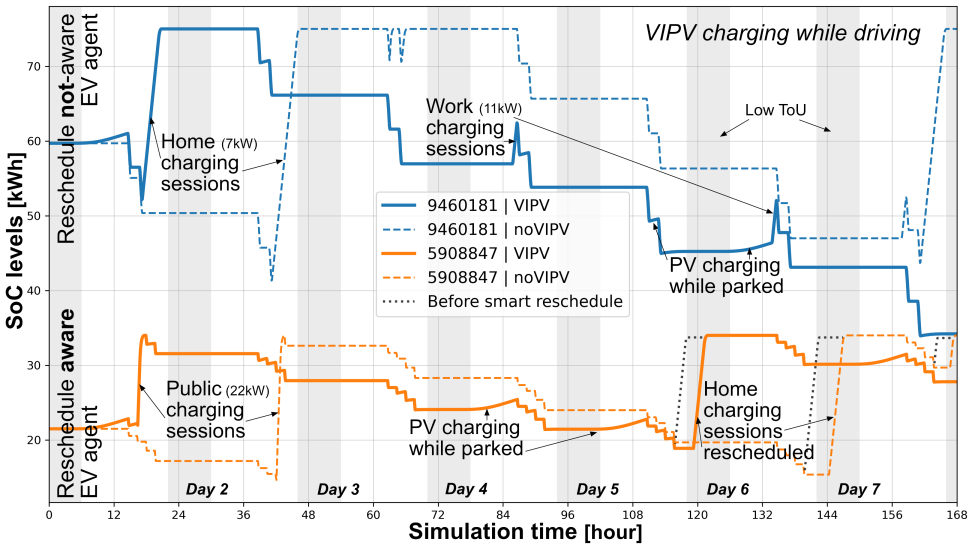


Figure 1: Representative state of charge trajectories of EV agents in the simulation.

The aggregate system response is shown in Figure 2, which compares seasonal charging demand profiles for the baseline and VIPV scenarios. Across all seasons, the VIPV profile remains below the baseline during most daytime periods, with the largest reductions in summer and smaller effects in winter. VIPV also interacts with ToU-based charging rather than replacing it: higher SoC before plug-in reduces daytime and post-trip charging, while the evening structure largely remains. The strongest reductions occur in the same seasons when stationary PV is most productive, suggesting partial substitution between VIPV and site-based solar generation. At the same time, VIPV does not remove the need for public charging, especially for users without private charging access. Figure 3 further shows that the VIPV effect is spatially heterogeneous, with the strongest localized demand reductions concentrated in specific zones during spring and summer, while autumn and winter exhibit a more mixed pattern with both decreases and localized increases.

Implications for infrastructure and energy planning

Table 1 summarizes the optimized planning outcomes. VIPV mainly leads to reconfiguration rather than strong downsizing of the charging system. The infrastructure effect is visible in the charger mix, with slow chargers increasing by 9.8% and medium chargers decreasing by 2.7%, while fast chargers remain unchanged. The clearer effect appears in annual energy flows: total grid purchase decreases from 135,679 to 127,483 MWh/year (-6.0%), direct grid supply to chargers falls by 6.1%, and home charging falls by 5.2%. Stationary renewable requirements also decline modestly, with PV panels decreasing by 4.6%, battery cells by 0.8%, and total PV production by 5.3%. VIPV therefore reduces demand on the fixed charging and energy system, but does not replace stationary PV, batteries, or public charging infrastructure.

Table 1: Optimization outcomes for the no-VIPV and 50% VIPV scenarios.

Metric	**no-VIPV**	**50% VIPV**	**Change (%)**
Infrastructure			
Slow chargers (11 kW)	245	269	+9.8
Medium chargers (22 kW)	5012	4877	-2.7
Fast chargers (50 kW)	3	3	0.0
PV panels	65793	62783	-4.6
Battery cells (10 kWh)	775	769	-0.8
Energy (MWh/year)			
Grid purchase (total)	135679	127483	-6.0
Direct to chargers	133782	125662	-6.1
Grid → battery	1897	1821	-4.0
PV produced (total)	24482	23172	-5.3
PV → chargers	21016	19686	-6.3
PV → battery	3466	3486	+0.6
Demand redirected	268	262	-2.3
Home charging (private)	132378	125437	-5.2
Cost variables (MSEK/year)			
Revenue (charging)	1159.5	1090.6	-5.9
Grid electricity cost	236.1	222.4	-5.8
Redirection cost	0.37	0.37	-0.9
CapEx chargers	11.55	11.28	-2.4
CapEx PV + battery	26.35	25.27	-4.1
Net profit	885.0	830.6	-6.1

The economic and system effects are best interpreted separately from three perspectives. From the VIPV user perspective, the reduction in charging revenue from 1,159.5 to 1,090.6 MSEK/year implies lower expenditure on public charging, corresponding to an average saving of about 1,300 SEK per VIPV-equipped EV per year. From the grid distribution perspective, total annual grid electricity purchase decreases from 135,679 to 127,483 MWh/year (-6.0%), and grid electricity cost decreases by 5.8%, indicating lower reliance on centralized electricity supply and reduced

charging-related demand on the power system. From the charging point operator perspective, lower charging demand reduces revenue and annual net profit, with net profit falling from 885.0 to 830.6 MSEK/year (-6.1%). Redirection volumes fall only slightly (2.3%), indicating that lower aggregate demand does not remove spatial mismatch in charging demand. Overall, VIPV reduces grid dependence and user charging expenditure, while the charging system still requires spatial planning under lower overall demand.

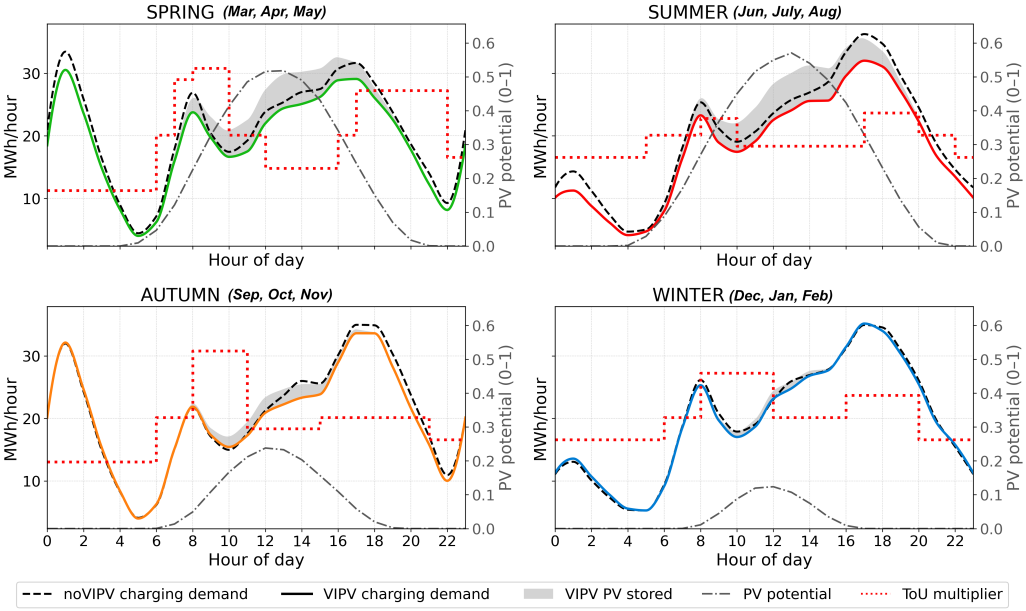


Figure 2: Seasonal charging demand temporal aggregations for Gothenburg, Sweden.

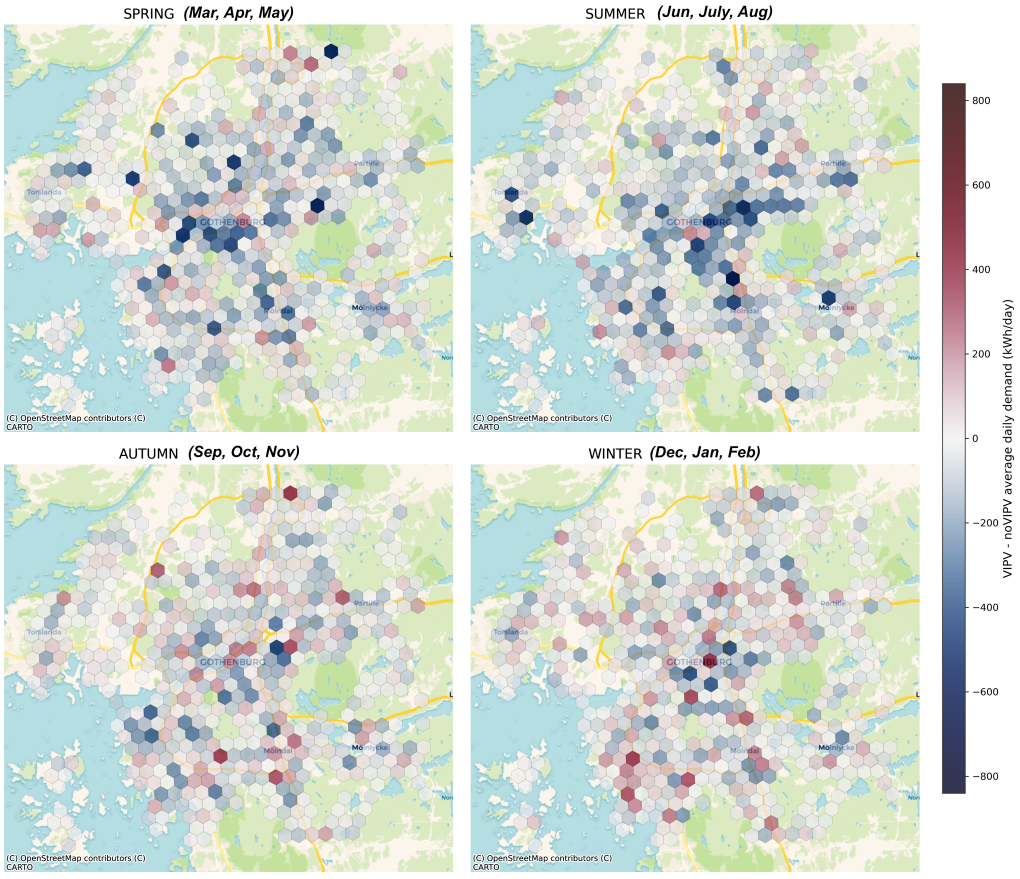


Figure 3: Seasonal charging demand spatial aggregations for Gothenburg, Sweden.

4 Conclusions

This study developed a sequential simulation-and-planning framework to assess how VIPVs affect urban EV charging demand and public charging infrastructure planning. An agent-based charging demand model was extended with onboard solar generation, and the resulting scenario-specific demand profiles were then used as exogenous input to a mixed-integer planning model. The results show that VIPV leads to a clear but moderate reduction in charging demand.

In the Gothenburg case study, a scenario with 50% VIPV in the EV fleet reduces annual grid electricity demand by about 6.0% and charging demand by about 5–6%, with the strongest effects during daytime and in high-solar seasons. VIPV therefore changes not only how much charging is needed, but also when charging becomes necessary.

From a planning perspective, VIPV reduces grid dependence and slightly lowers the need for stationary PV and battery storage, while only modestly changing the public charging network. For users and power-system planning, this means lower charging expenditure and lower electricity purchases from the grid. Charging operators may face lower revenues and profits, but these effects should be weighed against lower grid-based charging demand and the broader value of distributed renewable energy use. Overall, incorporating VIPV into behaviorally grounded charging demand models improves the assessment of urban charging infrastructure and energy planning. A natural next step is to integrate the latest MATSim EV contrib functionality for within-day and strategic charging behavior, to further improve behavioral and simulation accuracy (Hörl et al., 2025).

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