

Load Management Strategies for Electric Vehicle Charging

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Abstract: Climate change requires significant changes in many sectors, with transportation being a major contributor to global greenhouse gas emissions. The shift from conventional vehicles to electric vehicles (EVs) is essential for sustainable mobility and achieving climate targets. However, this transition depends on the availability of efficient charging infrastructure, especially in urban areas. Workplace charging is particularly important for employees without private charging options, making company-provided infrastructure a key factor for employee satisfaction and retention. This paper analyzes and optimizes the charging infrastructure at an office site, which already features several charging stations and a photovoltaic (PV) system. The study uses real building and mobility data to model different charging scenarios, evaluate energy demand, and assess grid impact.

Keywords: EV charging, Load Management, Photovoltaics, Kernel Density Estimation

1. INTRODUCTION

This study investigates the integration of electromobility and renewable energy into the energy infrastructure of an office building, addressing the urgent challenges posed by climate change and the transition to sustainable mobility solutions. The transportation sector is a major contributor to global greenhouse gas emissions, and the shift to electric vehicles (EVs) powered by renewable energy is a critical step toward achieving climate goals. This study specifically focuses on optimizing charging infrastructure, the ultimate goal being the maximization of the self-consumption of photovoltaic (PV) energy and reducing the strain on the electrical grid of the office building (Wang et al., 2025).

1.1. Framework Of Study

The considered building in this study operates with a PV system of 200 kWp and a charging infrastructure consisting of 14 AC charging stations, including 11 stations with a capacity of 11 kW and 3 stations with 22 kW. The charging system was previously managed under static load management, which limited the maximum charging power to 70 kW. This strategy is undesirable, for obvious reasons: on a high usage day (i.e. many charging events at the same time), where little to no PV generation occurs, the power limit of a building could be exceeded and therefore leading to a triggering of the main power switch. Therefore, the need for intelligent load management systems becomes apparent. Furthermore, analysis of the buildings energy consumption in connection with the PV generation data from 2024 showed essentially to opposite effects:

- A high energy for electric vehicle charging in the morning, when people were arriving for work.
- Underutilized PV generation during midday, when part-time workers were leaving the office and most of the generation electricity was fed back into the grid.

This mismatch in consumption and generation, motivated the present investigation in order to align these two parameters to achieve an optimal energy efficiency, while contributing to sustainable energy solutions.

2. METHODS

2160 charging sessions from 2024 were recorded on a total of 261 working days (i.e. Monday to Friday), with a daily variance of 3 to 15 charging sessions (outliers due to technical reasons or charging on weekends were neglected, since they do not contribute to the problem at hand). The distribution of daily sessions can be approximated by a normal distribution. Charging session start times are concentrated around 8:00 a.m., reflecting typical workday arrivals. Most sessions end at 12:00 p.m. or 5:00 p.m., corresponding to half-day and full-day work durations. Charged energy per session is broadly distributed and can be modeled as a mixture of two normal distributions: one centered at 19 kWh (Standard Deviation 9.5 kWh, 60% weight), the other at 42 kWh (Standard Deviation 10 kWh, 40% weight). Many sessions with less than 3 kWh are likely due to technical issues. Of all vehicles, 80% supported up to 11kW and 20% up to 22kW for charging. However, these discrete data points do not yield any dynamic (temporal and energetic) insight into the specific processes during charging.

Therefore, charging clusters were generated, to gain further understanding. They represented logical group of charging points within a sub distribution of the electrical grid and defined by the maximum available power, which in turn is determined by sub distribution's protection (i.e. the circuit breaker), the minimum charging per point (dependent on the hardware of the charging point) and the number of AC charging points (specified for 11 kW and 22 kW stations).

These clusters are then used to generate charging sessions, based on three distinct methods:

- Historical sessions: based on the previously mentioned data from 2024, including start/end times and charging power. These are used as a reference for validation and are shown in Figure 1.
- Synthetic sessions from parameter distributions: sessions are generated by independently sampling from the statistical distributions of each parameter. While simple, this approach may not capture correlations (e.g., between start time and duration). To improve realism, sessions are generated separately for different weekdays and once for each season as well as the overall distribution.
- Synthetic sessions from Kernel Density Estimation (KDE): KDE is used to generate synthetic sessions based on historical data, considering start time, duration, and energy jointly [Scott, 1992; Wand and Jones, 1993]. KDE is a non-parametric method for estimating probability density functions from sample data. Unlike histograms, KDE provides a smooth, continuous estimate. This work uses Gaussian kernels to model distributions of charging session parameters as defined by the following formula:

$$K_{Gauss}(x) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{x^2}{2}\right)$$

The synthetic clusters were compared to historical data for validation. Whereas synthetic clusters tend to request more energy, due to the fact that outliers are neglected (short/low energy

sessions), the share of PV energy and infrastructure utilization are similar across all methods. For further simulations KDE-based synthetic sessions were used, as they best match the real data.

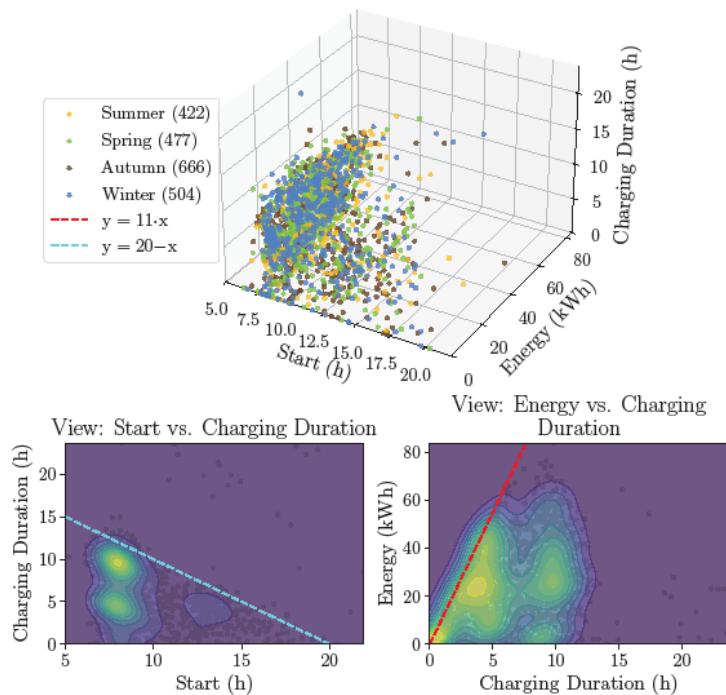


Figure 1: Analysis of charging sessions in 2024 with the start time, duration, and charged energy

2.1. Charging Simulation

The historical or synthetic charging sessions are fed into a Python-based simulation model, that incorporates real-world building data and mobility profiles. The simulation operates on a time-discrete model with 15-minute intervals, allowing for detailed analysis of charging sessions, load distribution, and energy utilization. This approach ensures that the simulation captures the complexity and varying conditions of real-world charging behaviors, leading to robust results that applicable to practical scenarios.

In a first step historical data on energy consumption and PV generation are gathered and via KDE synthetic charging sessions are generated, that are used as an input for the simulation tool. The simulation workflow includes the following steps:

- Assigning vehicles to charging points, where arriving vehicles are assigned to available points.
- Setting the available cluster power depending on the selected load management strategy.
- Unplug logic (optional): If enabled, charging points are freed after a pre-configured time once charging is complete, leading to an increased utilization of the employed infrastructure.
- The maximum available charging power is distributed among all active sessions.

- After the simulation is finished, results for all clusters are aggregated: total charged energy, PV share, utilization, and peak loads.

2.2. Assignment Strategies

Assignment of vehicles to charging points affects infrastructure utilization and energy distribution. Two strategies are implemented:

- Random assignment: Charging points are assigned randomly, regardless of vehicle charging power. This reflects typical user behavior.
- Clustered assignment: Charging points are split into two clusters (A and B) based on planned charging duration. Vehicles with shorter durations are assigned to A, those with longer charging sessions to B.

2.3. Available Charging Power

Charging systems must include control mechanisms to ensure safety (DIN EN IEC, 2022) and compliance with power limits (Alber, 2023). Using the simulation framework, three primary load management strategies were investigated:

- Static load management maintains a fixed maximum charging power, i.e. each cluster receives a fixed power limit (e.g. 70 kW in 2024). While easy to implement, this method is inflexible and can potentially lead to power outages on days with little to no PV generation or inefficiencies during periods of high PV generation.
- Dynamic load management adjusts charging power based on real-time building consumption, offering an improved grid stability while preventing overloads compared to static load management. Available power is allocated dynamically to charging stations, based on the available power from PV generation and building consumption.

$$P_{cluster} = P_{max} - P_{building}$$

- PV-optimized load management prioritizes charging during periods of high PV generation. It limits charging power during mornings, where PV output is low, rises it linearly with growing PV output and later in the day switches to dynamic management. This is shown in Figure 2. A PV-optimized load management system has to be implemented using an central energy management system (EMS) or building automation system (BAS). This enables coordinated control and distribution of the available power and PV generation to various consumers, such as heat pumps or charging stations.

The available cluster power $P_{Cluster}$ is defined as:

$$P_{Cluster} = \begin{cases} \max(P_{Charge} \cdot n_{active}, P_{PV}) & t < t_2 \\ P_{available} & t \geq t_2 \end{cases}$$

with P_{Charge} the available charging power per active session is the number of active charging sessions:

$$P_{charge} = \begin{cases} P_1 & t < t_1 \\ P_1 + \frac{P_2 - P_1}{t_2 - t_1}(t - t_1) & t_1 \leq t < t_2 \end{cases}$$

The other parameters are the number of active charging sessions n_{active} , the excess PV power P_{PV} , the minimum and maximum charging powers during the PV-optimized period P_1 and P_2 , the start and end times of the PV-ramp up window t_1 and t_2 and the dynamically determined cluster power $P_{available}$ after t_2 .

The advantage of this method is complete control of the charging power and integration into a larger system. However, the integration and setup of an EMS is very complex and costly, and the control system must be tailored to the specific circumstances and intended use. Another problem is that for PV optimized charging, the system has to wait for PV generation, which means that less energy can be charged and, above all, can lead to problems on busy days. To minimize the effects of load shifting, forecast models for PV generation and building consumption can be used to optimize the charging process on busy days. However, this is very complex and difficult to represent in the simulation, which is why this aspect is not considered further at this point.

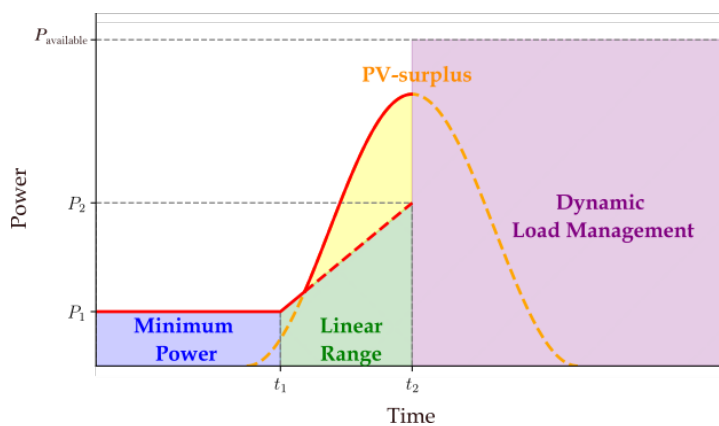


Figure 2: Load shifting depending on PV-generation

3. RESULTS

Static and dynamic load management were compared using current infrastructure limits. Simulations show that dynamic management adapts charging power to building load and PV generation, reducing peak loads and preventing grid overloads—unlike static management, which risks exceeding grid limits. Thus, dynamic load management is preferable for grid stability. Figure 3 illustrates how dynamic management reduces charging power below 70 kW during high building load, avoiding overloads that would occur with static management.

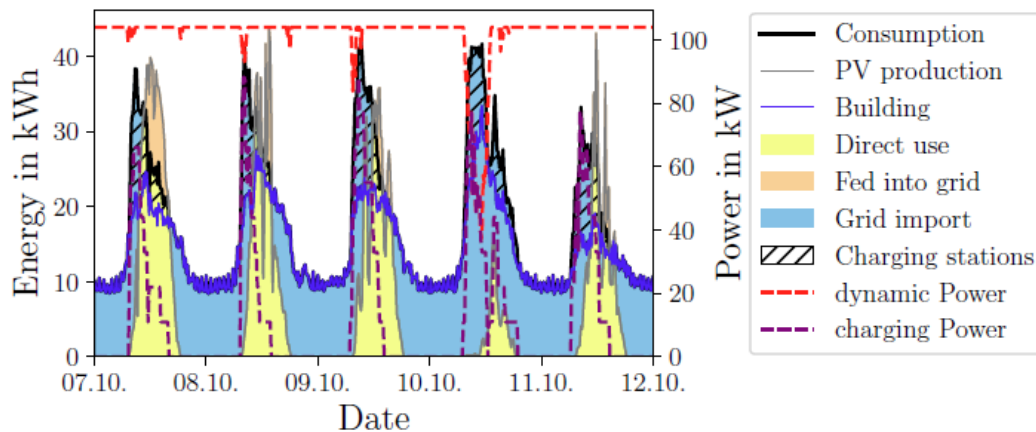


Figure 3: Results of the dynamic load management strategy.

For the PV-optimization the adjusted energy data for a planned future scenario with a PVT-systems and heat pumps was used. Dynamic load management already shows a high PV utilization due to daytime charging (about 24%), but further optimization is possible by shifting loads (up to 39% in an ideal scenario). The PV optimization scheme discussed in Section 2.3 is implemented with $t_1 = 7:30$ h (the typical start of PV generation). P_1 set to the minimum charging power of the charging station, and $P_2 = 11$ kW (the average supported charging power). The end time t_2 is varied from 7:30 to 14:00 (see Figure 4). The results show that increasing t_2 leads to a higher PV share, but this comes at the cost of a reduction in total charged energy. A balance must be found between maximizing PV utilization and ensuring sufficient charging capacity for users. At t_2 9:00 total charged energy drops more steeply, while the PV generation curve begins to flatten. Therefore, this setting offers a good compromise between maximizing PV share and maintaining sufficient charged energy.

3.1. Two-Cluster Approach

A two-cluster approach separates fast charging (short stays) and PV optimized charging (long stays) using the A/B-assignment strategy from section 2.2. This increases PV utilization up to 33%, which is a 34% improvement from the dynamic load management strategy while only reducing the total charged energy by 2% (see dashed lines in Figure 4). This method almost doubles the gain in PV-utilization compared to the single-cluster PV-optimized approach at $t_2 = 9:00$, with only a minor decrease in total charged energy.

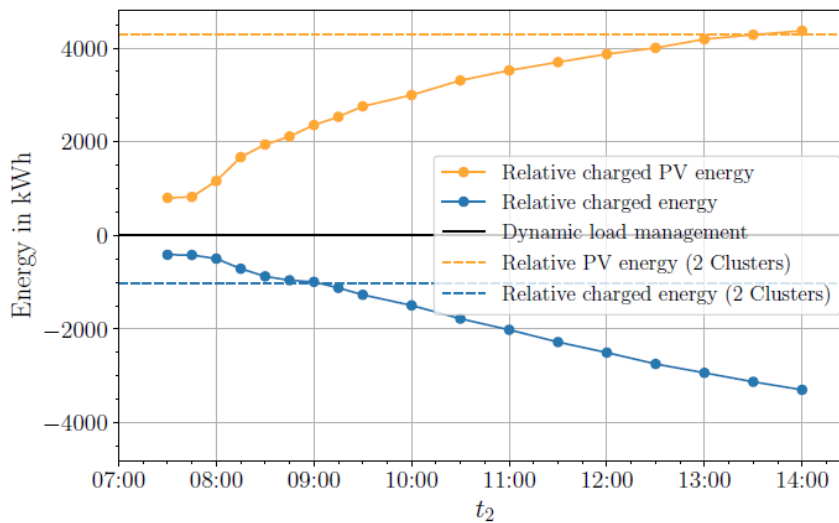


Figure 4: Impact of PV-optimized load management on PV share and total charged energy in comparison to a dynamic load management strategy.

4. DISCUSSION AND CONCLUSION

The study demonstrates that dynamic load management is essential for grid stability, especially with high building loads. PV-optimized strategies can increase self-consumption, reducing grid dependency and costs. Static and dynamic load management were compared using current infrastructure limits. Simulations show that dynamic management adapts charging power to building load and PV generation, reducing peak loads and preventing grid overloads, unlike static management, which risks exceeding grid limits. Thus, dynamic load management is preferable for grid stability and the recommended strategy. For a PV-optimized approach a more detailed cost-benefit analysis is needed, due to the additional complexity.

The project delivers significant benefits to both the economy and society through developing solutions for integrating electromobility and renewable energy into office buildings. By optimizing the charging infrastructure, the utilization of photovoltaic energy is maximized, ultimately leading to reduced CO₂ emissions and reducing grid load during peak hours. Companies benefit from increased employee satisfaction and additionally a more stable grid on-site. The implementation of intelligent load management systems can help companies reduce barriers for the adoption of electromobility and therefore help achieve the energy transition. Furthermore, the research provides a scalable framework for application in future scenarios, creating long-term economic efficiency.

In conclusion, the project demonstrates the feasibility and benefits of integrating electromobility and renewable energy into office building infrastructures. By optimizing load management strategies and employing innovative concepts like dual charging clusters, the study provides a scalable solution for enhancing renewable energy utilization and grid stability. The findings serve as a foundation for future research and development in sustainable energy systems. Due to the use of advanced simulation techniques and data-driven methodologies, the project enables the planning and parameterization of load management strategies for charging stations in real buildings.

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