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Exploring V2G Flexibility in Dresden: A Temporal and Spatial Mapping Approach using SUMO

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Executive Summary

This study examines Electric Vehicles (EVs) as flexible storage assets, particularly through bidirectional charging, to stabilize the energy grid amid the growing shift to renewable energy for a sustainable future. By integrating real-world travel data and smart charging algorithms into the Simulation of Urban Mobility (SUMO) software, the work establishes a synergy between energy and traffic networks, generating a flexibility map that captures the spatial-temporal characteristics of EVs in Dresden, Germany. The map reveals energy flexibility across times and regions, highlighting the potential of vehicle to grid (V2G) to enhance energy grid stability and meet regional demand.
Keywords: Electric Vehicles, Modelling and Simulation, Smart charging, V2G

1 Introduction

Transitioning to a sustainable energy system is essential for meeting long-term environmental goals and reducing reliance on conventional power sources. A notable example of this shift is Germany, which installed 14.4 GW of solar photovoltaic capacity in 2023, nearly doubling the previous year's total with a 92% increase [1]. This rapid expansion reflects the accelerating shift toward renewable energy. However, as more renewable sources are integrated into the grid, balancing supply and demand becomes increasingly challenging due to their intermittent nature, which can lead to frequent fluctuations in grid frequency and affect overall system stability [2].

During periods of high solar output, particularly around midday, the residual load, as the total electricity demand minus renewable generation, can drop significantly. On April 10, 2023, residual load in Germany turned negative for the first time, as renewable output exceeded total demand [3]. This highlights the need for rapid-response flexibility measures to ensure grid stability.

One common approach to addressing these challenges is stationary battery storage, which helps decouple the time of generation from consumption. However, this method comes with practical limitations, such as high costs, scalability issues, and environmental concerns [4]. Electric vehicles (EVs) present a promising alternative as decentralized, flexible storage assets, with considerable potential to enhance grid stability through V2G technology. In [5], the authors propose an exhaustive enumeration approach within a home energy management system to assess EV flexibility and pricing strategies. However, the individual storage capacity of EVs – typically below 100 kWh – falls short of the thresholds required for direct participation in demand-side management programs [6], limiting their standalone impact.

Aggregators play a crucial role in coordinating the collective response of numerous EVs, effectively bridging the gap between individual limitations and the large-scale flexibility needs of energy providers. To enable this, EVs must be organized into coordinated clusters, typically managed by third-party entities such as charge point operators, enabling a structured and scalable response to grid demands. Multiple aggregators may simultaneously serve a single energy provider, and with V2G technology and two-way communication, aggregator-managed EV fleets can function as dynamic energy buffers, helping to balance supply and demand by offering flexible grid support. However, for effective integration of EV-based flexibility, energy providers must have a clear understanding of three key parameters: the amount of flexible power an aggregator can provide, the duration for which this flexibility can be sustained, and the specific location within the grid where the flexibility is available.

Leveraging the full potential of EVs in grid management requires a clear understanding of their charging behavior. However, uncertainty in EV users' behavior, driven by both charging and driving characteristics, complicates this task. Consequently, studying the temporal and spatial patterns of EV charging is essential. Probabilistic approaches, such as probability theory and the Monte Carlo model based on travel chains, are widely used to model these uncertainties. For instance, [7] employed a travel chain model to simulate uncoordinated EV charging demands, analyzing location and time-based characteristics of EV behavior in China.

While recent studies have focused on sustainable smart charging goals [8], the energy flexibility potential of electric vehicles remains underexplored. Energy flexibility, defined as the ability to adjust charging behavior in response to grid conditions, is critical for effective integration into power systems. This study addresses this limitation by using the Simulation of Urban Mobility (SUMO) framework to model EV mobility, implement a smart charging algorithm, and quantify regional flexibility potential.
Our three main contributions are as follows:

1. Establishing the synergy between energy and traffic networks by extracting temporal and spatial EV travel characteristics from real-world data. These characteristics are used to create detailed travel plans, which are then fed into SUMO to generate trip data (distance, time, and battery usage).

2. Developing a smart charging algorithm aimed at maximizing flexibility and minimizing charging costs. The algorithm optimizes charging schedules to enhance the regional flexibility potential available for grid support.

3. Generating a regional flexibility map based on the spatio-temporal characteristics of EVs. This map visualizes flexibility potential across regions, supporting grid stabilization throughout the day.

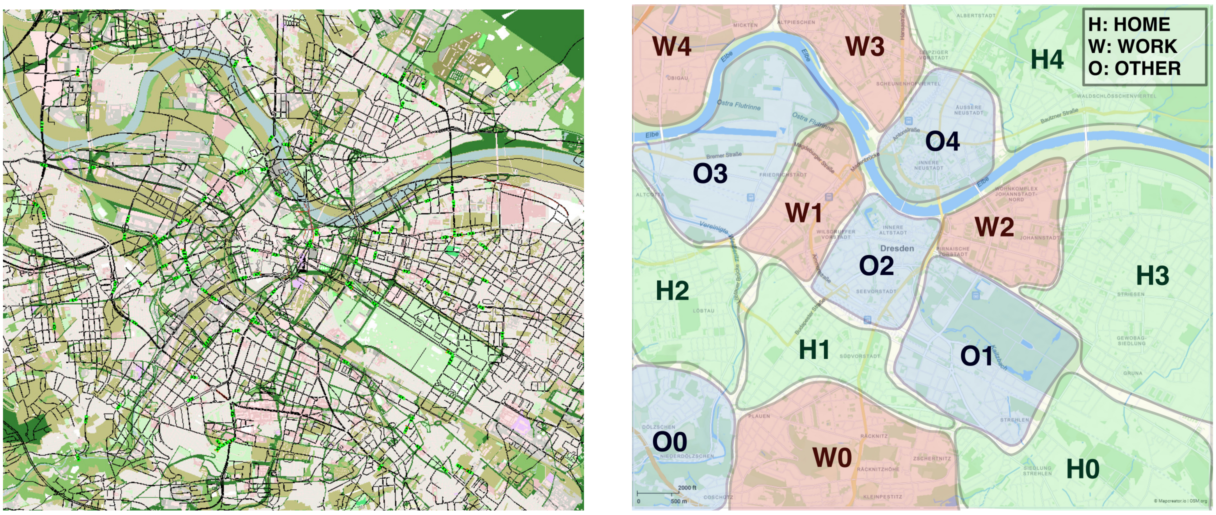
The remainder of this paper is organized as follows: Section 2 outlines the detailed methodology, including the SUMO-based simulation framework, the travel chain modeling approach, and the Mixed-Integer Linear Programming (MILP) formulation for smart charging optimization aimed at maximizing regional energy flexibility. Section 3 presents the results of quantifying flexibility across different regions. The paper concludes with key findings and potential directions for future research in the final section.

2 Methodology

This section provides an overview of the methodology for modeling EV mobility and assessing regional flexibility through local aggregators. The proposed framework incorporates three key components: a SUMO-based traffic simulation, a travel chain model, and a smart charging optimization algorithm.

SUMO is an open-source, microscopic traffic simulation platform developed by the German Aerospace Center [9]. It is widely used for modeling multi-modal transportation systems with high temporal and spatial resolution. While some studies have used SUMO to assign EVs to charging stations, estimate charging demand, and plan station locations, limited research integrates SUMO with smart charging solutions, especially for analyzing the flexibility potential of EVs to support the grid. This paper bridges that gap by using SUMO to construct the urban traffic network, simulate realistic EV driving behavior, and visualize vehicle movements for spatiotemporal flexibility analysis. Fig. 1a shows a snapshot of the SUMO interface, simulating EV traffic (green) in the city of Dresden. We select a map section of Dresden with a longitude of approximately 13.70°E to 13.80°E and a latitude of 51.02°N to 51.08°N. The map is obtained from OpenStreetMap, a publicly accessible website [10].

We divide the Dresden map into 15 regions, with 5 regions each for work, home, and other locations as illustrated in Fig. 1b. Each region has its own local aggregator responsible for performing local optimization. The objectives of each local aggregator are identical: minimizing costs and maximizing flexibility. In this scenario, we consider a total of 500 EVs, with 100 EVs allocated evenly across each home region. However, not all EV owners are assumed to participate in the flexibility program. We assume a 50% participation ratio, meaning that half of the EVs will actively contribute to the flexibility program, while the other half will charge uncoordinated, depending on availability. Furthermore, it is assumed that a charging station will be available whenever an EV arrives. To realistically model EV travel behavior throughout the day, travel chains for each vehicle were generated using the National Household Travel Survey (NHTS) dataset [11]. These travel chains represent typical daily trip patterns between home, work, and other regions. The generated travel chains are then fed into the SUMO interface to simulate traffic and generate detailed trip data, including distance traveled, travel time, and battery consumption.



(a) (b)

Figure 1: (a) Visualization of vehicle movement within the SUMO framework, (b) Dresden map divided into regions.

2.1 Travel Chain

A travel chain refers to a sequence of trips that begins and ends at the same origin, typically the home location, and includes multiple stops for activities such as work, shopping, or other purposes. As shown in Fig. 2, the travel chain model is divided into two complementary components: the time chain and the space chain. The time chain captures the chronological structure of travel behavior, detailing the start time of each trip, the duration of travel, the time spent at each stop, and the final return to the origin. This temporal information is crucial for estimating the availability windows during which EVs are parked and potentially available for charging or participating in flexibility programs. In contrast, the space chain represents the spatial transitions between different activity locations – categorized as Home (H), Work (W), or Other (O) – along the travel path. It maps how EVs move across regions throughout the day, providing insights into spatial distribution and mobility patterns. Together, the time and space chains offer a comprehensive view of EV behavior, allowing us to derive four key parameters: (1) initial trip start times, (2) stop durations, (3) travel distances between regions, and (4) transition probabilities between location types. Data from the 2017 NHTS was used to construct the travel chain [11]. Since EVs can only charge when parked, these chains are particularly valuable for estimating vehicle availability and flexibility potential across temporal and spatial dimensions.

Table 1 summarizes the key attributes used to construct travel chains. For this study, we consider only trips made using private cars. While the 2017 NHTS dataset covers a wide range of travel distances, our focus is on short-distance travel in urban areas. Following the approach in [7], we filter the data to include only trips under 100 km and use conditional probabilities to model short-distance travel behavior. This approach is suitable for the Dresden study area, where the maximum distance between regions is around 15 km.

Fig. 3 illustrates the probability distribution of the start time for the first trip of the day, which follows a Gamma distribution. The data reveals a distinct peak between 7:00 and 9:00 AM, indicating that the majority of EVs initiate their first trip during the early morning hours. This start time is critical for constructing the travel chain, as it determines the beginning of daily mobility. Once the departure time is selected based on this probability, the next step involves identifying the type of destination the EV is likely to travel to. The spatial transition probabilities, as shown in Fig. 4, guide this decision by indicating the likelihood of various trip types depending on the time of day and the trip's origin.
Fig. 4 (a) presents the transition probabilities for trips originating from home locations. It can be observed that during early time slots, especially around 7 AM, trips from home to work (HW) dominate,

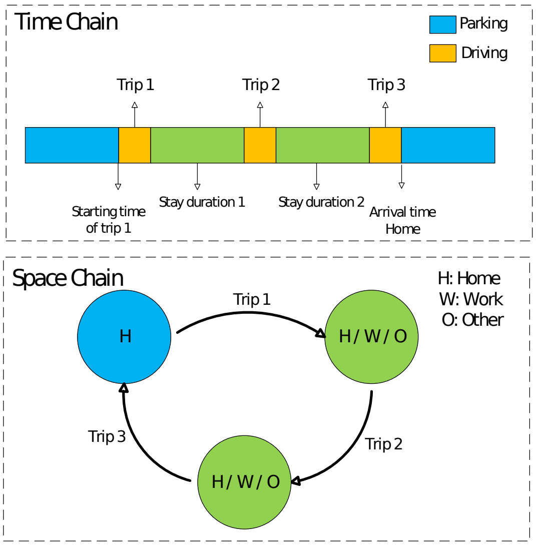


Figure 2: Travel chain model.

Table 1: NHTS data variables and descriptions

Column Name	Description
HOUSEID	Household identifier
PERSONID	Person identifier
BEGNTIME	Tour begin time (HHMM)
ENDTTIME	Tour end time (HHMM)
MODE_T	Mode of the transport
TOUR	Sequential tour number for person
TOURTYPE	Type of Tour
TOT_DWEL	Dwell time of the destination (MM)

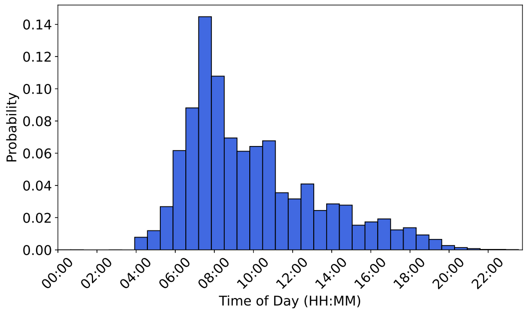


Figure 3: Probability distribution of the start time of the first trip.

reflecting typical commuting behavior. As the day progresses, the probability of trips from home to other destinations (HO) becomes more prominent. Conversely, Fig. 4 (b) shows the transition probabilities for trips starting from work locations. Here, a high likelihood of work-to-home (WH) transitions is observed during the late afternoon and evening hours, while work-to-other (WO) trips are distributed more broadly throughout the day. After selecting the destination type (e.g., Work), a specific destination location is randomly assigned using a uniform distribution over a predefined set of location IDs. For instance, if the destination is classified as 'Work', a location ID between 1 and 5 is randomly selected to represent a specific worksite. Following the destination assignment, the travel characteristics – such as trip duration, travel distance, and energy consumption – are computed using SUMO.

Upon arrival at the destination, the stopping time is determined using spatial stay duration distributions, as depicted in Fig. 5. The stay durations vary depending on the time of arrival and destination type. For example, longer stays are associated with work destinations during early hours, consistent with standard working hours. In contrast, shorter durations are more common later in the day. Once the stop duration is determined, the vehicle proceeds to its next trip, repeating the destination selection, trip generation, and stay duration steps to form a complete daily travel chain, ensuring a return to the home location by the end of the day.

To illustrate this process, consider an example where an EV begins its day at Home location H1. Based on the distribution in Fig. 3, the start time is assigned as 7:00 AM. According to the transition probabilities in Fig. 4 (a), this trip is most likely to be of type HW, indicating a commute to work. A specific work location, say W2, is then randomly selected. After simulating the trip with SUMO, the stay duration at W2 is assigned using the spatial distribution shown in Fig. 5, reflecting a long stay due to the early morning arrival. Later in the day, the EV departs W2, and based on the probabilities in Fig. 4 (b), it may either return home (WH) or travel to other location (WO), depending on the time slot and transition likelihood. In this work, we consider a maximum of three trips per EV, which allows for at most two destinations before returning to the home location. The travel chain is considered complete once the EV arrives back home, marking the end of its daily mobility cycle.

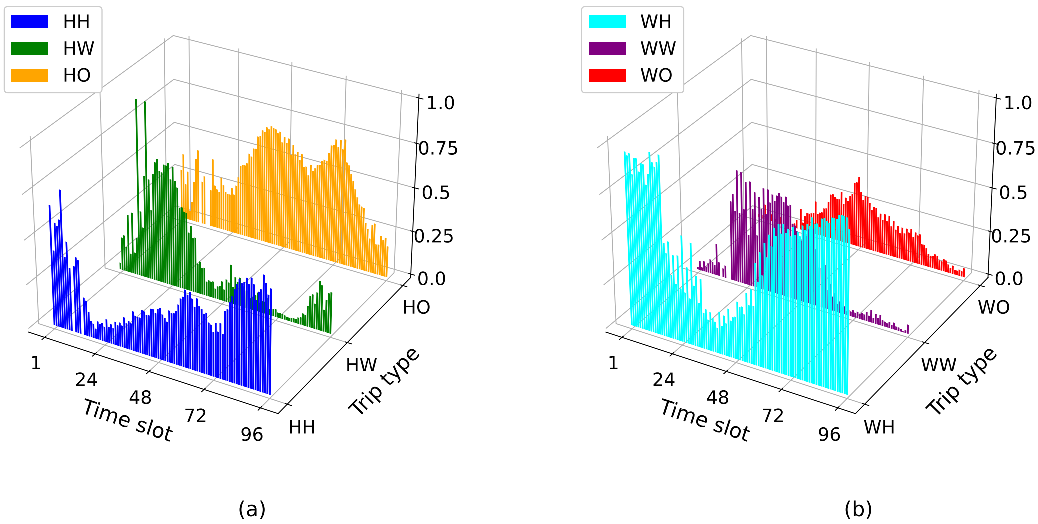


Figure 4: Spatial probability distribution (a) trip starting from Home, (b) trip starting from Work.

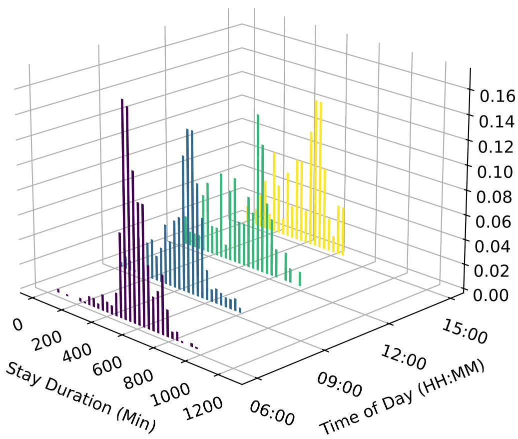


Figure 5: Spatial stay duration probability at Work location.

2.2 Smart Charging Model

To optimize the charging schedules of the EV fleet, we implement a smart charging method based on a mixed integer linear programming (MILP) framework. This method aims to coordinate EV charging in a cost-effective manner while reducing peak demand associated with uncoordinated charging behaviors. The approach ensures that each EV meets its energy requirement before departure, while also contributing to overall grid stability through flexibility provisioning. The MILP model is designed with two primary objectives as mentioned in Eq. (1): minimizing the total cost of energy consumed from the grid and maximizing the symmetric flexibility provided by the fleet as shown in Eq. (2) and (4) respectively. The key decision variable in the model is the charging and discharging power of each EV, which is treated as a continuous variable.
To solve this optimization problem, we utilize the Gurobi solver, which provides optimal solutions within a computation time of less than two minutes. The objective function is defined as:

$$\min \quad w_1 \cdot C_1 - w_2 \cdot C_2 \tag{1}$$

where C_1 represents the total energy cost from the grid, and C_2 denotes the total symmetric flexibility across all EVs. The parameters w_1 and w_2 are weighting factors to balance both objectives, where w_1 and w_2 have units of €$^{-1}$ and kW^{-1} respectively.

$$C_1 = \sum_{t=0}^{T} Cgrid_t \cdot \tau \cdot D_t \tag{2}$$

$$D_t = \max\left(\sum_{n=1}^{N} P_{n,t} + P_t^{load}, 0\right) \tag{3}$$

Here, $Cgrid_t$ is the unit cost of grid energy at time t, D_t is the demand from the grid, and τ represents the duration of a time slot (in hours). The term $P_{n,t}$ corresponds to the charging or discharging power of EV n at time t, while P_t^{load} is the charging demand of all uncoordinated EVs at time t.
The second objective, C_2, captures the total symmetric flexibility offered across the fleet:

$$C_2 = \sum_{n \in N} \sum_{t=t_n^{arr}}^{t_n^{dep}} S_{n,t} \tag{4}$$

Symmetric flexibility is defined as:

$$S_{n,t} = \min(P_{n,t}^{+}, P_{n,t}^{-}) \tag{5}$$

where $P_{n,t}^{+}$ and $P_{n,t}^{-}$ represent positive and negative flexibility, and are calculated as Eq. (6) and (7) respectively.

$$P_{n,t}^{+} = P_{\max} - P_{n,t}, \quad \forall n, t \tag{6}$$

$$P_{n,t}^{-} = P_{n,t} - P_{\min}, \quad \forall n, t \tag{7}$$

The terms $P_{\max}$ and $P_{\min}$ denote the maximum charging and minimum discharging power, respectively. SoC dynamics are given by:

$$SoC_{n,t+1} = SoC_{n,t} + \eta_c \cdot P_{n,t} \cdot \tau - \frac{P_{n,t} \cdot \tau}{\eta_d}, \quad \forall n, t \tag{8}$$

with η_c and η_d referring to the charging and discharging efficiencies, respectively. The model includes constraints to ensure safe battery operation, The model operates under several constraints as shown in Eq. (9)–(12), including maintaining the state of charge (SoC) within an allowed range, achieving a target SoC by departure time, and preventing excessive discharge that may degrade battery health.

$$SoC_{min} \leq SoC_{n,t} \leq SoC_{max}, \quad \forall n, t \tag{9}$$

where SoC_{min} and SoC_{max} represent the minimum and maximum allowable battery levels.

$$SoC_n^{departure} \geq SoC_n^{target}, \quad \forall n \tag{10}$$

Here, $SoC_n^{departure}$ is the actual SoC at the time of departure, while SoC_n^{target} is the required SoC.

$$P_{\min} \leq P_{n,t} \leq P_{\max}, \quad \forall n, t \tag{11}$$

$$\sum_{t=t_n^{arr}}^{t_n^{dep}} P_{n,t} \leq -0.5 E_n^{max} \quad \forall n \tag{12}$$

where E_n^{max} is the maximum battery capacity of EV n.
The optimized charging plan generated by this model is based on each EV's availability and stay duration at specific locations. It also serves as the basis for computing the aggregated positive and negative flexibility of each region. Since these values may differ, the symmetric flexibility is defined as the minimum of the positive and negative flexibility. In this work, each location is assumed to have a local aggregator that applies this framework to estimate the flexibility potential of its EV fleet.

Fig. 6 illustrates the role of a local aggregator in estimating the symmetric flexibility of an EV fleet at a single location. The energy provider interacts with the aggregator, which manages the flexibility of the fleet by optimizing charging and discharging schedules. Symmetric flexibility refers to the ability to increase or decrease charging power based on grid needs, helping to balance energy supply and demand.

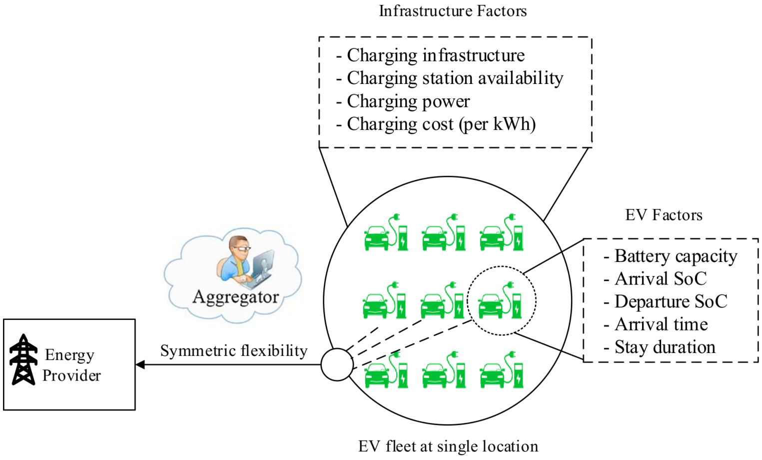


Figure 6: Role of aggregator in estimating symmetric flexibility.

The aggregator determines this flexibility by analyzing both infrastructure-related factors (charging infrastructure, station availability, charging power, and cost) and EV-specific factors (battery capacity, state of charge at arrival and departure, arrival time, and stay duration). These constraints define the extent to which the fleet can participate in the flexibility program without compromising individual EV requirements.

3 Results

To participate in the flexibility program, aggregators must meet two key criteria: First, they must be able to provide flexibility for at least 4 hours, ensuring they can remain on standby for a sustained period. Second, the allocated power must be available for a minimum of 15 minutes, guaranteeing reliability in meeting the grid's demand [13]. These criteria ensure that the aggregator can consistently and reliably contribute to the grid flexibility program.

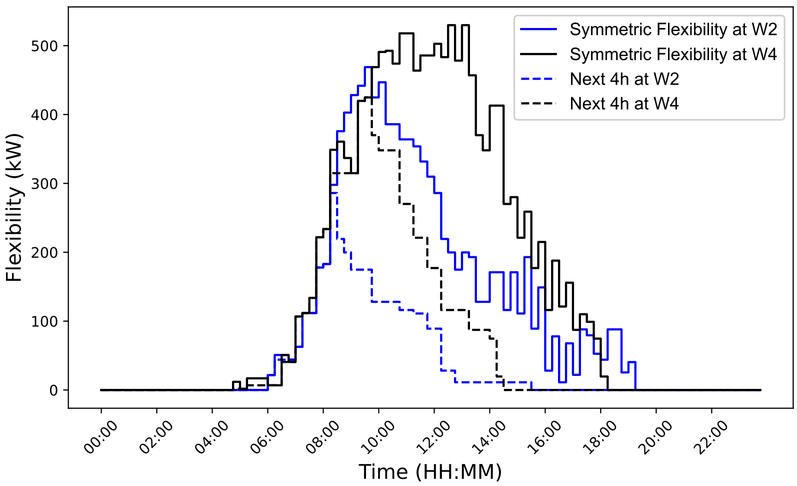


Figure 7: Spatial probability distribution at different work locations.

Fig. 7 shows the symmetric flexibility profiles at two work locations, W2 and W4. Solid lines represent the total symmetric flexibility available throughout the day, while dashed lines indicate the flexibility estimated for the upcoming 4-hour window. Specifically, the blue lines correspond to W2 and the black lines to W4. For instance, at 10:00 AM, the aggregator estimates approximately 350 kW of symmetric flexibility available at W4 over the next 4 hours. This means that if an agreement is made with the energy provider at that time, the aggregator commits to remaining on standby, ensuring that the allocated power can be provided on request for at least 15 continuous minutes during the contract window.

Fig. 8 illustrates the distribution of symmetric flexibility (in kW) across various region types and times of the day during daytime hours. The heatmap reveals how flexibility availability varies by region and time, providing insights into temporal and spatial patterns of EV availability for flexibility services. The X-axis represents the time (HH:MM), while the Y-axis categorizes region types into home (H0–H4), work (W0–W4), and other (O0–O4) locations. Flexibility in the home region is high in the early morning and late evening, with even greater potential at night as EVs return to their home locations after completing all trips. For this reason, nighttime flexibility potential is not shown. For the work region, the peak flexibility potential occurs between 08:00 and 13:00, and for the other regions, the flexibility is limited due to variations in EV arrival and departure times.

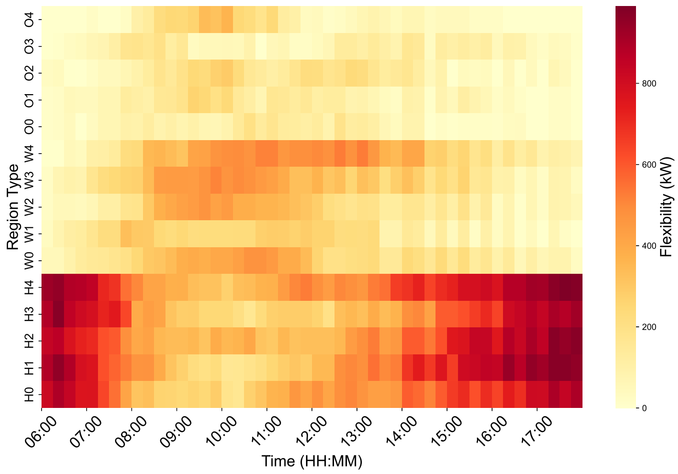


Figure 8: Daytime flexibility map by region.

Conclusion and Future Work

This paper establishes a synergy between energy and traffic networks through the integration of real-world travel data, the SUMO traffic simulation platform, and a smart charging algorithm based on a Mixed-Integer Linear Programming (MILP) approach. By modeling daily EV commute and optimizing charging schedules, we generate a spatial-temporal flexibility map that captures the regional flexibility potential of EV fleets in Dresden. This map highlights how local optimization at each region can maximize the flexibility available for grid support, revealing the crucial role of smart charging in balancing supply and demand. The optimization of charging schedules enhances grid stability by offering flexible energy provisioning, ensuring that EV fleets can contribute to grid management while minimizing costs and reducing the impact of renewable energy variability.

In the future, we will extend this framework to a joint optimization model, where aggregators coordinate across regions to better allocate flexibility resources city-wide. While the current results offer insights into daily flexibility patterns based on a one-day simulation, we also plan to explore the German Mobility Panel (MOP) dataset to evaluate flexibility over a longer time horizon, enhancing the statistical robustness and real-world applicability of our model.

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References

[1] B. Wehrmann, *Solar power in Germany – output, business & perspectives*, Clean Energy Wire, 2024. [Online]. Available: https://www.cleanenergywire.org/factsheets/solar-power-germany-output-business-perspectives

[2] Q. Hassan et.al., *A review of hybrid renewable energy systems: Solar and wind-powered solutions: Challenges, opportunities, and policy implications*, Results in Engineering, vol. 20, p. 101621, 2023.

[3] K. Balasubramanian, *Deutschlands Duck Curve – Erneuerbare Energien in Smart Grids integrieren*, gridX, Mar. 2024. [Online]. Available: https://www.gridx.ai/de/blog/deutsch\protect\discretionary{\char\hyphenchar\font}{}{}lands-duck-curve-der-energie

[4] A. A. Kebede, et.al., *A comprehensive review of stationary energy storage devices for large- scale renewable energy sources grid integration*, Renewable and Sustainable Energy Reviews, vol. 159, p. 112213, 2022.

[5] M. Zade et.al., *Prosumer Integration in Flexibility Markets: A Bid Development and Pricing Model*, in 2018 2nd IEEE Conference on Energy Internet and Energy System Integration (EI2), Beijing, China, pp. 1–9, 2018.

[6] Agency for the Cooperation of Energy Regulators (ACER), *Demand response and other distributed energy resources: What barriers are holding them back? 2023 Market Monitoring Report*, 2023. [Online]. Available: https://www.acer.europa.eu/en/market-monitoring-report-2023

[7] W. Shu et.al., *Temporal and Spatial Characteristics Analysis of Electric Vehicle Charging Behaviour Based on SUMO*, in 2021 IEEE Sustainable Power and Energy Conference (iSPEC), Nanjing, China, pp. 3544–3550, 2021.

[8] S. Shen et.al., *A Heuristic for Bi-Directional Charging of Fleet EVs*, Proceedings of IEEE Sustainable Power and Energy Conference (iSPEC), Kuching, Malaysia, pp. 595–601, 2024.

[9] P. A. Lopez et.al., *Microscopic Traffic Simulation using SUMO*, in 21st IEEE International Conference on Intelligent Transportation Systems, Hawaii, United States, pp. 2575– 2582, 2018.

[10] OpenStreetMap contributors, *Planet dump retrieved from https://planet.osm.org*, 2017. [Online]. Available: https://www.openstreetmap.org

[11] U.S. Department of Transportation, *2017 National Household Travel Survey*, June 2021. [Online]. Available: http://nhts.ornl.gov

[12] S. Zhao et.al., *EV charging demand analysis based on trip chain theory*, Electric Power Automation Equipment, vol. 37, no. 8, pp. 105–112, 2017.

[13] S. Englberger et.al., *Electric vehicle multi-use: Optimizing multiple value streams using mobile storage systems in a vehicle-to-grid context*, Applied Energy, vol. 304, p. 117862, 2021.

Presenter Biography

Syed Irtaza Haider holds an M.Sc. in Electrical Engineering from King Saud University and a B.E. in Electrical Engineering from the National University of Sciences and Technology. His research focuses on evolutionary computing, machine learning, AI in smart grids, and data science. He is currently a Ph.D. student at TU Dresden, working on the DymoBat project to develop energy grid solutions using distributed energy resources and 5G technologies.