

Framework to estimate the charging flexibility of EV fleets

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Abstract— The growing adoption of electric vehicles (EVs) offers significant potential to enhance grid flexibility. This study presents a comprehensive framework for estimating EV fleet charging flexibility, incorporating a differentiated assessment model based on vehicle types, charging scenarios, and user behaviors. Real-world charging data is analyzed across residential, workplace, and public contexts, with rigorous preprocessing to ensure data reliability. Clustering techniques identify distinct charging archetypes, such as “short-duration, high-power” and “long-duration, low-power” sessions, highlighting opportunities for load shifting and renewable energy integration. The framework has the capability to evaluate flexibility mechanisms, including temporal and power flexibility, smart charging strategies and assessing their potential impact on grid performance and stability. Results demonstrate the potential of optimized EV charging strategies, such as valley charging, to flatten load profiles, reduce costs, and integrate renewables. This study provides actionable insights regarding the potential of different users for participating in flexibility services.

Index Terms—Electric Vehicles (EVs), Flexibility, Smart Charging, Demand Response, V2G

I. INTRODUCTION

The integration of Electric Vehicles (EVs) into the power grid represents a transformative opportunity for energy system optimization. With the increasing penetration of renewable energy sources, grid stability has become a critical challenge for system operators and flexibility a valuable feature to address it. Vehicle-to-Grid (V2G) technology and smart charging strategies have emerged as viable solutions to enhance grid reliability by leveraging the charging flexibility of EV fleets. However, understanding the extent of this flexibility and its potential contributions to system services requires an in-depth analysis of real-world charging data. This study aims to assess the charging flexibility potential of different EV fleets by analyzing real-world charging behaviors and clustering users based on their charging patterns. By categorizing EV users, we identify key factors that influence their ability to participate in demand response programs, grid balancing mechanisms, and energy market optimization. The research focuses on evaluating

charging flexibility across various user clusters, determining their potential for participating in flexibility services.

The key contributions of this work include:

- A detailed clustering analysis of EV charging behaviors to classify users based on flexibility potential.
- A comprehensive framework for assessing EV time- and power-related flexibility of different EV user groups.
- A case study analysis highlighting the potential of integrating EV fleets into grid services.

By providing empirical insights derived from real-world charging data, this study supports the development of targeted strategies for optimizing EV-grid interactions.

The remainder of this paper is structured as follows: Section II provides an overview of EV participation in system services and related technical considerations. Section III provides an overview of methodology used to assess flexibility potential from real EV charging datasets. Section IV presents the case study results, analyzing flexibility potential across different user clusters. Finally, Section V concludes the paper with main conclusion from the study and insights on future research directions and technological advancements required for further enhancing EV-grid integration.

II. PARTICIPATION OF EVs IN SYSTEM SERVICES

The integration of EVs into power grids presents significant opportunities for enhancing system stability and efficiency. EVs can support key grid services such as frequency regulation, voltage control, congestion management, and load shifting through controlled charging and Vehicle-to-Grid (V2G) operations. Frequency regulation benefits from EVs' fast-response capabilities, allowing aggregated fleets to balance supply and demand fluctuations dynamically. Voltage control [1] is another key function, where smart charging adjustments help maintain stable voltage levels, particularly in grids with high renewable penetration. Additionally, EVs contribute to congestion management [2] [3] by strategically shifting charging loads away from peak periods, reducing stress on the grid infrastructure. Demand response programs [4] leverage EV

flexibility to optimize electricity consumption, aligning charging schedules with market conditions and renewable energy availability. By shifting demand from peak [5] to off-peak hours, EVs can enhance grid efficiency and reduce reliance on fossil-fuel-based backup power.

To facilitate widespread participation of EVs in system services [6], regulatory frameworks and market incentives must evolve. Aggregators play a crucial role in consolidating EV participation, ensuring a meaningful impact on the grid. Standardized communication protocols and real-time monitoring systems are essential for seamless coordination between EVs, charging infrastructure, and grid operators.

The successful integration of EVs into system services [6] offers a pathway to a more resilient and sustainable power system. However, overcoming technical and regulatory barriers remains critical to unlocking their full potential. To further understand how EV charging behaviors can be classified and optimized for system participation, the next section presents a clustering methodology that segments EV users based on their charging patterns, providing insights into their flexibility and responsiveness to grid demands.

III. METHODOLOGY

A. Data requirements

The development of a framework to estimate the EV charging flexibility needs to rely on a comprehensive dataset that ideally combines both public and private spaces charging events. While public charging data offer a broad range of scenarios and user behaviors—capturing significant variations in maximum power levels, charging durations, and demographics—integrating private or residential charging data further enriches the analysis. The mixed dataset provides a more complete picture of the diverse charging profiles and flexibility potentials that exist, ensuring that key influencing factors such as peak demand, user preferences, and charging constraints are accurately reflected. This comprehensive approach enables the model to generate more reliable predictions of EV flexibility under varying conditions.

To assess the flexibility potential of electric vehicle (EV) charging behavior, several critical data elements are analyzed. Each Transaction ID serves as a unique identifier, ensuring data integrity and enabling consistent linkage across analyses. Transaction Start/Stop Time records precise connection and disconnection timestamps, which are essential for identifying usage patterns and temporal trends. The Connected Time—the total duration an EV remains plugged in—provides insight into idle periods, indicating opportunities for deferred charging without disrupting user needs. Meanwhile, Charging Time (the active energy delivery duration) helps determine flexibility in rescheduling or delaying charging sessions. Total Energy, representing the aggregate energy transferred per session, reveals demand variability across different usage scenarios. Finally, Max Power reflects peak power draw, informing demand response strategies by highlighting periods of high grid load. Together, these metrics enable a comprehensive assessment of charging behavior and its potential adaptability to grid needs.

Data preparation involves cleaning, transforming, and organizing input data. Cleaning includes addressing missing values, normalizing formats, and filtering incomplete records. Transformation derives metrics like Connected Time and Idle Time while normalizing Charging Time and Total Energy to account for station and user different characteristics.

Prepared datasets are used for clustering analysis, revealing patterns and flexibility potential. Clustering algorithms group sessions by characteristics such as peak power and charging time, aiding in understanding EV behavior and optimizing grid services. This process ensures accurate, actionable insights, reducing biases and supporting effective EV integration into energy systems.

B. Clustering mechanisms

The clustering module is a pivotal aspect of our model, facilitating the aggregation of cleaned data from individual EV charging events. This aggregation consolidates data from all analyzed sites (charging stations), enabling insights into flexibility patterns, demand response opportunities, and site utilization based on cluster profiles derived from the clustering algorithm.

To analyze the flexibility potential of EV charging sessions, charging events are clustered based on shared attributes such as plug-in time, charging duration, energy consumption, and user behavior. This categorization identifies patterns, such as “short-duration, high-power” sessions representing quick charges or “long-duration, low-power” events, typically associated with parked vehicles. These distinctions are vital for tailoring strategies, like load-shifting for sessions with extended idle periods, aligning charging with renewable energy availability or off-peak grid conditions.

Key Steps in the Clustering Process are:

1. **Feature Selection:** Critical attributes such as plug-in time, charging duration, maximum power, and total energy are selected to capture flexibility-relevant behaviors. These parameters guide the clustering process, ensuring actionable insights.
2. **Data Normalization:** Standardizing features eliminates biases from varying scales, ensuring equal contribution to clustering. Using the StandardScaler, values are normalized to a mean of 0 and variance of 1, crucial for distance-based clustering methods.
3. **Clustering Algorithm Selection:** The proposed framework evaluates multiple clustering algorithms using metrics such as inertia and silhouette scores to determine optimal groupings. K-Means minimizes intra-cluster variance efficiently but assumes convex shapes, limiting its suitability for irregular distributions. Agglomerative Clustering hierarchically merges clusters, capturing nested structures effectively. Gaussian Mixture Models (GMM) leverage probabilistic distributions to model diverse cluster shapes, while DBSCAN identifies dense regions, excelling at irregular clusters and outlier detection. Each algorithm undergoes parameter optimization (e.g., cluster count k for K-Means, linkage criteria for Agglomerative Clustering, covariance types for GMM, and neighborhood radius ϵ for DBSCAN).

for DBSCAN). The best-performing model, selected based on evaluation metrics, yields the most distinct and well-separated clusters.

4. **Cluster Analysis:** Once clusters are established, their characteristics are analyzed to assess flexibility potential. Distinct behavioral patterns—such as commuter charging, overnight charging, and peak-demand charging—are identified, enabling targeted load-shifting strategies. Key metrics, including idle time ratios and responsiveness to demand-response signals, inform load management approaches. For instance, sessions with prolonged idle times can defer charging without user disruption, facilitating grid balancing or alignment with renewable energy availability. Clustering insights are derived from four primary features: Max Power, Charging Time, Connected Time, and Total Energy. Statistical analyses (e.g., means, variances, distributions) coupled with visualization techniques profile each cluster. This methodology categorizes charging behavior (e.g., commuter, overnight, peak-demand) to optimize demand response programs and infrastructure planning

5. **Flexibility Charging Assessment:** The final stage of the methodology further assesses the flexibility potential of each cluster, enabling actionable strategies such as time-shift charging, peak shaving, and dynamic power adjustments.

C. Flexibility assessment methods

Our methodology is based on [7] and considers EV charging flexibility in two main dimensions: time flexibility and power-specific flexibility. Time flexibility refers to the ability to shift the charging schedule without affecting the total energy delivered, while power-specific flexibility reflects the capacity to modulate charging power during a session. These flexibility aspects are quantified using two metrics.

Firstly, **Idle Time**, defined as the difference between Connected Time and Charging Time, this metric represents the window during which a vehicle remains connected but is not actively charging. High idle time indicates a greater opportunity for load shifting without impacting energy requirements.

$$T_{\text{idle}} = t_{\text{connected}} - t_{\text{charging}} \quad (1)$$

Secondly, **Time-shift flexibility**, expressed as (2) where t'_k is the total connection time (Connected Time) of charging event k and $t_{k,P}$ is the time required to deliver the same energy E_k at a specified charging rate P (i.e., $t_{k,P} = \frac{E_k}{P}$). A $Flex_{\text{shift}}$ value of 1 indicates that the entire connection duration is required for charging at rate P ; values above 1 reveal excess time that can potentially be shifted.

$$Flex_{\text{shift},k,P} = \frac{t'_k}{t_{k,P}} \quad (2)$$

Graphically, we represent these metrics using FlexBars [8]. In a FlexBar, time is plotted on the horizontal axis—the full width representing the total duration of the charging event—while the vertical axis displays power up to the maximum available rate. The resulting rectangle indicates the total possible energy delivery, which typically exceeds the actual

energy charged, thereby visually emphasizing the flexibility potential. By averaging FlexBars over all charging events within a defined period, we obtain a comprehensive view of the temporal and power-specific flexibility of a site or cluster of EV charging events.

This structured approach, combining data aggregation, statistical analysis, and graphical visualization, lays the foundation for robust clustering and flexibility assessments, ultimately supporting targeted strategies for load shifting or peak shaving.

IV. CASE STUDY ANALYSIS

A. Overview

The dataset, sourced from EVnetNL[9] in the Netherlands, includes data on 10,000 EV charging events from 2019, offering insights into charging behavior and infrastructure usage. This real charging events dataset includes all the necessary data elements outlined earlier, ensuring the proper application of the framework presented in this paper. It captures start and stop times, total connection duration, and active charging time, along with key energy metrics such as total consumption (kWh), peak power (kW), and periodic meter readings. These readings provide a granular view of energy transfer efficiency and variability, supporting a comprehensive analysis of charging flexibility and demand-side optimization. The dataset also includes 417,141 meter readings linked to the transactions, enabling in-depth temporal analyses. This allows for the study of patterns in charging duration, energy consumption, and peak versus off-peak behaviors.

By capturing both transactional and detailed meter-level data, the dataset supports assessments of charging stations utilization, user habits, and infrastructure needs. Its structured and anonymized format facilitates trend analysis, energy demand forecasting, and optimization of public EV charging networks.

B. Behavioral patterns of EV user clusters

Considering the selected features (MaxPower, ChargeTime, ConnectedTime, TotalEnergy) and the clustering algorithm that most accurately represents the real charging dataset events, 5 different clusters are identified and the results are visualized in scatter matrix images (Figure 1). The algorithm chosen for the clustering of the data was K-means due to its superior performance in clustering evaluation metrics.

The scatter matrix plots provide insights into the behavioral characteristics of each cluster based on the selected features. The diagonal plots in Figure 1 represent the density distributions for the four variables, while the off-diagonal scatter plots depict inter-feature relationships.

The main conclusions that can be retrieved from the Figure 1 analysis are:

- **MaxPower:** Cluster 0 and Cluster 4 exhibit low power usage (~3.7 kW), indicating opportunistic or routine slow charging. Cluster 1 shows moderate power peaks (~12 kW), associated with semi-fast public or workplace charging. Cluster 3 has the widest range (~11–20 kW), reflecting diverse behaviors from moderate to fast

charging. Cluster 2 relies mostly on slow charging (<5 kW), often linked to overnight residential use.

- **ChargeTime:** Cluster 2 has the longest sessions (8–20+ hours), reflecting overnight charging. Clusters 1 and 4 show intermediate durations (3–7 hours), suggesting structured workplace or residential charging. Clusters 0 and 3 demonstrate shorter charge times (~3 hours), with Cluster 3 often relying on fast-charging infrastructure.
- **ConnectedTime:** Cluster 2 exhibits the longest connection periods (>20 hours), often exceeding actual charging time, indicating inefficient station use. Clusters 1 and 4 have moderate connection times (5–15 hours), showing structured habits. Cluster 0 has the shortest connections (<5 hours), optimizing charger availability, while Cluster 3 varies widely, with some users leaving vehicles plugged in longer than necessary.
- **TotalEnergy:** Cluster 0 withdraws the least energy (<10 kWh), aligning with quick top-ups. Clusters 3 and 4 consume moderate energy levels (10–30 kWh), while Clusters 1 and 2 span the widest range, with some sessions exceeding 60 kWh, highlighting users with larger battery capacities and longer charging needs.

Based on these insights and analysis, each cluster can be categorized into a specific user type. The Table 1 summarizes the key findings and corresponding user classifications.

Additionally, to validate the charging profile classes, the dataset was sorted by cluster, identifying the most probable charging times as shown in the Figure 2.

Figure 2 shows that Clusters 0 and 3 predominantly charge between 08:00-19:00, aligning with public stations, while Clusters 1, 2, and 4 peak between 22:00-05:00, indicating household charging.

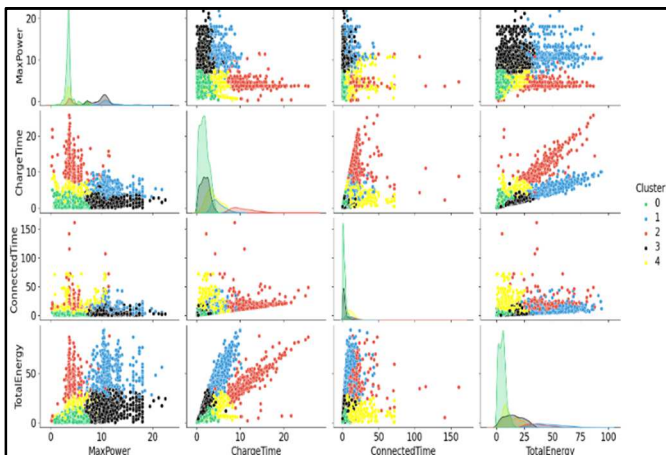


Figure 1 - Scatter matrix of the charging events dataset divided by 5 clusters

C. Charging flexibility potential estimation

After defining the clusters, an in-depth analysis of their time- and power-related flexibility was conducted in the following manner. Firstly, a boxplot (Figure 3) representation was used to examine the flexibility metric Idle Time across

clusters, highlighting variations in vehicle disconnection behavior after charging completion

- **Cluster 0:** Minimal idle time, users disconnect promptly, indicating high charger turnover in public/commercial settings.
- **Cluster 1:** Moderate idle time with some long-duration cases (>20 hours), typical of workplace or high-power residential charging.
- **Cluster 2:** Highly variable idle times, with extreme cases exceeding 100 hours, indicating long-duration household or fleet charging.
- **Cluster 3:** Short idle times (<10 hours), aligning with high-power public or highway fast charging.
- **Cluster 4:** Moderate-to-high idle times, suggesting structured workplace/household or fleet charging with potential flexibility.

Table 1- Cluster classification summary table

Cluster	Key Observations	Charging Flexibility	Class
0 (green)	Low ChargeTime and ConnectedTime. Low Power chargers	Low (already optimized)	Low Power Public (Opportunistic) / Commercial Areas
1 (blue)	High MaxPower (10-20 kW), balanced ChargeTime vs. ConnectedTime	Moderate (some users could optimize better)	High Power Household
2 (red)	Long-duration events. High ConnectedTime vs. ChargeTime, frequent excessive idle time	Highest (many users could optimize station turnover)	Low Power Household
3 (black)	Highest MaxPower, well-aligned ChargeTime and ConnectedTime	Low (optimized, minimal idle time)	High Power Public / Highways
4 (yellow)	Slow charging, low-moderate energy withdraw, high ConnectedTime	Moderate to High (long idle times can be optimized)	Low Power Household with PHEV or Fleet Charging

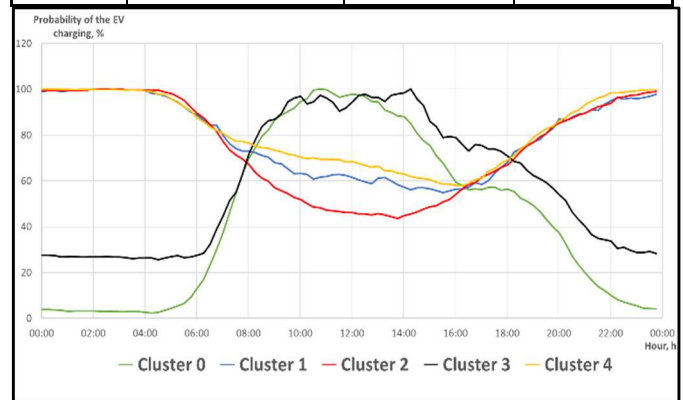


Figure 2 - Probability of the charging events occur at a certain hour for each clusters

Clusters 2 and 4 exhibit the highest idle times, making them prime candidates for demand-side management, while Clusters 0 and 3 show minimal flexibility.

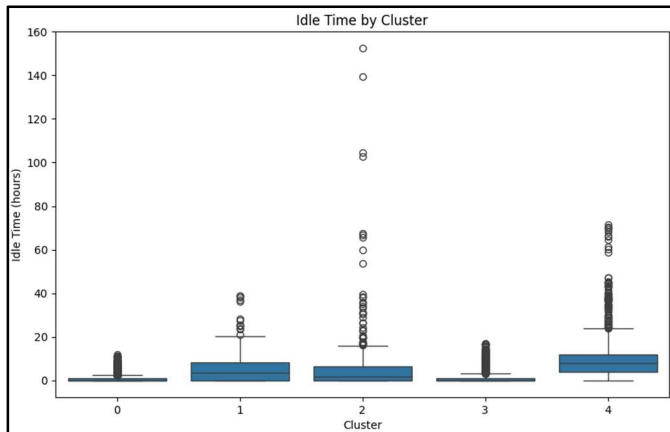


Figure 3 - Boxplot regarding Idle Time of each cluster

The study evaluated Time-Shift Flexibility, a critical metric that quantifies the temporal adjustability of charging sessions while ensuring EV energy demands are fully met. Three distinct charging power scenarios were analyzed: fixed low-power charging ($P_{fix} = 3.68$ kW), average observed charging power (P_{avg}), and maximum power utilization (P_{max}).

The analysis revealed distinct flexibility characteristics across clusters. Cluster 0 demonstrated low flexibility, as users in this group typically charged efficiently with minimal idle time. In contrast, Cluster 1 exhibited moderate flexibility, consisting primarily of high-power household and workplace users who often charged faster than strictly necessary, thereby allowing for some degree of load shifting. Cluster 2 showed particularly high flexibility potential, with its extended connection times suggesting ample opportunities for deferred charging. Cluster 3 displayed minimal flexibility due to its fast-charging users who required immediate energy replenishment. Cluster 4, similar to Cluster 2, exhibited high flexibility with its prolonged connection durations enabling significant adjustments to charging schedules. These findings highlight that Clusters 2 and 4 offer the greatest potential for load-shifting applications, while Clusters 0 and 3 show limited flexibility due to their time-sensitive or optimized charging patterns. Cluster 1 emerges as an intermediate case, presenting viable opportunities for demand-response optimization while requiring more nuanced management approaches.

The final analysis visualizes the time- and power-related flexibility of each cluster using FlexBars representing the average values of the charging events for each identified cluster. This method integrates both temporal and power flexibility into a single representation, summarizing idle time and time-shift potential. In the Figure IV-4 is presented, as example, the Flexbars for the Cluster 4. The horizontal axis represents charging duration, and the vertical axis displays charging power, capped at the maximum assumed power. The gray area illustrates available flexibility, while color-coded areas represent Time-Shift Flexibility metric at different power levels: P_{fix} in green, P_{avg} in orange, and P_{max} in blue.

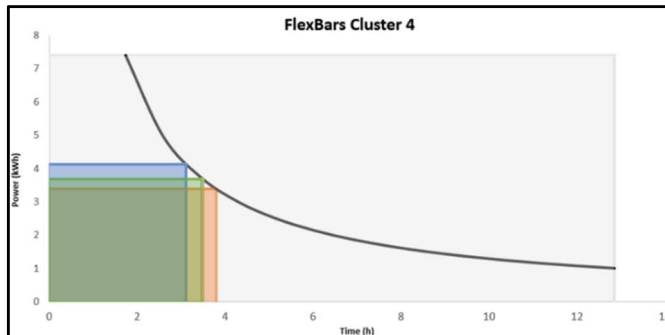


Figure 4 - Flexbars for cluster 4

The black curve maps feasible power-time combinations, ensuring total delivered energy remains consistent with the average cluster charging session. From these representations is concluded that charging sessions typically use only a small portion of their available energy capacity. In most cases, reducing charging power does not affect mobility needs. However, for Clusters 1 and 3, lowering power to 3.68 kW extends the charging time beyond the originally available connection period. Slower charging clusters show high flexibility potential, making them ideal for demand-side optimization. Overall, this analysis confirms that most charging events allow for time-shifting, enabling smart charging strategies without impacting EV usability.

V. CONCLUSION

This study provides a comprehensive analysis of EV charging flexibility based on real-world data and clustering analysis. We identified five distinct charging profiles: one group of opportunistic public charging users with short sessions, a cluster of high-power household users exhibiting structured charging, a group of low-power household users with extended connection times, fast-charging highway/public users with minimal idle periods, and a mixed group typical of fleet or workplace charging. Our findings reveal that clusters with prolonged idle times—particularly those characterized by extended connection durations in low-power household or fleet scenarios—offer the greatest potential for demand response and load shifting. In contrast, fast-charging users have limited flexibility due to their time-sensitive requirements, while structured high-power users show moderate potential for schedule adjustments. These insights suggest that targeted smart charging strategies, such as time-of-use tariffs and dynamic pricing, could optimize grid performance, enhance renewable integration, and improve overall energy efficiency. Future work should focus on advanced predictive modeling and tailored incentive mechanisms to fully exploit the flexibility potential of EV fleets in modernizing grid operations.

VI. ACKNOWLEDGEMENT

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