Understanding Car Usage Patterns for V2G Integration: Insights from Dutch Travel Diaries

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Keywords: Vehicle-to-Grid (V2G), Mobility Data Analysis, Car Usage Behavior, Clustering Analysis.

Abstract: Integrating renewable energy sources, such as solar and wind, challenges grid stability due to their intermittent nature. Vehicle-to-grid (V2G) technology provides a promising solution by utilizing electric vehicles (EVs) as decentralized energy storage systems, enabling the storage of surplus energy during low demand and its release during peak demand. The effectiveness of V2G depends critically on car usage patterns. Data from the Netherlands Mobility Panel (MPN) of 2022, comprising travel diaries from 2,505 households, was analyzed to explore this. A methodology was developed to create car usage profiles based on parking durations and locations, distinguishing weekday and weekend patterns. The analysis shows that vehicles are predominantly parked at home, with weekday profiles reflecting work-related parking and weekend profiles highlighting increased leisure activity. Households with shared cars showed higher driving activity and shorter parking durations than households with a 1:1 car-to-license ratio or surplus vehicles. Six distinct car usage clusters were identified for weekdays and four for weekends.

1 INTRODUCTION

The transition to renewable energy sources such as solar, wind, and hydro is accelerating worldwide. In 2023, renewable energy accounted for 48% of electricity generation in the Netherlands, equivalent to more than 55 billion kWh (Statistics Netherlands (CBS), 2024). While this progress brings significant environmental benefits, it also poses new challenges for the energy grid. The intermittent nature of solar and wind energy production means that supply often peaks when demand in residential areas is low, such as in the afternoon when the sun unfolds its full power or during periods of high wind, which are also typically in the afternoon, while the highest energy demand in these areas commonly occurs in the mornings and evenings when people are at home to take a shower or charge their cars, for example.

This mismatch between supply and demand is increasingly pushing the energy grid to its limits, as shown by the grid congestion in Figure 1 (Capaciteitskaart 2024), which occurs when electricity cannot be transported through the grid at that time. Without adequate energy storage solutions, excess renewable energy is wasted during periods of low demand, while fossil fuel-based generation may still be required to meet peak demand in the evenings.

An ideal solution is to store excess renewable energy at times of low demand and release it at peak times. Vehicle-to-grid (V2G) technology offers a promising approach to achieving this goal by leveraging electric vehicle (EV) batteries as distributed energy storage systems.

Although V2G is technically mature and ready for deployment, its adoption remains limited. Key barriers include a lack of standardization, limited availability of V2G-compatible vehicles, infrastructure challenges, battery degradation concerns, and insufficient regulatory and policy support. Besides infrastructural, technical, and

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Leu, S., Correia, G. H. A., van Lint, H. and Leonhardt, A.
Understanding Car Usage Patterns for V2G Integration: Insights from Dutch Travel Diaries.
DOI: 10.5220/0013412500003941

In *Proceedings of the 11th International Conference on Vehicle Technology and Intelligent Transport Systems (VEHITS 2025)*, pages 189-198
ISBN: 978-989-758-745-0; ISSN: 2184-495X

regulatory boundary conditions, the actual availability of EVs to serve as storage devices is key to the successful deployment of V2G. Therefore, gaining insights into car usage patterns is critical for assessing the practical potential of V2G.

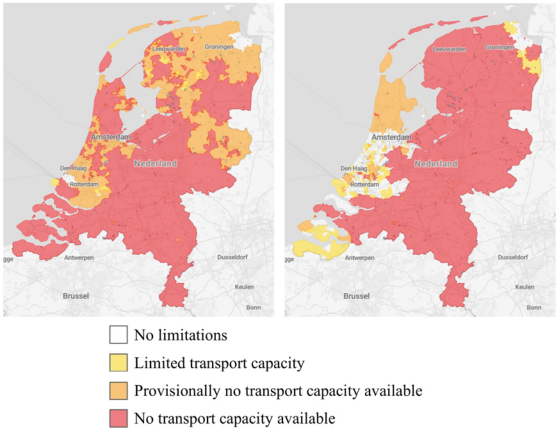

Figure 1: Grid congestion for consumption (left) and feed-in (right) in the Netherlands on December 9, 2024 (Capaciteitskaart 2024).

This paper examines car usage patterns using real-world mobility data from the Netherlands Mobility Panel (Mobiliteitspanel Nederland, MPN). The MPN includes travel diaries from individuals residing in the Netherlands and offers comprehensive household-level information such as details about household members, vehicle characteristics (e.g., engine type), and trips made.

The structure of the paper is as follows: Chapter 2 reviews relevant literature, highlighting key studies and gaps in the context of V2G applications. Chapter 3 presents an overview of the dataset and details the data preparation process, including filtering criteria and the estimation of trip departure times. In Chapter 4, car usage profiles are developed based on individual mobility patterns, and clustering analysis is conducted to identify relevant usage patterns for weekdays and weekends. The clustering analysis results are shown and discussed in Chapter 5, followed by a conclusion outlining the findings' implications and directions for future research.

2 STATE OF THE ART AND LITERATURE REVIEW

V2G technology has been extensively studied, with early research primarily focusing on its technical feasibility and potential benefits, such as peak-load shaving and reductions in total generation costs (Zheng et al., 2019). Kempton and Tomić (2005) demonstrated the viability of using EV batteries for grid stabilization and renewable energy integration. Their research highlights that automobiles are typically used only about 4% of the time, suggesting that V2G systems could utilize the parking time of electric vehicles to store and supply energy. This foundational work laid the groundwork for further studies exploring V2G's applications, including frequency regulation, peak shaving, and renewable energy integration.

Building on these technical foundations, subsequent research addresses gaps in understanding user behavior and mobility patterns for V2G implementation. Noel et al. (2019) highlighted a lack of research into user behavior in the context of V2G and stressed the importance of incorporating mobility patterns into V2G planning. Their findings revealed that a typical vehicle is used for driving only 4-5% of the day.

Several studies have delved into the relationship between mobility patterns and parking durations, showing the temporal availability of EVs for grid services. For instance, Fu et al. (2021) used travel surveys from the German Mobility Panel (MOP) to identify the V2G potential of passenger cars. They applied a two-level clustering method to analyze driving and parking patterns, focusing on parking locations and durations. The study identified ten different weekday driving patterns, highlighting a significant potential for V2G participation. Similarly, Demirci et al. (2023) noted that many studies fail to consider how driving and charging behavior patterns influence V2G integration. Their research proposed a framework for processing EV driving and charging behaviors to improve charging management operations, incorporating recent advancements and real driving data. By evaluating attributes such as charging location, charging duration, charging levels, and charging times, the study aims to create a realistic and consistent dataset reflecting new electro-mobility trends.

Crozier et al. (2018) clustered data from the UK National Travel Survey to identify five typical conventional vehicle usage profiles. They found that 70% of vehicles fall into the lowest usage group, while 30% account for 65% of total fleet mileage. These findings emphasize the importance of identifying underutilized vehicles as potential candidates for V2G integration. Sovacool et al. (2017) highlighted a significant gap in research on customer acceptance and driving behavior in the context of vehicle-grid integration.

Using real-world mobility data, such as the German travel survey analyzed by Fu et al. (2021), has significantly advanced our understanding of users' driving behavior. Building upon these methods, this study leverages data from the MPN, which provides comprehensive information on household travel patterns. To the best of our knowledge, this is the first study to process and analyze real-world mobility data from the MPN to gain comprehensive insights into the general car usage profiles of the Dutch population. By focusing specifically on home and workplace parking durations, this research offers a nuanced understanding of the temporal availability of vehicles for possible V2G applications. These car usage profiles form the foundation for assessing V2G potential in the Netherlands.

3 DATA: OVERVIEW AND PREPARATION

This chapter details the most recent MPN dataset of 2022 and its preparation for analysis. A comprehensive filtering process was applied to ensure data reliability. Trip departure times were estimated to improve the temporal accuracy of car usage profiles, as the raw data provided only aggregated time intervals.

3.1 Netherlands Mobility Panel

The MPN (Hoogendoorn-Lanser et al., 2015) gives insights into the travel behavior of fixed groups of individuals and households since 2013 of the Dutch population. Participants in the panel maintain a travel diary over three consecutive days (including weekdays and sometimes weekends) to record their mobility patterns. However, the MPN dataset only allows a general distinction between day types (weekday or weekend), as it does not specify the exact day of the week. These anonymous travel diaries capture detailed information such as travel times, modes of transport, the type of start and end location, and the purpose of each trip. Additionally, the diaries are supplemented with personal data (e.g., job or driver's license) and household details (e.g., number of people or cars).

Based on the travel diaries, parking times of cars at home, work, and other locations can be identified through a series of processing steps. The analysis begins with data preprocessing, which includes filtering out implausible entries and irrelevant households. Although the original MPN dataset was designed to be nationally representative, the sample's representativeness after filtering was not explicitly assessed. However, as filtering was based on diverse criteria, significant biases in spatial distribution are not expected.

3.2 Data Filtering

To ensure the reliability and consistency of the dataset, a filtering process was applied. The filtered dataset includes only complete households with at least one licensed driver and one car. A complete household is one, as Hoogendoorn-Lanser et al. (2014) defined it as when all members aged 12 and older fully complete the three-day online travel diary. Incomplete households were not included in the analysis, as missing data could compromise the accurate reconstruction of vehicle usage behavior. This step is crucial because individuals with car usage without a completed travel diary would result in incomplete or misleading data for household car usage. Table 1 outlines the sequential filtering steps and the corresponding number of households retained at each stage. The initial dataset consisted of 3,108 households. First, households without at least one member completing the full three-day online travel diary were excluded, reducing the sample to 2,505. Next, households without at least one licensed driver were removed, leaving 2,227 households. A further refinement excluded those without at least one car, leaving 2,059 households. Finally, only complete households that met all three previous criteria were included in the final dataset of 1,661 households, which formed the basis for detailed analysis.

Table 1: Filtering process to identify relevant households.

Travel diary ≥ 1	Driver' s license ≥ 1	Car ≥ 1	Complete households	Number of households
				3,108
x				2,505
x	x			2,227
x	x	x		2,059
x	x	x	x	1,661

Table 2 provides an overview of the relevant information extracted about the individuals and cars in these households.

Table 2: Details of relevant households.

Number of persons	3,246
Number of persons with driver's licenses	2,628
Number of cars	2,118
Number of households with fewer cars than persons with driver's licenses	546

In 546 households, there are fewer cars than individuals with driver's licenses, indicating that car sharing is necessary among household members. This aspect is particularly relevant for the methodology used to generate car usage profiles, as it directly impacts vehicle availability and utilization patterns.

A "record," as referred to in Table 3, can be either a trip segment or a survey day without any recorded trips by the members of the household. A trip must consist of at least one trip segment. If the mode of transport is changed during a trip or there is a brief interruption, but the destination remains the same, a new trip segment is created. The dataset contains 22,487 trip segments and 1,696 records representing days without trips.

Table 3: Overview of records in the dataset.

Number of records in travel data	24,183
Number of records in travel data with transport mode car	8,828

The trip segments in the dataset lack detailed information such as duration, segment destinations, or mileage. Instead, the dataset only provided aggregate information for the entire trip (e.g., total duration, final destination, and total mileage). This limitation did not pose issues for trips where all segments shared the same transportation mode. However, it became problematic for trips involving multiple modes, particularly those where the car was used as the driver for at least one segment. Without detailed segment-level data, it is impossible to reconstruct car usage or meaningfully analyze such trips comprehensively. To address this issue, all households where members recorded trips with multiple transportation modes and at least one trip segment involving a car as the driver were excluded from the relevant dataset. This adjustment impacted 72 households, resulting in a refined dataset of 1,589 relevant households with 2,027 cars. Among these households, 985 have an equal number of cars and individuals with driver's licenses, indicating a one-to-one correspondence between vehicle ownership and potential users. In contrast, 522 households have fewer cars than individuals with driver's licenses, which suggests that car sharing is necessary among household members. Additionally, 82 households have more cars than individuals with driver's licenses, indicating surplus vehicle availability.

Some inconsistencies were identified in the data set. In the travel diary, specific entries show individuals with two consecutive trips, both labeled with the objective "going home," where the first trip was not part of a round trip. Such a trip chain is logically impossible, as an individual already at home cannot take another trip with the objective of "going home" without leaving first. This inconsistency was observed in 18 instances, which were carefully analyzed. It was determined that, in most cases, respondents appeared to forget to mark a subsequent trip as part of a round trip. For example, a respondent might return "to home" by car and then take a walk, also marked as "to home." In such cases, the walking trip was corrected and classified as a round trip.

All respondents completed the travel diary in at least three days, though three recorded trips occurred before the first official day of the survey. To maintain consistency and comparability across the dataset, only the data from the officially recorded days for each respondent were included in the analysis.

3.3 Estimating Trip Departure Times

One of the most critical steps in the preprocessing of the data was the estimation of the departure times of the trips in the travel diaries. In the original dataset, departure times are summarized in predefined time classes, as shown in Table 4.

Table 4: Allocation of departure time classes to time ranges.

Departure Time Class	Time Ranges
1	00:00 to 04:00
2	04:00 to 07:00
3	07:00 to 08:00
4	08:00 to 09:00
5	09:00 to 12:00
6	12:00 to 13:00
7	13:00 to 14:00
8	14:00 to 16:00
9	16:00 to 17:00
10	17:00 to 18:00
11	18:00 to 19:00
12	19:00 to 20:00
13	20:00 to 23:59

However, departure times with a higher resolution are essential for the creation of vehicle usage profiles for later investigation of V2G potential. In this study, a time resolution of five minutes was chosen to improve accuracy. The process of estimating trip departure times is shown in Figure 2. At the beginning of the process, empirical normalized traffic count data at a one-hour resolution is interpolated to a five-minute resolution, incorporating departure time classes. Next, trip times for MPN travel diaries are estimated based on the empirical traffic count distribution. Finally, the refined normalized departure times are compared with the empirical traffic counts to ensure consistency and accuracy.

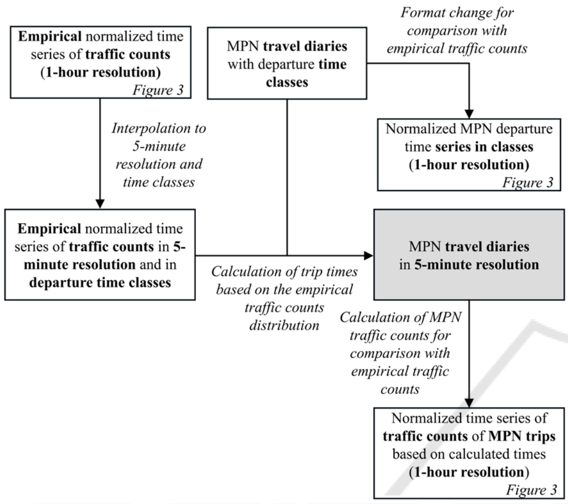

Figure 2: Process of estimating trip departure times.

Time series of traffic counts for the Netherlands were analyzed to estimate trip departure times with a five-minute resolution, referring to the empirical work of Andriesse et al. (2021).

The empirical traffic count time series used (orange curve in Figure 3) is the normalized one of the Waterleidingstraat, Rosmalen, as reported by Andriesse et al. (2021). This time series of traffic counts was taken from a cross-section of the street, covering both directions of traffic, in order to reduce peaks in a single direction. Although other traffic count time series could also be applied, the one presented here is representative. The time series chosen was the one that was most similar to the MPN departure time classes in the normalized form at one-hour resolution (blue curve in Figure 3). This curve was constructed by summing all values within each time class, normalizing them, and converting them to hourly values based on the intervals defined in Table 4. In particular, the MPN time series of departure times shows a less pronounced drop after the morning peak hour and a more subdued afternoon peak than the empirical time series.

To generate departure times in five-minute resolution, the trips were assigned within their corresponding time ranges while ensuring adherence to observed traffic patterns. The goal was to align the values within each time class with the empirical time series of traffic counts as closely as possible. To achieve this, the empirical curve from Andriesse et al. (2021) was divided into the same time classes as the MPN data for direct comparison. Every class was normalized, and all values from each class were interpolated into five-minute intervals for higher resolution. Then, trip departure times were assigned based on the empirical normalized times series of traffic counts for each time class.

The departure times directly affect the calculation of arrival times, which are calculated by adding the travel time, rounded to the nearest five-minute interval, to the departure time. For travel times between one and four minutes, the values are always rounded to five minutes to ensure they remain recognizable as trips.

Additionally, constraints were implemented to ensure data integrity, which may have caused slight deviations from the empirical curve.

- If a person makes a trip within a specific time range on a given day, any subsequent trip (with a higher trip ID) can only start after the preceding trip has ended.
- All records were adjusted to conclude at the end of the survey day for consistency. For instance, if a trip extended into the following day (e.g., ending at 01:25), it was truncated at 23:59 of the survey day. In the 77 cases where this occurred, the record reflects that the individual was still traveling at the cutoff time.
- While the departure times were aligned with the empirical time series of traffic counts, the MPN time series of traffic counts (red curve in Figure 3) is additionally influenced by the recorded travel times. This curve represents the normalized time series of traffic counts at a one-hour resolution, calculated based on the time trips occur—encompassing everything between departure and arrival times. It demonstrates that the calculated times align well with the empirical traffic counts, except for a slight deviation at the midday peak.

4 METHODOLOGY: IDENTIFICATION OF CAR USAGE PATTERNS

The principal aim of this study is to derive typical car usage profiles from the MPN data. Thus far, the analysis has considered complete travel diaries encompassing trips made via various transport modes. This section outlines the methodology for creating car mobility profiles, with a specific focus on trips where the transportation mode is recorded as "car as a driver."

The process comprises three principal stages. Initially, car usage profiles are generated for each individual based on the recorded trips. Subsequently, these profiles are aggregated to create actual car usage profiles for cars. Finally, clustering algorithms are employed to identify distinct usage patterns. The car usage profiles are generated based on recorded travel diaries, thereby providing insights into overall usage behavior without distinguishing between EVs and internal combustion engine vehicles. This approach ensures a comprehensive analysis of trip chains across the entire vehicle fleet.

4.1 Creation of Car Usage Profiles per Individual

A five-minute mobility profile (288 entries) was created for each person and survey day to capture individuals' daily car mobility patterns. Each profile tracks the individual's location and activity status throughout the day with the car, represented by the following states: H (Home), W (Work), and O (Other locations).

If no trips with a car were recorded for an individual on a specific day, the profile was filled entirely with H (Home), which means the individual had no car activity that day.

For individuals with recorded car trips, the departure and arrival times were used to mark periods of driving (D) and location changes based on the trip's purpose (H, W, and O).

4.2 Creation of Car Usage Profiles

The car mobility profiles of individuals are aggregated into car usage profiles per car and day type. Therefore, the households were classified into three groups based on the ratio of vehicles to licensed drivers:

- Households where the number of cars matches the number of individuals with driver's licenses
- Households with more vehicles than licensed drivers
- Households with fewer than licensed drivers

For households with the same number of cars and licensed drivers, each vehicle was directly assigned to a single individual's car usage profile.

For households with more cars than licensed drivers, unused vehicles were assumed to remain at home (H) throughout the day.

Conversely, for households with fewer vehicles than licensed drivers, individual mobility profiles are aggregated to simulate shared car usage. This approach aggregates vehicle usage profiles within households based on data on car usage profiles per individual. These data are assigned to vehicles, with vehicle locations updated accordingly to reflect their use. The final output is a structured dataset that captures the usage patterns of each car throughout the day.

The final dataset offered vehicle usage profiles, detailing each car's location and activity status throughout the day and distinguishing between weekday and weekend patterns, as shown in Table 5.

Table 5: Excerpt of car usage profiles per car.

Car ID	Usage Profile	Day Type
1-3026	…WWWWWWWWWWWWWWWWDDDDDDDDDDDDDDDDDDDDDHHHH…	Weekday
2-3005	…HHHHHHHHHHHHHHHHHDDDDDDDDDDDDDDDDDDDDOOOOOOO…	Weekend

4.3 Clustering of Car Usage Profiles

The k-medoids clustering algorithm, using Hamming distance, was applied to the aggregated car usage profiles, to identify patterns in car usage on weekdays and weekends. A critical parameter for the k-medoids algorithm is the number of clusters, which significantly influences the interpretability and accuracy of the clustering results. Both the elbow method (Thorndike, 1953) and silhouette analysis (Rousseeuw, 1987) were employed to determine the optimal number of clusters.

The elbow method evaluates the total within-cluster variance (inertia) for different cluster counts. The "elbow" point, where the variance rate decreases significantly, indicates the optimal number of clusters. The silhouette analysis measures the cohesion and separation of clusters, with higher silhouette scores suggesting better-defined clusters. According to Januzaj et al. (2023), the highest silhouette score generally corresponds to the optimal number of clusters.

For weekdays, the silhouette analysis indicated the highest score with two clusters, as shown in Figure 3. However, this result was deemed insufficient to capture the diversity of car usage patterns, as it oversimplifies the behavior observed in the dataset. While not yielding a definitive "elbow," the elbow method suggested a potential range between four and six clusters. Upon analyzing results with more than six clusters, it became evident that the additional clusters offered little meaningful distinction. For example, with seven clusters, two clusters represented shopping and leisure activities with only minimal differences in timing, making them difficult to interpret or justify as separate groups. Therefore, six clusters were selected for weekday data to balance interpretability and detail. Although the silhouette score for six clusters was slightly lower than for five, the additional cluster provided more nuanced and precise insights into car usage profiles.

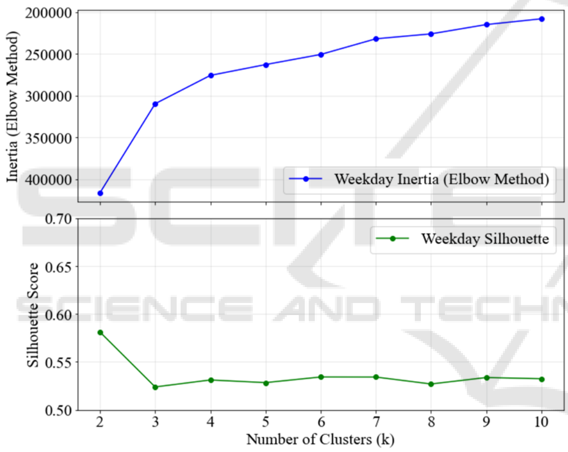

Figure 3: Determining the number of clusters for weekdays.

For weekends, the elbow method suggested a similar range, with a noticeable bend around four or five clusters (see Figure 4). However, the silhouette score analysis showed a significant decline in cohesion with five clusters compared to four. Based on these findings, four clusters were chosen for weekend data.

In summary, six clusters were selected for weekdays and four for weekends, showing characteristics of Dutch vehicle usage during these periods.

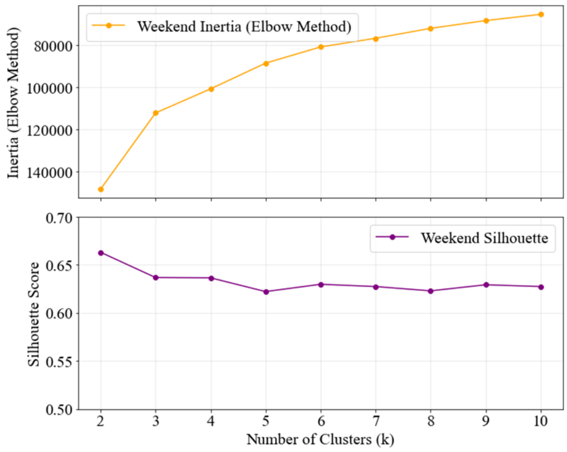

Figure 4: Determining the number of clusters for weekends.

5 RESULTS

The six distinct car usage patterns for weekdays are illustrated in Figure 5. Each cluster represents a typical car usage profile, showing obvious differences in the temporal distribution of vehicle activity states (home, work, other locations, driving).

The largest cluster (#1), representing 71.7% of the dataset, is characterized by cars that remain predominantly at home throughout the day with minimal driving activity. This cluster indicates a significant portion of vehicles that are primarily parked, suggesting a high potential for V2G applications, as these vehicles are readily available for energy storage and grid interaction. The dominance of this cluster reflects the overall low utilization of vehicles during weekdays, consistent with findings in mobility studies in Chapter 2, where most private vehicles remain unused for most of the day.

The second-largest cluster (#2), comprising 15.0% of the dataset, corresponds to the classic commuter profile. Vehicles in this cluster are primarily driven in the morning and evening, with extended parking durations at work during the day. This pattern emphasizes the potential for workplace-based V2G systems.

Cluster #4, comprising 3.6% of the dataset, also presents a commuter profile, indicating the driving activities in the morning and evening and parking at work during the day. However, the only difference with cluster #2 is that the car is parked overnight at a different location from home.

Cluster #3, accounting for 4.0% of the dataset, represents vehicles primarily used for shopping. These cars exhibit sporadic driving activity throughout the day and are parked at various non-work locations for extended periods.

In clusters #5 and #6, representing 3.5% and 2.2% of the dataset, respectively, the car is parked at another place at the beginning and at home at the end of the day. The other place could be a hotel, a second home, or a partner's place. During the day, cars show sporadic driving activity. They are parked for extended periods at different non-work locations, which could indicate less typical weekday use, such as non-routine travel for work or leisure. These patterns highlight the diversity of weekday travel scenarios, including overnight stays or irregular driving patterns.

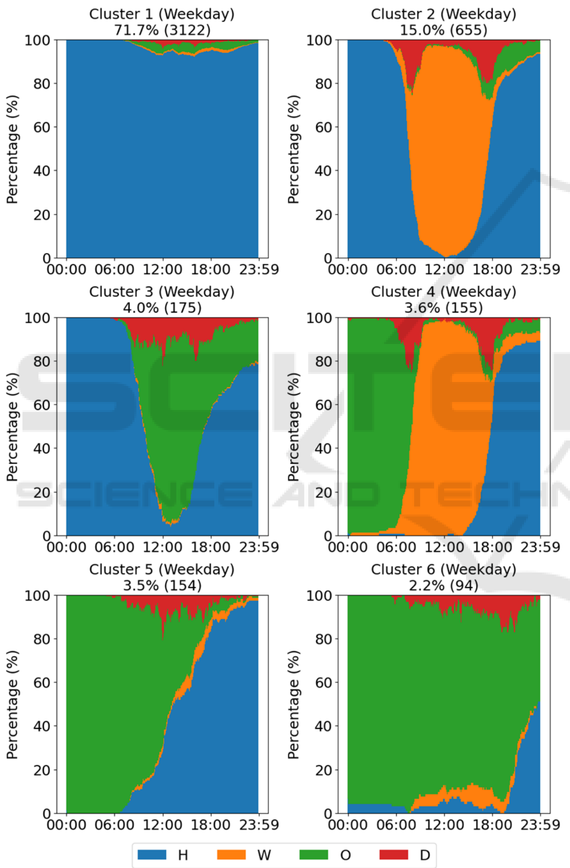

Figure 5: Car usage profiles for weekdays.

Figure 6 presents the clustering results for weekend car usage, showing four usage patterns.

The largest cluster (#1), representing 81.7% of the dataset, captures vehicles that remain predominantly at home throughout the day. This cluster highlights a significant portion of cars with no activity on weekends, reflecting limited driving needs during these days.

The second-largest cluster (#2), comprising 4.9% of the dataset, corresponds to cars used primarily for shopping and leisure activities. Vehicles in this cluster are typically driven mid-morning, parked at non-home locations throughout the day, and return to their home by evening.

Cluster #3 and #4, accounting for 4.6% and 3.1% of the dataset, reflect cars used for extended weekend trips (e.g., visiting friends, family, or travelling). Vehicles in cluster #3 start their day at home, are driven throughout the day, and end at another location. Cluster #4 describes the opposite, starting at another place and ending at home. These profiles align with weekend getaways or extended leisure trips, where vehicle availability for V2G is limited during daytime hours. The unequal ratio of vehicles leaving home and returning at the end of the day may be attributed to some individuals being driven away already during the week or to the dataset’s uneven representation of Saturdays and Sundays. However, precise information on this distribution is unavailable because the MPN dataset, as mentioned above, is only distinct between weekdays and weekends.

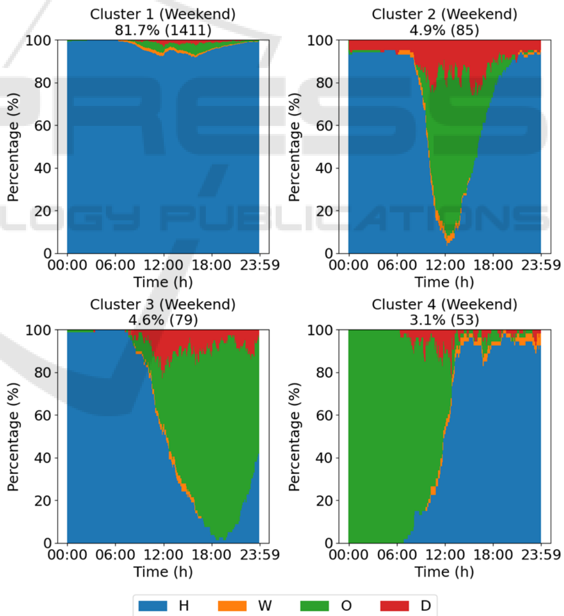

Figure 6: Car usage profiles for weekends.

The clustering results reveal distinct differences in car usage between weekdays and weekends.

Cars are predominantly parked at home during both periods, with slightly higher home parking times on weekends. The stationary behavior of vehicles at home, evident in the largest cluster for both periods, underscores the potential for V2G applications, particularly in residential settings.

While weekday profiles are dominated by work-related activity and commuting, weekend profiles emphasize leisure-related mobility (e.g., for leisure or shopping) and less work-related parking. The shopping and leisure cluster highlights midday availability, while the travel-related clusters capture more dynamic and less predictable usage patterns. Driving times remain minimal on both weekdays and weekends. Table 6 provides a detailed summary of mean parking times, standard deviations, and differences based on the ratio of vehicles to driver's license holders.

Table 6: Mean times of activity state and standard deviation for weekdays and weekends for different ratios of cars to license holders.

Ratio of Cars to License Holders	State	Mean Weekday (hours)	Standard Deviation Weekday (hours)	Mean Weekend (hours)	Standard Deviation Weekend (hours)
Less	Parking at Home	19.73	6.12	19.93	6.05
	Parking at Work	1.46	3.19	1.12	2.87
	Parking at other	2.24	4.64	2.41	4.84
	Driving	0.57	1.09	0.54	1.14
Equal	Parking at Home	19.68	6.10	20.06	6.02
	Parking at Work	1.91	3.59	1.41	3.19
	Parking at other	1.89	4.19	2.03	4.43
	Driving	0.52	0.92	0.50	1.14
More	Parking at Home	21.40	5.14	21.73	4.93
	Parking at Work	1.22	2.97	0.90	2.61
	Parking at other	1.06	3.02	1.09	3.30
	Driving	0.31	0.64	0.27	0.59

The analysis of vehicle usage patterns based on the ratio of vehicles to individuals with driver's licenses shows that households with fewer cars than driving license holders exhibit higher driving activity and lower parking durations compared to households with one or more cars per driving license holder. Specifically, in households where cars are shared, vehicles spend 19.73 hours on weekdays, and 19.93 hours on weekends parked at home, and 0.57 resp. 0.54 hours being driven. In households with a 1:1 ratio, the corresponding figures are 19.68 hours on weekdays and 20.06 hours on weekends parked at home, and 0.52 resp. 0.50 hours driven, while in households with more cars than licensed individuals, vehicles spend 21.40 hours on weekdays and 21.73 hours on weekends at home and are driven for only 0.31 resp. 0.27 hours.

6 CONCLUSIONS AND OUTLOOK

This study presents a methodology for creating and analyzing car usage profiles from the Netherlands Mobility Panel (MPN) data, laying the groundwork for assessing Vehicle-to-Grid (V2G) potential. In the data, six car usage patterns are identified for weekdays and four for weekends. For weekdays and weekends, the most significant cluster is parking at home over the whole day. On weekdays, there is also a substantial share of parking at work, whereas at the weekends, cars are often parked at other locations than home or work. Households with shared vehicles exhibit higher driving activity and lower parking durations, whereas households with more vehicles than driver license holders demonstrate longer stationary periods. The clustering results further illustrate the diversity in vehicle usage, capturing patterns ranging from daily commuting to irregular travel scenarios, such as overnight trips or extended errands. The breakdown of these usage patterns highlights that vehicles are predominantly parked at home and additionally at work on weekdays.

The vehicle usage profiles developed in this study are critical for evaluating V2G potential, as they provide insights into when and where vehicles are stationary and available for grid interaction. Understanding these patterns enables the development of tailored strategies for energy storage and grid stabilization, optimizing V2G integration into residential, workplace, and public settings.

Future research on creating and analyzing car usage profiles should prioritize using more recent and detailed datasets to capture better current trends in vehicle usage and adoption of electric vehicles (EVs). Incorporating a classification by specific days of the week, rather than the general distinction between weekdays and weekends, would provide a more accurate representation of mobility patterns, as travel behavior is likely to vary across different days. Additionally, improving spatial granularity—such as distinguishing between urban, suburban, and rural areas—would allow for a more nuanced analysis of car usage. This enhanced approach would help identify regional variations and offer deeper insights into V2G potential across diverse geographic and socio-economic contexts.

ACKNOWLEDGMENTS

This research is part of the project MORE – Munich Mobility Research Campus. The project is funded by dtec.bw – Digitalization and Technology Research Center of the Bundeswehr. dtec.bw is funded by the European Union – NextGenerationEU.

This publication makes use of data from the Netherlands Mobility Panel, which is administered by KiM Netherlands Institute for Transport Policy Analysis.

The first author conducted this research as a guest researcher at the Department of Transport & Planning (TU Delft), as part of the V2G-QUESTS project (F-DUT-2022-0241). This project was funded by the Dutch Research Council (NWO) under the Driving Urban Transitions Partnership which is co-funded by the European Commission.

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