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Individual driver emission reduction due to electric vehicle-based residential load shifting: Insights from Germany

Jessica Bollenbach [a,b,c], Niklas Eiser [a,b,d,*], Felix Baumgarte [a], Robert Keller [e], Jens Strüker [a,b,c]

[a] Branch Business & Information Systems Engineering of the Fraunhofer FIT, Alter Postweg 101, 86159 Augsburg, Germany
[b] FIM Research Center for Information Management, Alter Postweg 101, 86159 Augsburg, Germany
[c] University of Bayreuth, Universitätsstraße 30, 95447 Bayreuth, Germany
[d] Technical University of Applied Sciences Augsburg, An der Hochschule 1, 86161 Augsburg, Germany
[e] Kempten University of Applied Sciences, Bahnhofstraße 61, 87435 Kempten (Allgäu), Germany

A R T I C L E I N F O

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A B S T R A C T

Commuters require measures tailored to their individual behavior to reduce emissions associated with their residential electricity demand. This paper investigates the operation of a spatiotemporal residential load-shifting concept where Electric Vehicles (EVs) charge low-emission electricity from the grid at the workplace (rather than at a commuter's residence), function as mobile energy storage device, and cover residential electricity demand through battery discharging. The success of this strategy in reducing emissions hinges on aligning electricity demand with the country- and time-specific emissions associated with grid electricity constrained by individual behavioral habits. In this paper, we analyze why and how much seasons and driver behavior (in terms of both the commuter's driving and residential electricity demand behavior) change the emission reduction impact of EV-based residential load shifting. We contribute to the literature by explaining the changes in emission reduction and validating previous results with German conditions using real-world behavioral and grid data. While winter yields a −0.3 % median emission reduction, summer offers a promising median potential of 24 % and a maximum of 42 %. Commuters with a daily driving distance above 110 km who arrive home after 08:00 p.m. stand out, as they reduce emissions by more than 10 % above the average. These insights contextualize optimistic assessments of EV-based residential load shifting, indicating that the individual impact for Germany-like conditions is rather small.

Abbreviations

CO_2	Carbon Dioxide	RES	Renewable Energy Sources
CRISP-DM	Cross Industry Standard Process for Data Mining	SHAP	Shapley Additive Explanations
EU	European Union	SRED	Average Standard Residential Electricity Demand
EV	Electric Vehicle	V2B	Vehicle-to-Building
GHG	Greenhouse Gas	$V2B^2$	Building-to-Vehicle-to-Building
kW	Kilowatt	Wh	Watt-Hour
kWh	Kilowatt-Hour	XGB	Extreme Gradient Boosting
PV	Photovoltaic		

1. Introduction

Accelerating the transition toward a more sustainable society requires a set of different measures, including decarbonizing residential electricity demand. For this reason, the European Union (EU) has legally committed to a 40 % increase in the share of Renewable Energy Sources (RES) in the EU electricity mix by 2030 (European Parliament, 2021). Germany announced it would target an 80 % RES share by 2030 (Federal Government, 2022a). The utilization of RES in the residential sector is essential to increase the overall RES share and reduce residential Greenhouse Gas (GHG) emissions since this sector accounts for around

* Corresponding author.
E-mail address: niklas.eiser@fit.fraunhofer.de (N. Eiser).

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28 % of total German electricity demand in 2023 (Bantle, 2024). Although the share of renewables in the electricity mix is steadily increasing (Federal Government, 2024), residential emissions have stagnated in recent years. As emission minima associated with the electricity mix and residential consumption peaks decouple over time, residential emissions remain challenging to reduce (Federal Environmental Agency, 2021). Residential demand of residents who leave home for work (referred to as commuters in this paper) typically peaks twice: during morning and especially during evening hours (Fischer et al., 2015). At the same time, emissions associated with the country-specific electricity mix find their lowest point at divergent times. For regions with grid conditions similar to Germany, for example, emissions in summer are typically lowest during midday, primarily due to high Photovoltaic (PV) output. In winter, emissions might also reach their daily low during the night when production from wind turbines is high and electricity demand is low. Thus, RES are particularly challenging to integrate into established residential demand profiles. With the growing share of RES in the electricity mix, households need solutions for energy storage to combine their morning and evening demand peaks with periods of high RES output.

Here, the ongoing decarbonization of transport via electrification (Federal Transport Authority, 2024) presents a promising remedy when EVs are integrated into the energy ecosystem (Buonomano, 2020). Currently, up to 88 % (Baresch and Moser, 2019) of charging occurs at home, typically overnight after commuters plug in their EV upon arriving home. This additional electricity exacerbates evening residential peak demand and aggravates the decoupling of electricity demand and RES on-peak hours (Muratori, 2018). Wu et al. (2024) advocate expanding daytime charging options like workplace charging. Buresh et al. (2020) emphasize its necessity to ensure grid stability, while workplace charging is also identified as a key strategy to reduce charging-related emissions (Rangaraju et al., 2015). Longer idle times of EVs at the workplace that typically occur during the daytime enable an emissions-optimized timing of charging processes. However, the electricity mix plays a crucial role in integrating RES into the charging process, thus charging related emissions (Rangaraju et al., 2015). On top of this, challenges persist, such as insufficient parking and charging infrastructure, for example, due to a lack of parking lots (Su et al., 2025). Appropriately expanding workplace charging infrastructure is therefore critical to unlock these benefits. If accomplished, Fu et al. (2025) report high acceptance of this new strategy among EV owners.

To extend the potential of EV workplace charging, different papers include bidirectional workplace charging, i.e., Vehicle-to-Building (V2B), in their investigation. Thereby, they all prove the effectiveness of combining these two for various objectives, such as peak-shaving (Odkhuu et al., 2018) and operational cost reduction (Englberger et al., 2021), or reduction of electricity demand from the grid (Lo et al., 2023). However, these papers focus on the temporal shifting of charging processes. Thus, benefits remain with the employer, and in particular, night-time discharging is not available for private vehicles, given that they are driven home. Here, the literature suggests Building-to-Vehicle-to-Building (V2B^2) as an attractive concept for commuters to make the advantages of increased RES output accessible to residential buildings (Barone et al., 2019). In essence, the V2B^2 approach, as implemented within our study, involves an EV that charges grid electricity at a workplace building, acts as mobile energy storage device, and discharges at the residential building to cover household demand. Effectively, the shift of (dis)charging processes in both spatial and temporal dimensions enables a corresponding spatiotemporal shift in electricity grid demand (Barone et al., 2019). This means residential electricity demand is shifted virtually to times at the workplace via the mobile battery of the EV. Yu et al. (2022) find V2B^2 to substantially reduce the net load volatility for a microgrid with multiple offices, residential buildings, and EVs in Beijing. Other V2B^2 literature provides insights into individual benefits and reveals a reduction of electricity consumption from the grid (Barone et al., 2019) or total system costs (Niu et al., 2024). However, so far, V2B^2 literature lacks insights into the emission reduction potential and its dependence on the interaction between country-specific electricity mixes and individual driver behavior (in terms of both the commuter's driving and residential electricity demand behavior) to integrate more sustainable energy sources.

To account for personal habits, literature agrees on the importance of relying on empirical and real-world input data (Rangaraju et al., 2015). Existing V2B^2 literature mostly neglects the influence of individual profiles and simulates only a few synthetic ones (Barone et al., 2019). Recently, Niu et al. (2024) started to fill this gap by modeling stochastic driving behavior based on real-world data and optimizing numerous derived profiles concerning total system cost minimization. However, they enhance V2B^2 literature only by an overall cost margin, i.e., by giving insights into how much absolute values change. They lack insights into the key characteristics of individual profiles that cause changes in their results, i.e., why and how much results change for individual profiles. To add knowledge to this blind spot, we also account for individual behavior but now identify the essential driving and residential electricity demand profile features that drive the ecologic potential of V2B^2 and the changes they cause. Understanding the impact of individual behavior in detail marks a central cornerstone for focusing measures and incentives on the target group with the most promising potential. Therefore, our paper investigates numerous driving and residential demand profiles based on empirical and real-world observations from Germany to account for individual behavior. To depict individual habits precisely, we use a high temporal resolution of 15-min intervals (Rangaraju et al., 2015).

In addition, the V2B^2 system requires coverage by the electricity grid, regardless of additional infrastructure (e.g., PV or stationary energy storage) installed (Barone et al., 2019). Therefore, timing electricity grid demand and considering the grid's country- and time-dependent associated emissions is crucial (Nilges et al., 2024), although V2B^2 literature neglected this effect so far (Barone et al., 2019). Niu et al. (2024) consider grid electricity for charging their EV but calculate the emissions in their economic optimization only with a yearly emission factor, neglecting volatile RES. We fill this knowledge gap by investigating the current German grid electricity mix with a RES share of up to 88 %. Following Goldsworthy and Aryai (2023), we calculate average emission factors for every 15-min interval to determine emission reduction from shifting demand. Förster et al. (2024) applied this approach in a similar context to quantify the emission reduction potential of energy flexibility measures.

On the one hand, this enables us to contribute to the question of why and how much the emission reduction potential of spatiotemporal load shifting within V2B^2 varies for individual driver behavior. On the other hand, we validate V2B^2 results of more solar-intensive regions like Italy (Barone et al., 2019) and Beijing (Yu et al., 2022) with central European weather conditions, given by a case study of the German electricity mix.

We use empirical and real-world data on German driving behavior and residential electricity demand to realize this goal. The associated emissions from grid electricity are calculated based on the 2023 electricity mix of the German electricity grid. To obtain operational emission savings of V2B^2 operation, we benchmark our approach against a typical at-home charging-only scenario. We simulate 35,000 combinations of driving and residential electricity demand behaviors for both scenarios, ensuring that daily driving requirements are met, to calculate the corresponding CO_2-equivalent emissions. With the simulation results, we train an Extreme Gradient Boosting (XGB) machine learning model predicting emission reduction based on commuting behavior and residential electricity demand. This enables us to examine why and how much the interaction between the available electricity mix and individual behavioral characteristics changes the V2B^2 potential using Shapley Additive Explanation (SHAP) values. The remainder of this paper is structured as follows. In Section 2, we present our methodology and parameterize our case study before we examine the results in Section 3. Section 4 discusses the results and outlines political and practical implications, limitations, and possible future work. Section 5 concludes this paper.

2. Methods

Our overarching methodology for simulating and analyzing V2B^2 builds on the Cross Industry Standard Process for Data Mining (CRISP-DM) (Wirth and Hipp, 2000), which is considered an appropriate framework for our goal-driven simulation approach (Martinez-Plumed et al., 2021). We derive a six-step methodology (cf. Fig. 1) comprising six phases: Business understanding, data understanding, data preparation, simulation model (modeling I), explanation model (modeling II), and evaluation.

Business Understanding: In the first phase, we contextualize our research. Based on existing literature of more solar-intensive regions like Italy (Barone et al., 2019) and Beijing (Yu et al., 2022), spatiotemporally shifting residential electricity demand to the workplace using EVs as mobile energy storage seems to yield a promising potential for emission reduction. This potential, however, depends on individual driving and residential electricity demand behaviors and their compatibility with country-specific times during which low-emission electricity is available. Therefore, we aim to analyze why and how much the emission reduction potential of spatiotemporal load shifting varies for individual driver behavior. Further, we validate V2B^2 results of more solar-intensive regions with central European weather conditions. To answer questions of "why" and "how", Benbasat et al. (1987) identify case studies as a particularly suitable research method. Similar to Nilges et al. (2024), we apply a case study for Germany to investigate our quantitative energy systems design question.

Data Understanding: To provide insights into the topic of our research question and adequately account for personal habits, we require data with high temporal resolution on emissions associated with the grid's electricity mix as well as data on individual driving and residential electricity demand behaviors (Rangaraju et al., 2015). We rely on properly fitting existing datasets that contain wide ranges of empirical and real-world profile data from Germany, described in Sections 2.1.1 and 2.1.2 in detail.

Data Preparation: To prepare our datasets for the simulation model (modeling I) and the explanation model (modeling II), we extract relevant features from the datasets and ensure high data quality using the two-stage LANG approach (Zhang et al., 2019). We refer to Section 2.1.2 for a more detailed data description.

Simulation Model (Modeling I): We first obtain the V2B^2 emission reduction potential for every individual profile by simulating an at-home charging benchmark and a V2B^2 scenario to prepare the evaluation of causal relations with the explanation model. Section 2.2.1 describes our simulation development process based on Balci (1989) and both cases in detail.

Explanation Model (Modeling II): For the explanation model described in Section 2.3, we first reduce the feature space to features that are causal for the V2B^2 emission reduction potential. Using that feature space, we train an Extreme Gradient Boosting (XGB) supervised machine learning and analyze causal relations using the post-hoc interpretation technique of Shapley Additive Explanation (SHAP) values (Lundberg and Lee, 2017), a technique becoming increasingly popular across various fields for providing insights into model results (Bollenbach et al., 2024).

Evaluation: We analyze our simulation results and causal relations in Section 3.

2.1. Data understanding and data preparation

2.1.1. Electricity mix emissions data

Our study aims to identify the emission reduction potential of implementing a V2B^2 approach based on electricity mix emissions associated with individual demand patterns. Therefore, it is crucial for our work to select the metric that is best suited to capture emission-reducing behavior. For this purpose, the literature describes two primary methods: marginal emission factors and average emission factors (Goldsworthy and Aryai, 2023). Both marginal (Koebrich et al., 2025) and average (Förster et al., 2024) emission factors are widely used in research, and no standardized method has yet evolved (Goldsworthy and Aryai, 2023).

Marginal emission factors refer to the emissions emitted or saved by increasing or decreasing electricity demand by one unit. The calculation of this factor depends on the price-determining power plant in operation during the respective settlement period and the emissions associated with the operation of this power plant. Marginal emission factors are

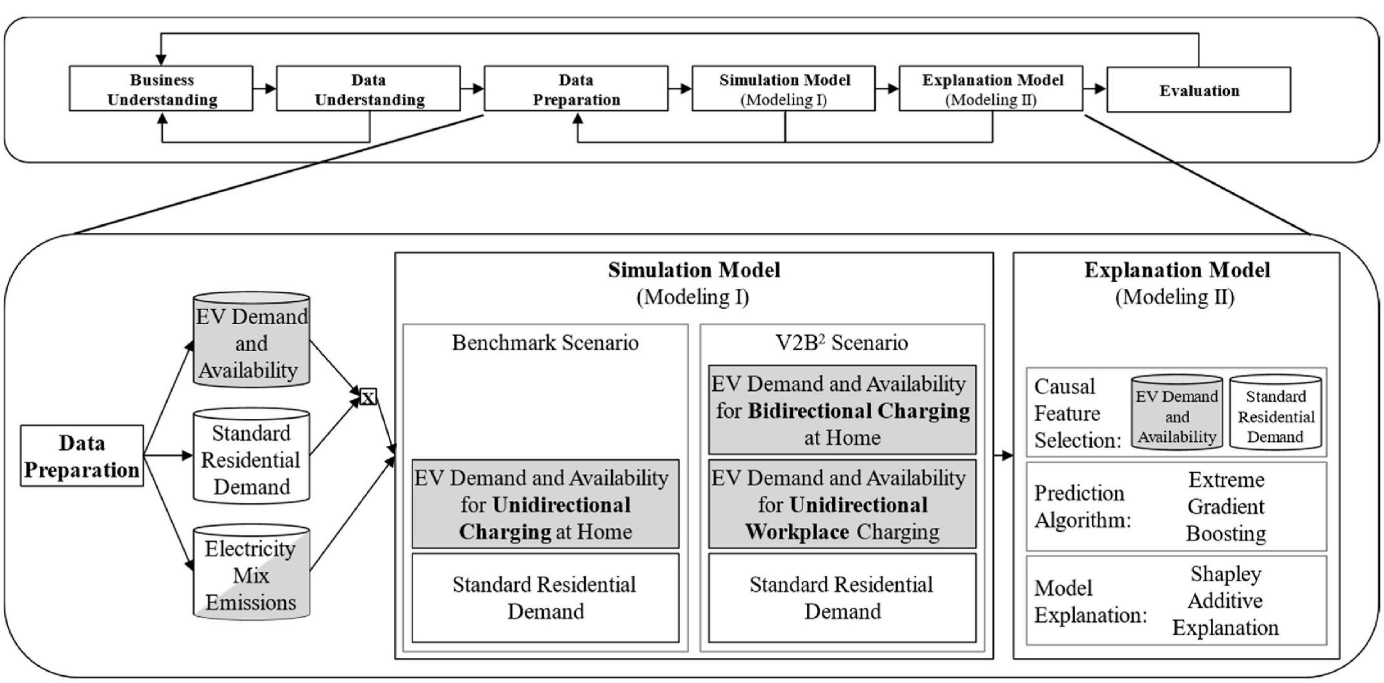

Fig. 1. Illustration of our six-step CRISP-DM adaptation.

very regional due to local grid stabilization measures (Koebrich et al., 2025). Thoroughly including those effects introduces considerable complexity.

Average emission factors represent a time interval-related average of the emissions associated with the power plants in operation, weighted by their respective net electricity generation. Ryan et al. (2016) recommend using average factors to allocate emissions to existing consumers and marginal factors to attribute emissions to load changes. Shu et al. (2023) demonstrate the latter's application by attributing emissions to a large-scale EV adoption in India. However, if the change in electricity consumption is small compared to the whole system's power, Baumgärtner et al. (2019) state that average emission factors can also be used for load changes. Goldsworthy and Aryai (2023) take it one step further and recommend employing average emission factors to determine emission reduction from shifting demand. Their paper compares the results of applying both marginal and average emission factors to investigate the impact of shifting residential electricity demand. They conclude that shifting demand to reduce marginal emissions yields negligible emission reduction, while average emission factors as an objective variable significantly cut emissions. Förster et al. (2024) build on that and demonstrate the practical application of average emission factors to quantify the emission reduction potential of energy flexibility measures.

Thus, we follow the recommendation of Goldsworthy and Aryai (2023) and rely on average emission factors for the remainder of this paper. To properly account for the time-dependency of emissions associated with a country-specific electricity generation mix, we calculate the GHG emissions resulting from the energy required to generate one unit of grid electricity (i.e., net electricity) (Canals Casals et al., 2016).

The data set employed in this study comprises electricity generation in Germany, recorded at 15-min intervals and classified according to the type of energy generation (ENTSO-E, 2024). Based on this data, we calculate the CO_2-equivalent emissions associated with net electricity generation, considering the supply chain of each energy generation type (Lauf et al., 2021). We apply these steps for 2017, 2019, 2021 (cf. Fig. A1), and 2023 (cf. Fig. 2) to obtain the emissions per 15-min interval in [g/kWh] for different years to ensure the transferability of our results.

A monthly comparison of the daily trajectory across these four years indicates a high degree of transferability. Since we examine the emission reduction by shifting electricity demand from the grid within one day, these daily trajectories of time-dependent emissions are decisive for our analysis. Furthermore, the difference between maximum and minimum emissions throughout the day varies over a year, necessitating the investment of different seasons. In summer, the monthly correlation coefficients between years are almost exclusively above 0.9. In winter, one year's month typically deviates from the trend, with the other correlation coefficients still at around 0.9. Given that the winter difference between the electricity mix maximum and minimum emissions is small, the results remain transferable to previous years. Based on this observation, we select the 2023 electricity mix in our simulation to investigate the most recent data of the German electricity grid with a RES share of 58 %. To account for minor fluctuations between years, we further discuss the transferability after this paper's results.

2.1.2. *Driver profiles: EV demand data and standard residential electricity demand data*

We derive data for EV driving profiles and charging needs from the data set "Mobility in Germany (2017); Nobis and Koehler (2018). The dataset contains specific information about 259,509 respondents and their driving profiles. Each respondent recorded their daily mobility behavior in detail, providing a holistic picture of existing driving profiles across all days of the week. Over the past decades, comparative analyses of mobility behavior have demonstrated that cars are primarily used for commuting to work and shopping trips (Wittwer et al., 2019). While car usage has peaked and is gradually declining in many European cities (Wittwer et al., 2019), it continues to be regarded as the most essential mode of transportation (VDA, 2023). Although factors such as increased public transportation use in cities or a rise in home office work have led to minor changes in the frequency of these patterns, the fundamental composition of mobility behavior remains unchanged. Consequently, the 2017 dataset remains a valid resource for analyzing which mobility behaviors have the highest potential for emission reduction through V2B[2]. First, we rely on the two-stage LANG approach that Zhang et al. (2019) developed for data preprocessing to clean the dataset syntactically and semantically. Since our investigation focuses on residents who drive to dayshift work by car daily, we exclude all profiles without a car ride, as well as profiles of holidays or weekends and profiles where no journey to work or home occurs. For the remaining profiles, we reduce the feature space to features containing information about a journey's time, distance, and purpose. Finally, we round each journey's departure and arrival times according to our 15-min intervals for evaluation and will continue our analysis with the remaining 26,220 profiles.

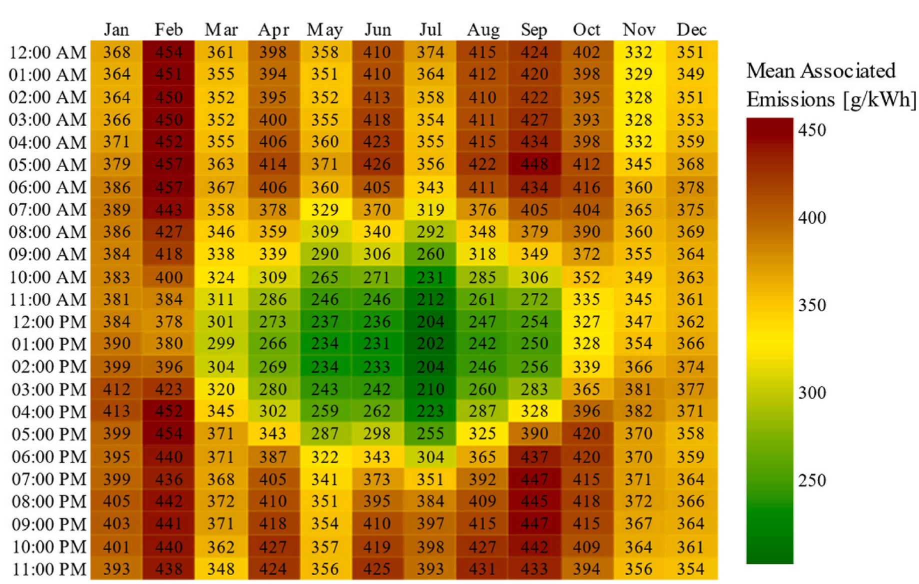

Fig. 2. CO_2-equivalent emissions associated with producing (including energy type-specific supply chain emissions) the German electricity mix in 2023 per hour and month.

To obtain the standard residential electricity demand profiles, we rely on data from the project "Modern Residential Energy Saving Systems" (Hoffmann et al., 2012). This dataset contains electricity data for 211 German households measured in 15-min intervals between 1st October 2009 and 30th April 2011, as well as characteristic information about the residents. For our analysis, we consider data from 1st January 2010 to 31st December 2010. Due to the unavailability of more recent data with a comparable number of observations, temporal resolution, and available metadata, we opted for the 2010 data. To appropriately contextualize the data, it's essential to consider the following trends from recent years: The energy efficiency of household appliances has improved, resulting in a slight reduction in overall electricity consumption (Federal Environment Agency, 2024). At the same time, the number of electronic devices in households has increased, presenting a compensating trend (United Nations, 2024). Since 2010, there has been a substantial rise in the number of PV systems (KfW Research, 2024), which meet electricity demands during daylight hours when residents are typically at work. However, they do not cover the crucial morning and evening peak demand. While incorporating a stationary battery system could mitigate this issue (Malhotra et al., 2016), it demands additional resources beyond those required for the EV battery. Therefore, we examine the emissions reduction potential of the V2B^2 approach without relying on a stationary battery at home. Additionally, the anticipated increase in heat pump installations may boost residential electricity consumption in the future (Federal Government, 2022b), which is why their impact is discussed in Section 4.2. Finally, EVs represent a significant new energy consumer, yet they are also a central focus of this study and are explicitly modeled within this paper. Considering that some trends have counterbalanced each other, resulting in relatively stable total residential electricity demand in recent years (Federal Environment Agency, 2024) and that EVs are the primary new consumer explicitly modeled, data from 2010 provides a reliable basis for our investigations. We keep relying on Zhang et al. (2019) for data preprocessing. We remove values below 0 kWh or above 10.8 kWh (DIN e.V., 2021) and impute missing values. Finally, we only keep profiles likely to host at least one resident working regularly before continuing our analysis with the remaining 160 profiles.

To analyze the V2B^2 emission reduction potential, we select a representative subset of the profiles obtained by the previous steps. Using stratified sampling (Cohen, 2014), we sample a set of 500 driving and 70 standard residential demand profiles. To obtain individual driver profiles, we cross-join the 500 driving profiles with each of the 70 standard residential demand profiles, resulting in 35,000 individual driver profiles, which we will use in our two modeling phases.

2.2. Benchmark and V2B^2 simulation model (Modeling I)

2.2.1. Generic simulation model

To investigate why and how much different driver behavior changes the emission reduction potential of V2B^2 in its interaction with the country-specific electricity mix, we implement a simulation model based on the ten-step simulation procedure outlined by Balci (1989). Fig. 3 illustrates the system layout of our simulation scenarios. Similar to Niu et al. (2024), we compare our grid-dependent V2B^2 layout to the currently dominating EV charging behavior, using it as our benchmark, resulting in two scenarios. The benchmark scenario combines the standard residential demand, covered by the at-home grid connection, with established at-home charging habits. This way, it accounts for the currently dominating charging routine, as up to 88 % of charging processes are at home (Baresch and Moser, 2019). The grid-dependent V2B^2 builds upon this concept by extending the model to include workplace charging and bidirectional at-home discharging, with the EV functioning as mobile energy storage. This configuration enables the transfer of electricity charged at the workplace to the residential side. Choosing these two scenarios allows us to answer whether grid-dependent V2B^2 is worth adapting existing behavior and which individuals would profit the most from a behavioral change.

Fig. 4 presents an exemplary artificial power demand profile, closely modeled on real-world data, for the benchmark case and V2B^2 approach. The figure demonstrates the concept of spatiotemporally shifting electricity demand from the grid for a portion of residential electricity demand and the EV charging process to the workplace. In this example, the commuter departs home with the EV at 07:00 a.m. and returns at 06:00 p.m.

For the exemplary commuter, the benchmark scenario leads to a power demand peak after arriving home at 06:00 p.m., primarily due to at-home EV charging. This electricity demand peak for EV charging can be shifted to the workplace if only one daily charging process is required. Further, when the EV is charged during the day, the parked EV at home could cover residential demand between 06:00 p.m. and 07:00 a.m. Therefore, the residential electricity demand during this period is virtually shiftable to alternative EV charging times. The actual residential electricity demand covered by the EV depends on the EV's remaining battery capacity and the capacity needed to satisfy commuter-specific driving needs the following morning, including a buffer.

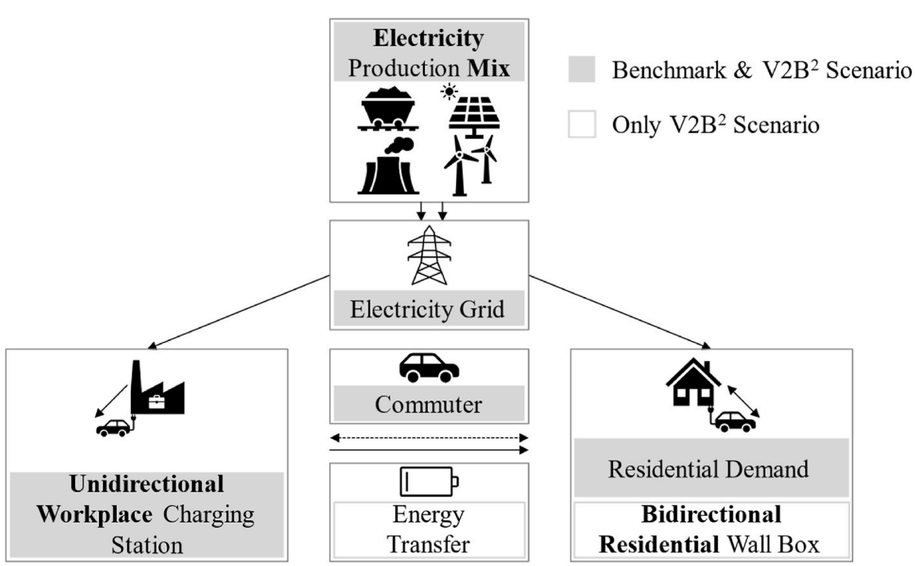

Fig. 3. Investigated system layouts.

In the $V2B^2$ scenario, the EV charges via the workplace grid connection and can meet residential electricity demand while parked at home. For the exemplary profile of Fig. 4, the driver's EV has sufficient battery capacity to cover the residential demand between 06:00 p.m. and 07:00 a.m. At the same time, we assume residential electricity power demand will remain below the EV's maximum discharging capability. Consequently, power demand at the at-home grid connection is reduced to zero between 06:00 p.m. and 07:00 a.m., virtually shifting residential demand to the EV's workplace charging time. However, it is essential to note that for real-world driver profiles within our simulation, some residential electricity demand during an EV plug-in period at home may remain unshiftable due to driving need-related constraints or constraints of discharging power capabilities.

In summary, the EV charging demand and residential electricity demand remain identical for both the benchmark and $V2B^2$ scenario (except for (dis)charging efficiency losses, which our simulation accounts for, as well). Consequently, $V2B^2$ only changes the electricity mix for these two demands, i.e., the mix of production types.

To adequately address our research question, we specify two additional aspects for the simulation and result calculation of both scenarios:

- *Monthly operational emissions calculation*: We determine the $V2B^2$ emission reduction potential by comparing the monthly CO_2-equivalent emissions from operating our two scenarios for one month on working days, excluding holidays and weekends. To avoid underestimating this key metric, we incorporate both the energy required to generate one unit of the net, i.e., consumed electricity and its associated supply chain and electricity production emissions (c.f. Section 2.1.1), as well as (dis)charging efficiency losses.
- *EV (dis)charging*: Similar to Rangaraju et al. (2015), we assume uncontrolled (i.e., ad-hoc or immediate) EV charging upon a driver's arrival home in the benchmark scenario. For $V2B^2$ charging, we heuristically optimize the charging process to maximize RES utilization. Specifically, we distribute the EV charging time symmetrically around each day's minimum emission period associated with grid electricity production while the EV is parked at the driver's workplace. For both charging and discharging, we assume intermediate charging powers and account for efficiency losses to calculate resulting CO_2-equivalent emissions accurately.

2.2.2. Simulation parametrization

To parameterize our model, we derive three EV classes based on data from the Electric Vehicle Database (2022). Therefore, we stick to the original data's distinction between average winter and summer consumption. Table 1 outlines the specifications obtained per class and considered in the simulation.

For charging and discharging the EVs, we consider a maximum available power of 11 kW (EV Database, 2022). Further, we assume an efficiency of 89.4 % (Sears et al., 2014) for the charging and discharging processes to account for downstream emissions. We define a buffer of 5 % for discharging in addition to the preserved energy required to meet the driving needs to the next charging possibility at home, i.e., at the workplace.

We match the same weekdays rather than the same dates to link daily electricity demand with electricity mix data from different years. We

Table 1
EV battery size and seasonal consumption per vehicle class.

	Compact	Mid- and Full-size	Sport utility vehicle (SUV)
Battery Size [kWh]	45	87	72
Ave. Consumption Winter [Wh/km]	170	190	194
Ave. Consumption Summer [Wh/km]	112	130	131

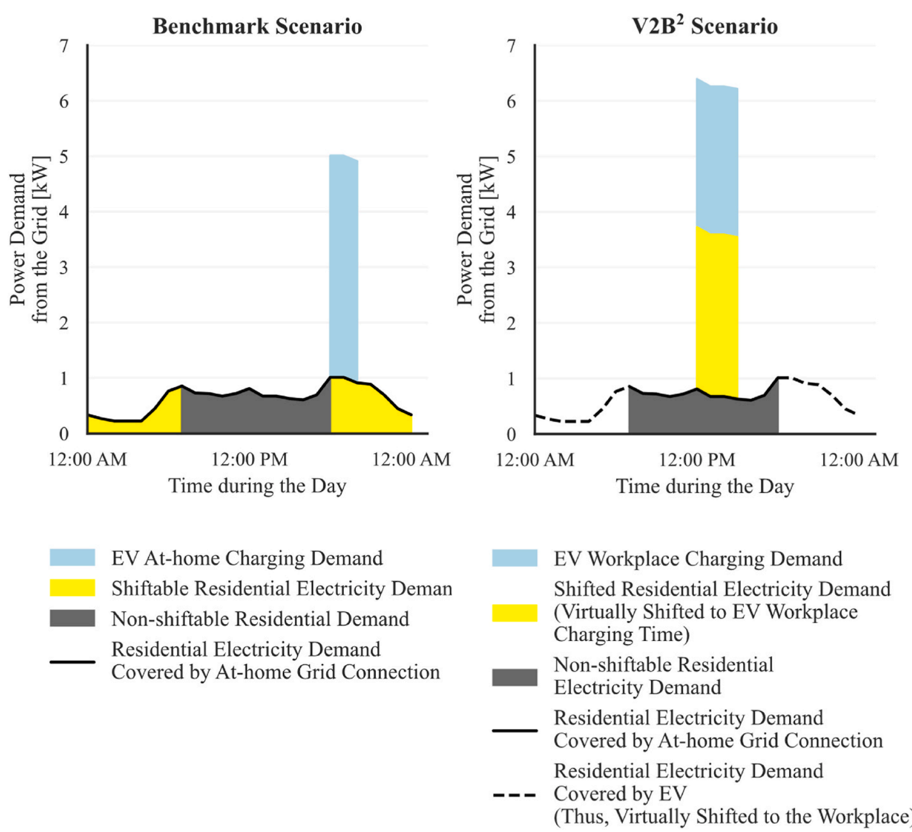

Fig. 4. Exemplary load profiles.

analyze one month of operation in January and July to examine the emission reduction potentials of a typical winter and summer month to account for seasonal factors (cf. Fig. 2). Every month, we simulate benchmark and V2B^2 operation for each of the 35,000 driver profiles; thus, every simulation run has driver-individual parameters for driving behavior and residential electricity demand.

2.3. Emission reduction explanation model (Modeling II)

After obtaining the simulation results, i.e., the relative emission reduction potential of applying V2B^2, we build the emission reduction explanation model. With this second model, we aim to analyze our research question of why and how much the operational emission reduction of V2B^2 changes for the interaction between the available electricity mix and different driver behavior. Here, SHAP values (Lundberg and Lee, 2017) offer a great way to investigate and visualize how individual features influence a model's outcome. For that reason, they are becoming increasingly popular across various fields for providing insights into model results (Bollenbach et al., 2024) and find application in our paper as well. In general, SHAP values are calculated for each feature of every observation, enabling the decomposition of a model's output. For any given observation, adding the specific feature SHAP values to the overall mean model output results in the observation's specific output (Amiri et al., 2021). In the context of our results, SHAP values quantify how each observation's feature values change the overall mean relative emission reduction. Beforehand, however, our causal research objective necessitates some unique design requirements for the underlying model, compared to the conventional use of SHAP values in analyzing the performance of predictive models (Shmueli and Koppius, 2011).

To effectively capture non-linear relations and interaction effects between features, we employ the Extreme Gradient Boosting (XGB) ensemble machine learning model (Chen and Guestrin, 2016), which is recognized for its high accuracy (Bentéjac et al., 2021). In their prediction, however, XGB and ensemble models generally favor a single feature that combines information from several other features. Consequently, SHAP values reveal high feature importance for that one feature, even if it lacks causal influence on the target variable. This is very helpful in achieving the best prediction result with as few features as possible, but concluding actual causality is impossible. Therefore, our explanatory modeling approach requires a feature space reduction to causal features ahead of model training. This process builds on Wu et al. (2016), who identify four driver-individual features as decisive in a comparable context: EV battery capacity requirements for driving, EV plug-in and plug-out times, and residential electricity demand. We validate the potential causality of these features for our model through domain and simulation design knowledge (Gefen et al., 2003), as well as quantitative analyses employing double machine learning (Chernozhukov et al., 2018). We find that driver-individual driving distances are decisive in determining EV battery capacity requirements, leading us to focus on daily driving distance as the primary causal feature. Furthermore, plug-in and plug-out times at home impose hard constraints on the at-home (dis)charging process, providing explanatory power for the V2B^2 emission reduction potential. Finally, we determine the ratio of shiftable residential demand in relation to non-shiftable demand as decisive for the relative V2B^2 emission reduction potential rather than the total residential demand alone.

In summary, we base our modeling and explanations on these four features:

- *'Time of First Departure from Home'* provides information about when a commuter leaves home for the first time and unplugs the EV from the residential building. This corresponds to the latest possible end of EV battery discharging to cover residential demand. Derived from the real-world behavioral data described in Section 2.1.2, the feature takes on values in the range [03:15 a.m., 03:00 p.m.].
- *'Time of Final Arrival at Home'* defines when a commuter arrives at home and stays there afterward. At-home arrival corresponds to the charging start within the at-home charging benchmark scenario. For the V2B^2 scenario, it marks the discharging start. Derived from the real-world behavioral data described in Section 2.1.2, we observe values in the range [09:30 a.m., 11:45 p.m.].
- The *'Daily Driving Distance in km'* sums up a commuter's daily driving distance. As our simulation defines EV consumption as a function of driving distance, 'Daily Driving Distance in km' directly determines the daily EV demand for driving. Distances for our individual profiles fall within [4 km, 207 km], based on the real-world data of Section 2.1.2.
- *'SRED while EV at Home to SRED while EV away' (SRED ratio)* provides information about a commuter's residential electricity demand. Standard residential electricity demand (SRED) is the average residential electricity demand without EV charging. In the V2B^2 scenario, the EV is available to discharge its battery at home, thus covering residential demand as long as the EV parks at home. This option is lost when the EV drives away from home. SRED ratio puts the SRED of the two scenarios in relation. i.e., if the EV is at home to while the EV is away. For example, if the SRED ratio is above one, the SRED during the time the EV is at home exceeds the SRED during the time the EV is away from home. In other words, if the SRED ratio exceeds one, the EV with sufficient battery capacity can cover more than half of a driver's daily SRED. For our real-world based (cf. Section 2.1.2) driver profiles, the SRED ratio is in the range [0.23, 1.31].

Based on the four features described, we train the XGB model. In contrast to predictive modeling, we intentionally avoid techniques such as cross-validation that optimize predictive power for unseen test data. We train the model to achieve the best possible performance with the entire dataset, as we are particularly interested in the relationships within this dataset (Gefen et al., 2003).

3. Results and evaluation

In the following section, we will first briefly describe and compare the V2B^2 emission reduction potential before providing detailed insights into why and how much the potential changes depending on established individual driver behavior. All simulations and analyses were carried out using the programming language Python.

3.1. V2B^2 emission reduction potential (Modeling I results)

To provide an understanding of the effectiveness of operating a V2B^2 concept under German conditions, we present our results as the relative emission reduction compared to the current typical home charging as a benchmark.

At first, we find the emission reduction potential to be fairly independent of different vehicle characteristics, as captured by our three vehicle classes. This suggests that established demand patterns rather than EV specifications dominate the relative emission reduction. For that reason, we focus only on the wide-spread compact vehicle class to continue our analysis.

Fig. 5 visualizes the distribution of the relative V2B^2 emission reduction across all driver profiles for January and July to reflect a typical German winter or summer month. When comparing electricity grid-powered V2B^2 operations for different seasons, significant differences occur between winter and summer.

January has a negative emission reduction potential for the majority of profiles. The median emission change is −0.3 %, with the interquartile range spanning from 0.6 % to −1.0 %. In other words, spatio-temporal load shifting of residential demand predominantly increases emissions. Even in the best cases, the maximum observed emission reduction is only 5.5 %. In the worst cases, emissions increase by up to

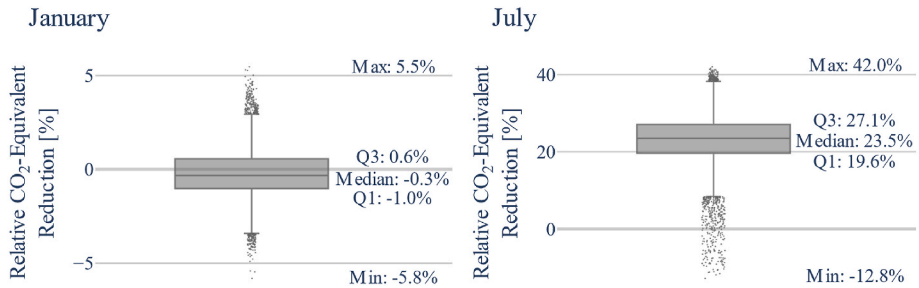

Fig. 5. Distribution of the relative operational CO_2-equivalent reduction with $V2B^2$ for January and July.

5.8 %, resulting in a total range of 11.3 %. These observations originate from the German electricity mix in January 2023, where average emissions were lower during the night compared to the daytime. Consequently, shifting nighttime residential demand to the day results in coverage by a more emission-intensive electricity mix. In addition, the slight difference in emissions over the course of a winter day keeps the overall range of emission reductions small.

In contrast, July exhibits a positive emission reduction for almost all driver behaviors. The median reduction is 23.5 %, with an interquartile range between 19.6 % and 27.1 %. At the maximum, drivers decrease emissions by up to 42.0 %. Only a few increase their emissions in summer, with values as low as −12.8 %, resulting in a total range of 54.2 %. Due to the higher difference in RES production in summer months with a high daytime PV output, shifting nighttime residential electricity demand to daytime has a substantial positive influence. At the same time, the increased difference in emissions throughout a summer day also affects a broader range of emission reduction values, highlighting the importance of individual behavior in timing electricity demand.

In summary, these results yield two main findings. First, only summer months like July seem to offer significant positive emission reductions when operating $V2B^2$ in Germany. In German winter months like January, emissions might even increase. Second, winter's range of relative emission reductions is narrower than in summer. Both seasonal differences arise from the characteristics of volatile RES-intensive electricity mixes in weather conditions similar to Germany. Wind energy output primarily shapes the emissions associated with the electricity mix in winter months. This means that winter months with comparatively low emissions have a high share of wind-produced electricity and vice versa. However, while wind power influences the overall emission levels, its independent production from the time of the day results in relatively stable emissions throughout the day. In summer months, PV output dominates the emissions associated with the electricity mix. The RES-share, and thus the difference in emissions, follows a clear daily pattern. Consequently, shifting electricity demand from nighttime to daytime aligns better with renewable generation and leads to greater emission reduction. The higher difference in emissions throughout the day is also responsible for the broader range of potential emission reductions in summer (cf. Fig. 5), as individual habits become more decisive for the emission reduction potential.

Therefore, we will focus our following $V2B^2$ analysis on July and analyze why and how much the average relative emission reduction changes for individual driver behavior. In the discussion, we come back to the January results and discuss the implications and transferability of January's shortfall compared to the results of July.

3.2. $V2B^2$ feature influence (Modeling II results)

In the following, we present the SHAP values of the XGB model for a sophisticated understanding of why and how much the relative emission reduction changes for individual driver behavior. First, we look at an overview to understand general trends and identify features requiring a deeper analysis of individual effects. Second, we dive into the specific influence of single feature values by examining the two most relevant feature pairs and their interactions in more detail.

3.2.1. *Feature trend summary*

To provide a summary of general trends for all features, we present a summary plot of the estimated SHAP values in Fig. 6. The profile features rank from top to bottom by their declining mean SHAP values. Additionally, each point representing an observation of a feature is color-coded according to its value.

On average, the 'Time of Final Arrival at Home' marks the most decisive feature for determining a commuter's individual change to the average $V2B^2$ emission reduction potential. Commuters who arrive at home late benefit particularly strongly from $V2B^2$, i.e., their emission reduction potential increases by up to 10 % above average. In the benchmark scenario, they plug in their EV as soon as reaching home, resulting in major grid electricity demand in the evening with high associated emissions. By shifting both their EV and residential demand to emission-reduced times during midday, they significantly reduce their emission output. At the same time, the reduction potential for commuters who get home relatively early falls to almost zero (−23 %). If they only work part-time, they have to charge before leaving work when emissions are higher than at the time they could charge at home. The increased charging emissions offset the savings in residential emissions through V2B, almost vanishing the emission reduction potential for commuters arriving home early.

'Daily Driving Distance in km' marks the second most important feature on average. Medium and high values, i.e., average and long driving distances, are primarily responsible for this observation. While both impact the average emission reduction potential by more than 10 %, medium values seem to do so negatively; high values impact the potential positively. For lower values, the potential both decreases and increases by less than 5 %. Since both high and low values seem to both decrease and increase the potential, the results indicate interaction effects with other features, which we will examine in more detail later.

'Time of First Departure from Home' marks the third most decisive feature on average. Similar to the 'Time of Final Arrival at Home', the average emission reduction potential seems to increase for high values (up to 7 %), while it decreases by almost 15 % for low ones. If commuters leave home very early (i.e., low feature values), they lack the ability to cover morning residential electricity demand with their EV battery, which is now covered by comparatively emission-heavy grid electricity. As a result, the emission reduction potential of these commuters falls

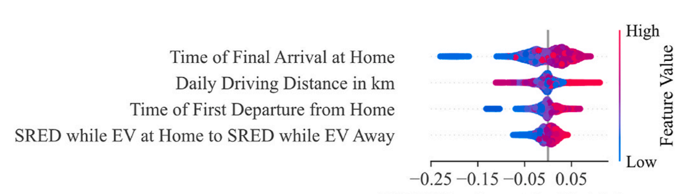

Fig. 6. Summary Plots of SHAP values colored by feature value.

short compared to commuters with later departures (i.e., higher feature values). By leaving home later and in time with falling emissions of the electricity grid, commuters plug out their EV at times when grid emissions are low anyway. This implies that, from this point forward, the building's grid supply will be low in emissions.

The final feature, 'SRED while EV at Home to SRED while EV Away' (referred to as SRED ratio), also exhibits a clear trend for the single feature. Driver profiles with a high SRED ratio exhibit a V2B^2 emission reduction potential of up to 5 % above average. High SRED ratios correspond to an SRED ratio above one, which tells us that SRED during times the EV is plugged in at home is higher than SRED during times the EV is away from home. It seems intuitive that the V2B^2 emission reduction potential increases, as more residential electricity demand is potentially coverable by lower emission electricity of the EV battery. At the same time, the average potential for reducing emissions decreases if the residential demand during EV absence exceeds the residential demand while the EV is at home. In this case, the SRED ratio takes on low values below one, and the average emission reduction potential drops by up to 8 %.

3.2.2. *Detailed feature influence and interaction analysis*

To understand the impact of individual features in more detail and to shed light on some key interactions between two features, we present SHAP dependence plots in the following. The vertical dispersion indicates the SHAP values of specific profile feature values, i.e., how different values change the average emission reduction potential. Additionally, the coloring of the dots displays possible interaction effects with another feature. We compared all possible combinations to select the most relevant feature combinations and checked for potential interaction effects. As a result, we found two relevant feature pairs and will discuss their interactions and influence on the V2B^2 potential in the following.

Fig. 7 displays a SHAP dependence plot to examine the influence of 'SRED while EV at Home to SRED while EV Away' (SRED Ratio) on the V2B^2 emission reduction potential. We colored the dots by the 'Time of Final Arrival at Home'. We generally observe a clear trend in how an increasing SRED Ratio changes the average V2B^2 potential. With a higher SRED ratio, the associated emission reduction potential of V2B^2 operation also increases regardless of other features. This confirms a similar observation we already described for the summary plot of Fig. 6 and seems intuitive as the share of potentially shiftable residential demand increases. In detail, an SRED ratio below 0.6 exclusively reduces the average V2B^2 potential between −2 % and almost −8 %. As SRED ratios exceed 0.6, the V2B^2 emission reduction potential starts to increase from there on as well. Starting at an SRED ratio of 0.7, the first profiles begin to outperform the average potential. At an SRED ratio of around 0.95, most profiles begin to exceed the average V2B^2 emission reduction potential by up to 4 %, which remains the upper bound for higher SRED ratios.

For the interaction with 'Time of Final Arrival at Home', we make two key observations. First, higher SRED ratios tend to pair with earlier arrival times at home, specifically before 06:00 p.m. If commuters get home earlier from work, they tend to have shorter working times and, thus, spend more time at home. As a result, their EV exhibits longer idle times at home with the possibility of EV battery discharging, i.e., spatiotemporal residential load shifting, which increases the SRED ratio. Second, we observe that commuters who arrive home later at the same SRED ratio tend to profit more from V2B^2. As the potential for residential load-shifting is equal, those commuters profit more from shifting their later and, thus, emission-intensive charging process to the workplace.

Fig. 8 visualizes the influence of the 'Daily Driving Distance in km'. The colored dots illustrate the effects of interaction with the time a commuter returns home ('Time of Final Arrival at Home'). We observe three ranges for daily driving distances with noticeably changing patterns: below 25 km (range 1), between 25 km and 110 km (range 2), and above 110 km (range 3).

For driver profiles with daily driving distances below 25 km (range 1), the V2B^2 emission reduction potential deviates less than+/-5 % from the mean. The time a commuter arrives at home appears to be decisive for whether a deviation is positive or negative. Early arrival at home tends to pair with a high share of potentially shiftable residential load, i. e., a higher SRED ratio (cf. Fig. 7). If the driving range and, thus, EV demand is as low as within range 1, the potential for residential load shifting dominates EV demand and charging timing. As a result, early arrival at home increases the average V2B^2 emission reduction potential for daily driving distances below 25 km and vice versa.

For distances between 25 km and 110 km (range 2), the interaction effect with the arrival at home times flips but remains the decisive factor for positive and negative deviation from the mean V2B^2 potential. Individual driver behavior can reduce the reduction potential by up to 10 %, while a possible increase remains below 5 %. In contrast to range 1, commuters who arrive home late (after around 08:00 p.m.) within range 2 seem to profit from V2B^2 above the average. This is because, in addition to the spatiotemporal shift of their residential demand, they benefit particularly strongly from shifting the charging time of their higher EV demand to the workplace.

If the daily driving distance exceeds 110 km (range 3), almost every driver outperforms the average V2B^2 emission reduction potential. For some profiles, the potential increase amounts to more than 10 %. This exclusively above-average performance is due to the high demand for daily EV charging. Based on our model, it amounts to over 12 kWh for all profiles within range 3. As a result, the daily charging demand dominates daily residential demand, and range 3-commuters benefit significantly from shifting their charging process to the workplace. Similar to range 2, the potential increase is lower for early arrival times at home (before 08:00 p.m.). This again originates from the fact that the charging process of the at-home charging benchmark scenario can be started earlier. Therefore, charging-related emissions are reduced compared to

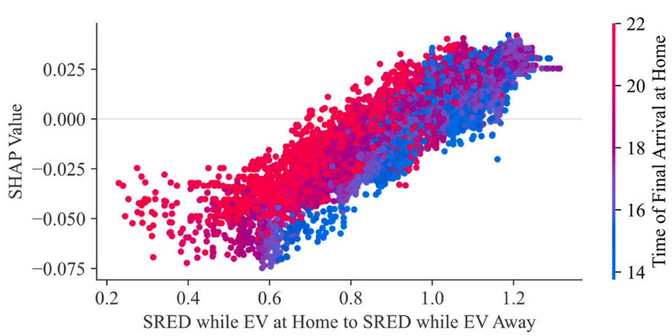

Fig. 7. SHAP Dependence Plot of 'SRED while EV at Home to SRED while EV Away'
(SRED Ratio) colored by the 'Time of Final Arrival at Home'.

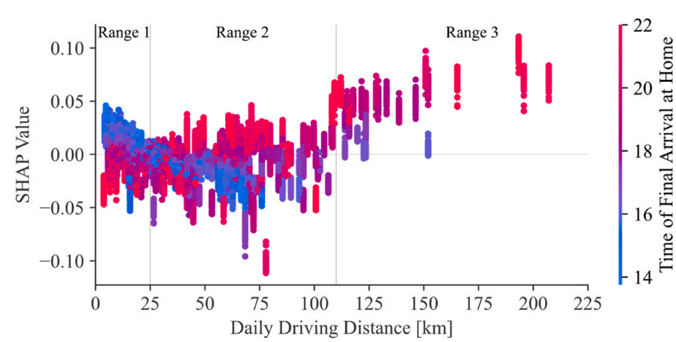

Fig. 8. SHAP Dependence Plot of 'Daily Driving Distance in km' colored by the 'Time of Final Arrival at Home'.

later at-home charging times, and commuters profit less from V2B^2 than those arriving home later.

4. Discussion, implications, limitations, and future research

Our results reveal a pronounced seasonal variability in the emission reduction potential of a grid-dependent V2B^2 operation in Germany. Further, individual driver behavior patterns strongly influence the emission reduction potential. In the following, we elaborate more closely on both effects, consolidate our contributions in tandem with existing literature, and discuss broader transferability. Finally, we provide a detailed insight into practical and policy-related implications.

4.1. V2B^2 emission reduction potential (Discussion modeling I)

For January, we observe an increased average emission level from operating V2B^2. This increase was primarily due to greater daytime emissions compared to nighttime emissions that the German electricity mix had in January 2023. However, whether these results are transferable to other winter months and years remains to be determined. When comparing January's emissions to other winter months and earlier years, we find the months of January, February, October, November, and December to be particularly interesting (cf. Fig. A1). Regardless of total RES shares, average grid emissions were lower at night than during the day for at least one month in 2017, 2019, and 2021. During wind-heavy months with low PV output, conventional power plants had to compensate for the high daytime electricity demand, heightening emissions. Conversely, during the night, the high output from wind turbines decreased electricity mix emissions. This results in yearly repeating months like January 2023, where average emissions are lowest during the night. The pattern observed in this paper is characteristic for regions in central Europe like Germany.

Thus, our results contradict existing V2B^2 literature, which finds benefits independent of local prerequisites for RES production. These papers investigate operations in more solar-intensive regions like Italy (Barone et al., 2019) or Beijing (Yu et al., 2022) and often add on-site PV systems to their scenarios. However, even with on-site PV at the workplace, a generally positive emission reduction potential, regardless of individual driver profiles, remains challenging for central Europe's winter weather conditions. As the number of EVs at the workplace increases, so does the number of charging processes that depend on emission-heavy grid electricity. These results align with existing literature that finds a strong dependence of the load-shifting emission reduction potential on local weather conditions (Nilges et al., 2024), possibly leading to nighttime charging being the most ecological decision (Rangaraju et al., 2015).

In summary, our January results reveal that the V2B^2 emission reduction potential in winter months strongly depends on local weather conditions, questioning an effective, emission-reducing implementation for similar circumstances.

In July, there is a substantial positive shift in average emission reduction potential. This shift arises from the German electricity mix in July 2023, where daytime emissions were temporarily reduced to almost half that of nighttime emissions. However, whether these results apply to other summer months and years arises. When comparing our sample years 2017, 2019, 2021, and 2023 (cf. Fig. A1), we find that from March to August, consistently similar patterns occur. Despite fluctuations in the absolute difference between average nighttime and daytime emissions, the daytime emissions consistently rank lower, dependent on the month. Thus, our results, especially regarding the influence of individual driver behavior, seem transferable very well for similar weather conditions. In the summer months, our findings align with the promising V2B^2 potentials identified in existing literature (Barone et al., 2019). This correlation may be attributed to the similarities between German summers and the summer months in Italy (Barone et al., 2019) and Beijing (Yu et al., 2022), which are referenced in these papers.

In addition to the analyzed emission reduction potential based on the electricity mix of 2017, 2019, 2021, and 2023, it is insightful to discuss future trajectories. The analysis of these four years within a seven-year span demonstrates that despite the expansion of RES, i.e., an increasing share of RES in electricity generation, the timing of emissions has remained relatively stable. This suggests that the findings are likely to be transferable to future years with similar trends in winter and summer.

From a long-term perspective, the future of V2B^2 emission reductions will largely depend on political decisions regarding the further expansion of renewable energies. As the energy system moves toward fully renewable electricity generation, factors beyond emission reductions, such as grid stability, will become more critical. For example, prioritizing electricity generation with PV or wind turbines will influence generation peaks and, thus, grid-friendly consumption, depending on seasonal weather conditions. Additionally, the regional distribution of RES and the future expansion of grid infrastructure are key areas for further research into whether regionally specific charging policies are recommended.

4.2. V2B^2 feature influence (Discussion modeling II)

Starting from the average emission reduction potential, the driver-specific potential varies considerably depending on individual behavior. Thus, relying on empirical and real-world data is necessary to account for individual behavior and provide further insights compared to Niu et al. (2024). Especially under circumstances as volatile as emissions associated with the electricity grid, an analysis of individual behavior is crucial. Other papers also support this finding (Rangaraju et al., 2015). Furthermore, this approach allows for the representation of behavioral characteristics unique to cultures and countries. Even within short distances, established habits sometimes differ significantly. Compared to Germany, it is a common practice in Southern Europe to engage in the evening meal later. As a result, residential demand peaks may appear at times of higher grid emissions, and V2B^2 could contribute substantially to emission reduction. However, drawing profound conclusions about causal relations in other regions requires specific studies based on local behavioral data.

In detail, we determine for Germany that the primary factors shaping the potential for V2B^2 emission reduction in July are individual charging times and the transition of charging procedures to the workplace. With this insight, we extend previous results, primarily focused on the charging process (Powell et al., 2022), to the residential sector. In contrast to January 2023, we identify daytime as the best charging time for emission reduction, similar to Powell et al. (2022). To summarize, our results reveal that both charging at night (Rangaraju et al., 2015) as well as during the day (Powell et al., 2022) could represent preferable charging times, depending on the conditions.

Our analysis focuses on the commuting patterns between home and work, as these locations typically provide the most extended periods of EV idle time. However, it should be noted that other mobility patterns with activities outside working hours and potentially multiple intermediate charging stops also exist. Since we explicitly consider charging from the grid without any additional infrastructure requirements, such as a PV system, the transferability of our findings can be discussed. As long as our time-dependent results are considered when making charging decisions, results remain transferable to other locations.

Concerning the V2B^2 emission reduction potential, our analyses also highlight that the potential increases with the proportion of household consumption that an EV's battery can cover. Since this ratio depends on EV availability and the basic course of demand rather than on absolute consumption, these findings are well transferable to future conditions. Nevertheless, the question of absolute emission reduction coupled with relative ones remains crucial. Its relevance could grow further with the ongoing electrification of residential heating and, thus, the rising share of heat pumps as governments start fostering their adoption. Germany, for example, aims to install around 500,000 new heat pumps yearly beginning in 2024 (Federal Government, 2022b).

4.3. Practical and political implications

In summary, our results reveal that V2B^2, as a strategy for emission reduction through spatiotemporal residential load shifting, exhibits a strong seasonal dependence under central Europe weather conditions and a significant dependence on individual driver behavior. Here, our paper contributes insights into the most important causal relations, drawing essential political and practical implications for targeted measures toward a more sustainable society.

On the one hand, we note that V2B^2, which draws electricity exclusively from the grid, demonstrates limited potential for reducing emissions during winter in weather conditions such as those in Germany. Consequently, the development of alternative winter policies appears necessary to achieve meaningful emission reductions. On the other hand, V2B^2 might be a promising concept during summer when adopted by drivers with high-potential behavior. This way, the potential of EVs to decarbonize individual transport extends to decarbonizing the residential sector (Federal Environmental Agency, 2021). Based on these findings, it seems advisable to refrain from a large-scale V2B^2 implementation in the summer and instead focus on establishing the conditions necessary for a V2B^2 implementation where it yields the highest potential.

However, fostering such a concept raises reasonable concerns about social justice. EV ownership in Germany is predominantly concentrated among high-income households (Vanhaverbeke et al., 2024). Implementing V2B^2 unlocks additional opportunities for these individuals to optimize their electricity demand, potentially generating financial benefits through their EVs. Although the large-scale adoption of EVs remains a policy goal, car ownership continues to be more prevalent among higher-income households in comparison (Ko et al., 2019). Consequently, the potential benefits of spatiotemporal load shifting are limited to those individuals. Further research into the socio-economic characteristics of those who would benefit the most from V2B^2 could provide valuable insights. It is clear, however, that employees who commute using public transport or other means are generally excluded from V2B^2 opportunities.

One potential approach to mitigate this unequal distribution of potential RES use is the expansion of more stable RES sources, such as wind power. This could support public transport electrification through nighttime charging infrastructure, reducing societal emissions. Germany has recognized this need, spurring onshore and offshore wind expansion through the Onshore (Federal Office of Justice, 2024a) and Offshore (Federal Office of Justice, 2024b) Wind Acts. However, PV remains the only RES source that allows almost everyone to participate in electricity production. Moreover, the levelized cost of electricity for both wind and solar falls within a similar range, typically below that of conventional energy carriers (Kost et al., 2024). Thus, further promoting the expansion of both carriers seems appropriate, which will sustain the need for solutions to integrate PV electricity effectively. Simultaneously, especially in rural areas, the car, i.e., EV, will likely remain the dominant mode of transportation (Hensher, 2024). Therefore, leveraging long EV idle times to align with volatile RES output should be a strategic priority.

Expanding workplace charging infrastructure presents a promising remedy by enabling the distribution of EV charging demand in time (Fischer et al., 2015), which is utilized by V2B^2 as well. Our results advocate for a target group-specific incentivization strategy to ensure the most efficient implementation. As the literature primarily recommends monetary incentives (Kacperski and Kutzner, 2020), implementing time-dependent private electricity tariffs seems particularly effective. Especially in summer, tariff makers could attempt to encourage a shift to daytime charging by increasing the costs for late and night-time charging (Chakraborty et al., 2019).

If EV owners shift their charging processes to the workplace, employers do not necessarily have to bear the associated costs. The employer can offer workplace charging as a free employee benefit or charge employees a tariff below their at-home charging costs to sustain incentives for a charging shift. Additionally, Englberger et al. (2021) identify economic advantages for employers when integrating employee charging into their electricity demand optimization strategies, such as peak load shaving. Adding bidirectional charging capabilities unlocks further revenue streams, including spot market trading opportunities. In the end, German law mandates that business owners with more than 20 parking spaces provide charging infrastructure since the beginning of 2025 (Federal Office of Justice, 2021). As a result, employers face increasing pressure to develop strategies for effectively integrating charging processes. However, given the rising pressure within the German economy, companies first require supportive measures to cope with the additional investment burdens imposed. As a first step, Germany should reinstate subsidies to expand corporate charging infrastructure, like the KfW Bank's 441 subsidy, which expired at the end of 2022 (KfW Bank, 2022).

4.4. Limitations and future research

Naturally, our approach entails some limitations. The combination of residential electricity demand and driving behaviors uses a simple cross-join, as the residential electricity demand data lacks a clear indicator for determining EV departure times. Exploring more sophisticated methods and determining their influence on the results might be interesting. Our analysis of causal relations with SHAP values requires reducing the feature space to causal features before modeling. Naturally, this selection process is a potential limitation that could benefit from further validation.

Furthermore, our analysis neglects the influence of additional and locally dependent grid conditions, such as grid stability and capacity. When charging multiple EVs, the maximum available grid power might restrict possible charging times. Our choice of average emission factors represents another limitation of this paper. We select these for our investigation of a single EV in consideration from the national rather than local perspective in line with existing papers. At the same time, practice will continue to allocate emissions based on average factors, as it is very locally specific and challenging to determine individual marginal emissions. Nevertheless, literature continues to lead a debate about the standardized application of average and marginal emission factors. Marginal factors could be particularly useful for investigating multiple EVs and local-grid-specific conditions.

This paper's investigation of the German case provides insights into the V2B^2 potential for central Europe-like weather conditions, adding a more moderate view to previous literature of more solar-intensive regions like Italy (Barone et al., 2019) and Beijing (Yu et al., 2022). Future research could combine and enhance these results to provide a comprehensive global-scale picture. One way of doing this may be by building upon this paper's approach and extrapolating the V2B^2 potential based on local weather conditions, assuming similar driver behavior. Additionally, considering empirical country-specific behavioral patterns provides room for further analyses. Another very insightful path for further research could be using marginal emissions to validate our average factors-based results. Future papers might as well combine this validation with a locally grid-specific investigation or a scale-up of the potential to a nationwide level. However, the decentral character of RES generation combined with locally different grid conditions necessitates a high spatial granularity. Papers focusing on this would also contribute insights into the V2B^2 potential to support local grid stability, including regional charging patterns. Next to assessing the socio-economic characteristics of those who would benefit the most from V2B^2, further research could address future electricity mix developments toward fully renewable electricity. Integrating ecologic analyses with economic factors to enable precise conclusions about the requirements for pricing mechanisms that economically incentivize the ecologic potential found in this paper might also be very insightful (Kacperski and Kutzner, 2020).

5. Conclusion

In this paper, we present a simulation and a feature influence model to investigate why and how much the potential for emission reduction of a V2B^2 concept for spatiotemporal residential load shifting changes. We consider individual driver behavior (in terms of both a driver's driving and residential electricity demand behavior) in interaction with a country-specific electricity mix for the case of Germany. For our analysis, we consider combinations of 35,000 German driving and residential electricity demand profiles obtained from empirical and real-world data, as well as the 2023 German electricity mix. By using these profiles to simulate V2B^2 operation and benchmark it against the established at-home charging scenario, we obtain the monthly reduction in operational emissions, measured in CO_2-equivalents for both winter and summer. We select the individual profile features that are causal to our simulation results and use them to train an XGB machine learning model. For the model, we apply a SHAP value analysis to identify why and how results change, uncovering the influence of both single features as well as their interactions.

Our results reveal that Germany's V2B^2 emission reduction potential hinges heavily on the season and driver behavior. For January, we find a negative median potential of −0.3 %. This small to negative potential for German-like weather conditions applies primarily to October to February. For July, we find a median potential of 24 %. This positive trend extends from March to August. We find the time of arrival at home and, thus, typically, the start of EV charging to be particularly decisive for the individual V2B^2 emission reduction potential. If commuters who return home late shift their charging process to the workplace within V2B^2, they profit by up to 10 % above average. On top of that, our results indicate that commuters with long driving distances profit above average from implementing V2B^2, especially if they arrive home later. In detail, we find that commuters who drive at least 110 km a day and arrive at home after 08:00 p.m. exceed the average potential by more than 10 %. In addition, the concept seems particularly suitable for drivers who can cover a high share of their daily residential demand with the EV. This tends to be the case for commuters who arrive home before 06:00 p.m., resulting in an increased potential of 4 % above the average.

In summary, our results reveal that the potential of V2B^2 for residential load shifting in Germany strongly depends on country-specific weather conditions and individual driver behavior. With these findings, we contextualize more optimistic conclusions of existing V2B^2 literature. This seems to be of key relevance to enable well-founded country-specific investment decisions and to prevent overly optimistic V2B^2 emission reduction potential assumptions. Further, the findings guide measures for locally targeted and group-specific incentivization of the highest potential. This helps to further increase the efficiency of a V2B^2 implementation, especially in countries where the application of V2B^2 appears to be the most promising due to the higher full-year potential.

Based on our paper's results, we recommend that future research thoroughly consider the impact of local weather conditions and individual driver behavior on its results regardless of the specific goal. We also conclude that V2B^2 implementation for spatiotemporal residential load shifting can be a partly effective remedy to reduce individual residential emissions in central European weather conditions. However, a possible V2B^2 implementation must be carefully aligned with established driver behavior and region-specific electricity generation via RES to realize the most efficient ecological outcome. In summary, the individual impact seems rather small for central European weather conditions, necessitating alternative solutions to achieve our target of a more sustainable energy future.

CRediT authorship contribution statement

Jessica Bollenbach: Writing – review & editing, Visualization, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Niklas Eiser:** Writing – original draft, Visualization, Validation, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation. **Felix Baumgarte:** Writing – review & editing, Supervision, Conceptualization. **Robert Keller:** Writing – review & editing, Supervision, Conceptualization. **Jens Strüker:** Writing – review & editing, Supervision, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2025.145894.

Data availability

For the "Mobility in Germany" (2018) and "Modern Residential Energy Saving Systems" (2012) data, the authors do not have permission to share the data. All other datasets are openly available online

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