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SPAGHETTI: a synthetic data generator for post-Covid electric vehicle usage

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Abstract

The Covid-19 pandemic has resulted in a permanent shift in individuals' daily routines and driving behaviours, leading to an increase in remote work. There has also been an independent and parallel rise in the adoption of solar photovoltaic (PV) panels, electrical storage systems, and electric vehicles (EVs). With remote work, EVs are spending longer periods at home. This offers a chance to reduce EV charging demands on the grid by directly charging EV batteries with solar energy during daylight. Additionally, if bidirectional charging is supported, EVs can serve as a backup energy source day and night. Such an approach fundamentally alters domestic load profiles and boosts the profitability of residential power systems. However, the lack of publicly available post-Covid EV usage datasets has made it difficult to study the impact of recent commuting patterns shifts on EV charging. This paper, therefore, presents SPAGHETTI (Synthetic Patterns & Activity Generator for Home-Energy & Tomorrow's Transportation Investigation), a tool that can be used for the synthetic generation of realistic EV drive cycles. It takes as input EV user commuting patterns, allowing for personalised modeling of EV usage. It is based on a thorough literature survey on post-Covid work-from-home (WFH) patterns. SPAGHETTI can be used by the scientific community to conduct further research on the large-scale adoption of EVs and their integration into domestic microgrids. As an example of its utility, we study the dependence of EV charge state and EV charging distributions on the degree of working from home and find that there is, indeed, a significant impact of WFH patterns on these critical parameters.

Keywords: Electric vehicle, Synthetic data, Probabilistic modeling, Work-from-Home, Electric vehicle charging, Commuting patterns

Introduction

Climate change is an increasingly pressing issue for both the environment and human populations. Many governments, therefore, have set ambitious goals for climate mitigation through the transition into more sustainable energy sources, resulting in a rapid growth in storage-coupled PV systems and the electrification of the transportation sector. The mass uptake of EVs is also seen as a key ingredient of this transformation, with the global fleet of passenger EVs expected to expand from 26 million in 2022 to over 400 million by 2040 (International Energy Agency 2023). The increasing penetration of EVs and their integration into PV-powered residential microgrids leads to further innovations, such as their use as bidirectional storage through vehicle-to-grid (V2G) technology, which enables users to consume locally-generated PV energy outside of sunlight hours. Indeed, bidirectional EVs provide a cost-effective storage alternative to conventional stationary batteries, by reducing the amount of necessary storage required and improving the efficiency of renewable energy usage (Ehsani et al. 2012; Lazzeroni et al. 2019).

Existing data suggests that EVs are parked for an average of 22 h per day, with 16 h of uninterrupted parking (Pasaoglu et al. 2014). This provides opportunities to reduce EV charging demands, charge EV batteries directly with solar energy during daylight hours, flatten the EV charging curve and use them as a backup source of energy throughout the day. However, if the PV installation is at an EV user's home, during commuting days its generation is unavailable to charge the EV. Thus, it is clear that increasing the ability for workers to work from home makes their EVs more likely to be charged from their own PV installation (Powell et al. 2022).

The Covid-19 pandemic altered peoples' daily schedules and driving habits, with a notable reduction in commuting journeys. Globally, WFH policies had been adopted to mitigate the spread of the virus, with a significant number of individuals working remotely (Company 2024). Importantly, while non-work-related travel is expected to return to pre-pandemic figures, work-related trips have decreased by approximately 14%. This is because the pandemic has normalised remote work and the desire to work from home for countless former commuters worldwide. According to a recent study, a majority of employees want to double their WFH frequency compared to before the pandemic (The Economist 2024).

Post-pandemic, individuals plan to undertake fewer commuting trips, but of longer duration (Forum 2024). With reduced workplace attendance, some individuals have opted to relocate further from urban centres, trading frequent, shorter commutes for occasional, lengthier ones in favour of lifestyle enhancements, such as increased living space.

Despite the reduction in work-related travel during and subsequent to the pandemic, there is a growing interest in acquiring EVs. The latest EY Mobility Lens Consumer Index reveals significant shifts in purchasing intentions and motivations among consumers across 13 key global markets, with a remarkable 41% of prospective new car buyers contemplating an EV (Forum 2024). This trend is attributed to heightened environmental awareness and various fiscal incentives introduced during the pandemic to stimulate electric vehicle sales (Agency 2021).

As a result of increases in EV purchases combined with increased working from home, the availability of EVs has risen but they are less frequently utilised and tend to remain idle and at home for extended periods. This allows EVs to be used as bidirectional energy storage units, while their owner is working from home, fundamentally altering domestic load profiles. We anticipate that this change in load profiles will significantly impact the design and operation of residential microgrids. However, the lack of publicly available post-Covid EV usage datasets hinders the study of these emerging patterns. Moreover, the intricate nature of EV user behaviour, influenced by a range of factors such as climate, traffic conditions, and policy decisions, makes modelling challenging. We, therefore, investigate recent changes in EV usage patterns by developing SPAGHETTI.

Specifically, we present SPAGHETTI, a tool for the synthetic generation of realistic EV drive cycles based on a probabilistic modeling framework, taking into account user-defined commuting and non-commuting patterns. SPAGHETTI builds on a detailed literature survey on emerging WFH patterns and can be used to generate both general realistic EV traces for the most common WFH types, as well as user-specific drive cycles that are based on the driver's expected commuting and non-commuting patterns. Thus, SPAGHETTI permits more realistic research on the impact of large-scale adoption of EVs, their integration into domestic microgrids and their impact on the grid.

We make the following contributions:

- We investigate shifting trends in post-Covid EV usage to derive and model the most common WFH types.
- We develop SPAGHETTI, a tool for the synthetic generation of EV traces, which considers both commuting and non-commuting behaviours. This enables the production of realistic general EV traces for prevalent WFH categories, in addition to drive cycles tailored to individual users, reflecting their anticipated travel patterns.
- We demonstrate the impact of commuting frequency on EV battery state of charge and EV charging distributions, two critical parameters.

The remainder of this paper is laid out as follows. The section Related Work surveys existing work and provides insight on different EV usage modeling approaches. In the section Post-Covid EV Usage Patterns, we analyse the relationship between EV usage and commuting and present evidence for shifting WFH patterns. In the section Modeling WFH Types we characterise the three most common commuter profiles. The section SPAGHETTI presents the software for the generation of EV traces. In the Evaluation we show that SPAGHETTI allows us to study the impact of commuting frequency on EV state of charge and charging distributions. Finally, the Discussion and Conclusion summarises our work and provides suggestions for future work.

Related work

We now discuss the most relevant prior work on generating synthetic EV usage patterns. Note that, over the past decade, the field of EV usage modeling has been expanding rapidly. Nevertheless, many researchers have emphasised the scarcity of charging data required to study EV usage patterns and develop EV load models (Calearo et al. 2021). Additionally, the few available public EV datasets are typically outdated and most only account for public charging stations (Amara-Ouali et al. 2021).

Li et al. review EV usage modelling and identify three types of models: temporal, spatial and energy usage models (Li et al. 2023).Our interest lies in temporal models, which track the start and end times of EV usage events, facilitating the estimation of trip distance and energy use. Thus, temporal models are useful for the optimisation of home energy management systems in residential microgrids. Current research in temporal models for EV usage patterns falls into two categories: statistical models and Markov chain models. We consider each in turn.

Statistical approaches model the temporal patterns of EV usage as probability distributions of behaviour, based on survey data (Tepe et al. 2022; Yi et al. 2020; Liu et al. 2017).

For instance, Brady *et al.* use a stochastic simulation methodology to create a schedule of daily travel and charging profiles for a population of EVs using GPS travel data (Brady and O'Mahony 2016). The authors use an iterative method of conditional distributions with Bayesian inference to generate synthetic travel patterns that account for the input uncertainties. These synthetic datasets capture the level of uncertainty in EVs' travel and charging behaviour. This method is primarily used to analyse the drive cycles and charging requirements of large fleets of EVs. Similarly Iqbal et al. present a probabilistic approach to model the load and charging state of EVs (Iqbal et al. 2021). The mathematical model was based on a travel survey conducted in Finland. Although the data used to tune the model is outdated, the work takes commuting patterns into account to model charging load. The model categorises the car owner's travel patterns into three different activity types: trips related to "work and school", "shopping and business" and "leisure and vacation". Then, probability distributions for arrival and departure times, as well as the energy consumption of each travel activity are defined. Schäuble et al. explore the mobility and charging characteristics of three electric mobility datasets from the south-western region of Germany (Schäuble et al. 2017). They simulate EV loads based on the statistical properties of empirical EV load profiles. Two methods are developed for creating synthetic load profiles: a direct method that use multiple data streams as inputs and requires measuring equipment attached to the charging point, and an indirect method that only requires information on the start and end times of charging events, as well as the corresponding state of charge (SOC). Both approaches yield similar results, but the indirect method offers the advantage of incorporating different assumptions for load profile calculation when data is unavailable or for simulating alternative scenarios.

Although Markov Chain models can be used as an alternative method for temporal analysis, they require a pre-existing dataset to generate the transition matrix (Ul-Haq et al. 2018; Iversen et al. 2014, 2016). For example, Wang et al. utilise a Markov chain to model the EV's velocity at the next moment, with a transition probability matrix extracted from the real-world driving data of 40 electric taxis over 6 months in the Beijing area to describe velocity change characteristics during the driving process (Wang et al. 2019). Similarly, Zhao et al. uses speed and acceleration data to model EV driving cycles, employing the Markov Chain and Monte Carlo method, and field data collected in Zhao et al. (2020). Zhang et al. also utilise a Markov Chain to develop a model of travel behaviour (Zhang et al. 2023), incorporating a machine learning strategy to forecast travel patterns. However, this model also relies on historical data.

Although these models are useful for studying EV energy consumption and efficiency, most of them do not provide the necessary information for home energy management systems (HEMS), such as the daily times when the EV is parked at home and the associated residential charging demands. Moreover, they are usually based on location specific and (by now) outdated datasets that do not incorporate post-Covid working patterns.

Furthermore, some open-source algorithms (International Energy Agency 2023a; Lahariya et al. 2020) for the synthetic generation of large EV fleet drive cycles and charging sessions are available. These tools are useful for analysing the large-scale impacts of extensive EV integration but are not suitable for modeling individual EV drive cycles.

In summary, the challenge with each of these methodologies lies in their need to model pre-existing datasets, which, in the current post-Covid situation, are unavailable.

All these studies also overlook the shift in post-pandemic commuting attitudes, which significantly affect EV usage patterns. This oversight may hinder the applicability of these models to the post-pandemic context. Additionally, many models do not adequately represent the diverse range of commuting and non-commuting behaviours across different demographics and geographical areas, as they often rely on datasets that are highly specialised towards particular geographical areas and user demographics.

To illustrate this research gap we compare our work with three representative papers from prior work (Table 1).

Iqbal et al. (2021) and Schäuble et al. (2017) introduce statistical models for EV usage that subsequently inform the modelling of EV charging demand. These models take into account the state-of-charge of EVs along with their times of arrival and departure. Nonetheless, they overlook WFH patterns and rely upon outdated, location-specific data from before the pandemic. Furthermore, these models lack the capability to be customised for individual users, thereby not accommodating specific EV models or the distinct commuting and non-commuting behaviours of users. Zhang et al. (2023) employ a Markov Chain approach to model travel behaviour, offering insights into journey durations and charging requirements. The model differentiates between commuting and non-commuting journeys by categorising destinations into various types. Although the model incorporates certain characteristics of occupants, including age, gender, and household income, it does not facilitate inputs tailored to individual users.

SPAGHETTI addresses these gaps by facilitating the modelling of various WFH scenarios and offering adaptability to the unique requirements of users and countries through customisable inputs for specific commuting and non-commuting behaviours.

Post-covid EV usage patterns

Owing to the Covid-19 outbreak, numerous organisations have implemented WFH policies in compliance with public health regulations to promote social distancing and curtail the spread of the disease. As these policies have persisted for over a year, individuals have become more comfortable in remote work settings, and a significant portion of the population favors the continuation of WFH arrangements even as pandemic-induced restrictions are eased. This has brought attention to the potential applications of the prolonged idleness of vehicles, notably EVs, in a post-pandemic world (Kong et al. 2022). To understand the shifts in commuting patterns and investigate their impacts, we gather recent evidence from various countries to quantify the changes in WFH patterns. The results are used to identify the characteristics and probability distributions of the three

Table 1 Comparison of EV Usage Generation tools

	Iqbal et al. (2021)	Zhang et al. (2023)	Schäuble et al. (2017)	SPAGHETTI
Post 2022 / Accounts for WFH	×	×	×	✓
Model EV SOC, Arrival and Departure Times	✓	✓	✓	✓
Distinction Commuting vs. Non-Commuting	✓	✓	×	✓
Location agnostic / No training data	×	×	×	✓
Personalisable to specific user	×	×	×	✓

This table illustrates whether different properties have been demonstrated/implemented (✓) or not (×)

most common WFH profiles in "Modeling WFH types" section and investigate their impacts on different metrics in "Evaluation" section.

We first explore how commuting patterns influence EV usage, with a particular emphasis on the wide-ranging variations observed in commuting behaviours. Subsequently, we present empirical evidence of the shifting WFH patterns, providing support for the observed trend. By accomplishing these objectives, the study aims to contribute to a better understanding of the ongoing changes in work culture and their impact on EV usage.

Typical EV-based commuting patterns

Pre-pandemic studies on the commuting usage of EVs have highlighted the importance of identifying typical commuting patterns. This allows us to accurately predict charging needs and understand how people use their EVs.

In the space of all existing work on private vehicle usage, we distinguish between the works that look at EVs and those that look at general vehicles, and within the first category, those that use private charging datasets and those that use public charging datasets. Some look at commuting types and some don't. We will not consider the works that do not present any commuting types. To ensure thoroughness, we offer a concise summary of studies in the field that, for diverse reasons, are not relevant to our analysis.

First, one influential study does not consider EVs and only gives the average commuting distances and times for different cities (Schwanen 2002). Moreover, the study is quite outdated, as the data is from 2001. Another study from 2008 also does not consider EVs and while commuting distances for northern Sweden are given, no commuting types are derived (Sandow 2008). Similarly, one study from 2014 shows maps of commuting distances in London, but no commuter types are derived (Beecham et al. 2014). Another study from 2021 analyses travel data from China, but no commuter types are given (Xing et al. 2021). Other work investigates commuting behaviour in Australia, but no commuting types are given (Philip et al. 2022). While one dutch study looks at EV drivers in particular, no explicit commuting types are derived (Spoelstra 2014). Another dutch study presents different EV charging session types (Helmus et al. 2020), but does not investigate the commuting patterns. Moreover, the data only provides information on public charging stations. Additionally, one study looks at 5 clusters for UK drivers, but much less information is given compared to the studies presented below (Crozier et al. 2018). Lastly, a study from China presents different EV user clusters, but we did not consider this work as 66% of the users have "no trip pattern" Li et al. (2019).

In summary, most existing work only reports average values for commuting distances and times. The few papers derive actual commuting types are presented in the case studies below.

In a study from 2020, clustering techniques were applied, using a combination of k-medoids and SCA (Subspace Clustering Algorithm) to categorise a total of 215 actual EV users into distinct profiles (Giordano et al. 2020) (Table 2). Through this clustering approach, the study aimed to capture the diverse characteristics and behaviours of EV users. The insights were then used to predict anticipated patterns of EV usage in an EV charging control algorithm. To account for seasonal variations, four specific weeks were selected for the analysis: one in January, May, July, and October respectively. The

Table 2 EV commuter types (Giordano et al. 2020)

Clustering Group	Characteristics
EV#1	This category consists of long-distance commuters who consume more energy than typical workers for working day trips and use their EV to commute to work every weekday. EV#1 owners typically keep their EV at home approximately 70% of the time.
EV#2	This cluster comprises typical workers, working not far from home, who commute to work with their EV every weekday, and the car is mainly present at home during the night and weekends. Weekend trips typically have higher energy consumption than those on weekdays, and on average, the EV is at home around 80% of the time. This category presents the most systematic behaviour during the week compared to other profiles.
EV#3	This category consists of freelancers who frequently keep their EV at home (approximately 90% of the time) and use it less regularly. This category is defined by the highest presence of the car at home and also a less regular use.

Table 3 Commuter types (Mattioli et al. 2019)

Clustering Group	Characteristics
VDC1	This cluster accounts for 23.3% of vehicle-day sequences and is characterised by peaks in car usage during the morning and afternoon periods. The morning and afternoon peaks are slightly later for this cluster compared to other clusters. Some sequences in this cluster do not include any vehicle use in the morning.
VDC2	Similar to VDC1, this cluster (7.9%) also exhibits morning and afternoon peaks of car use. However, the vehicle use in this cluster is more synchronised at specific times in the morning and afternoon. The peaks are slightly later in the day for VDC2. VDC1 and VDC2 have lower overall car travel distance and duration but similar frequency compared to other clusters.
VDC3	This cluster (14.3%) comprises sequences with vehicle use mainly in the mid-afternoon, around 16:00. The degree of synchronisation in this cluster is relatively low, with car use episodes before 12:00 and after 18:00.
VDC4	Vehicle use in this cluster (7.4%) shows a mid-late afternoon peak, and it is more concentrated at a specific time of day (slightly later than VDC3's peak). Most sequences in this cluster also include some vehicle use in the morning, although it is less synchronised. VDC4 stands out as having the most intensive car travel patterns, as well as the highest average vehicle occupancy.
VDC5	This cluster (13.6%) demonstrates a clear concentration of car use around noon (from 10:00 to 14:00). There is relatively little vehicle use outside of these hours, primarily in the afternoon, and it is not particularly synchronised. VDC5 has the lowest values in terms of travel frequency, duration, and distance.

findings obtained from this clustering methodology enable a comparative analysis of the distinct EV usage profiles, providing valuable insights into the variations and similarities among EV users across different time periods.

The study demonstrates the existence of discernible user categories among EV drivers, primarily based on their commuting patterns. However, it is evident that not all EV users adhere to the conventional nine-to-five schedule. Additionally, the distance traveled to work plays a crucial role in determining the energy consumption of the EV, leading to the identification of two distinct commuter categories: long distance commuters and short distance commuters. These variations in commuting distances contribute to the considerable variability in energy usage among EV users, underscoring the importance of considering the heterogeneity of commuting patterns when studying EV usage patterns.

Similarly, a study from the UK analyses the 2016 UK National Travel Survey (NTS) to classify cars based on their patterns of use over a day (Mattioli et al. 2019) (Table 3).

While this work looks at temporal patterns of car usage in general (and not exclusively at EVs), it provides valuable insight into the relationship between nine-to-five commuting and EV usage.

The study points out that there is a tendency to overlook the potential heterogeneity of vehicle usage patterns. Specifically, much existing research assumes that temporal patterns of EV use will reflect the rhythms of commuting with a daily return trip at "rush hour" (e.g. 9 am and 5 pm), and little car use outside of that (Huang and Infield 2009; Lund and Kempton 2008). The results show why these assumptions are misplaced. The five vehicle day clusters (VDC) exhibit differences in terms of frequency, distance, duration, and average vehicle occupancy, which may be attributed to systematic variations in travel purposes.

Indeed, within VDC1 and VDC2, approximately 60% of the recorded days encompass at least one commuting trip; however, VDC2 demonstrates a greater prevalence of trips related to education. Conversely, VDC3 exhibits a higher proportion of trips with purposes other than commuting, business and education, with approximately 50% of vehicle days encompassing at least one leisure trip. This characteristic suggests that VDC3 is representative of typical weekend days. Furthermore, VDC4 displays a large proportion of trips linked to education and personal matters, thereby leading to the hypothesis that this cluster encapsulates the behavioural patterns of parents and students.

This underlines the importance of accounting for different types of commuters, as well as non-work related trips, especially for the parts of the populations that are not typical nine-to-five workers. In fact, research on the temporality of working patterns has shown that they have become less standardised over time and this is reflected in an increasing heterogeneity of commuting patterns (Lesnard and Kan 2011).

In a related study, the relationship between commuting practices and peak energy demand in the UK is investigated (Ramirez-Mendiola et al. 2022) (Table 4). Through a cluster analysis, the researchers identify three distinct commuting schedules that exhibit clear differences in terms of the timing of commuting trips.

Examining the distribution of start times for driving commuting trips during a typical work day reveals the presence of substantial heterogeneity in commuting patterns. As expected, notable peaks in commuting activity occur at specific times of the day, such as during the morning and evening rush hours. However, the shape of this distribution also highlights significant variations in commuting patterns, particularly during the evening

Table 4 Commuter types (Ramirez-Mendiola et al. 2022)

Clustering Group	Characteristics
Cluster 1	The "earlier commuting" group comprises 32% of the analysed sample and exhibits two distinct yet dispersed peaks: one in the morning between 06:00 and 09:00, and another in the afternoon between 14:00 and 16:00.
Cluster 2	The group known as the "later commuting" segment represents 37% of the EV drivers in the sample and exhibits relatively more prominent peaks at approximately 08:00 and 18:00.
Cluster 3	The cluster referred to as the "staggering community" represents 31% of the EV drives in the sample and exhibits similarities to cluster 2 in terms of the timing of the morning peak. However, it displays a less distinct peak in the afternoon. In contrast, cluster 3 shows reduced commuting activity during the evening hours. Notably, this cluster demonstrates significantly higher levels of "other" travel around the expected time of the journey home from work. This behaviour aligns with individuals who make stops along their way home, such as picking up children or running errands at the shops.

commuting period. Unlike the gradual and steady increase followed by a sharp decline observed during the morning peak, the evening peak demonstrates a more discontinuous progression towards its maximum point, accompanied by distinct but relatively smaller surges in activity levels. Furthermore, a notable time gap of 2 hours is observed between the predominant departure times of “early” and “late” commuters as they begin their journey back home after work.

Overall, this study underscores the diverse working arrangements of individual employees and the significant differences in the temporal characteristics of the commuting patterns of EV users. In particular, it has outlined the inherent variability in the peaks of commuting activity and the typical times of home arrival across three clusters of commuters.

Although the overall proportion of vehicles exhibiting commuting-dominated usage patterns in the UK is slightly below 50%, the diverse and fluctuating nature of these commuting patterns can have notable implications for household energy consumption patterns, particularly as the adoption of EVs continues to rise (Mattioli et al. 2019).

In summary, these existing studies emphasise three ideas. First, we need to consider both commuting and non-commuting trips when modeling EV usage. Second, it is crucial to obtain a detailed understanding of the temporal patterns of EV use for individual household types. Third, modeling the synchronisation of car usage periods and periods of non-use, both in terms of time and space, is necessary. We incorporate these insights into SPAGHETTI.

Evidence for commuting shifts

We now demonstrate that the changes in commuting patterns, first initiated during the Covid-19 pandemic, are both significant and persistent.

The temporal organisation of daily routines is dominated by standard institutional rhythms, such as the nine-to-five working day. Nevertheless, in recent years, there has been a growing push to increase flexibility and reduce the rigidness of these work schedules (Clarke and Holdsworth 2017; Lesnard and Kan 2011). The onset of the Covid-19 pandemic has further accelerated this trend. This has significant implications for both individual EV usage and their large-scale adoption.

Despite the limited availability of publicly accessible post-pandemic EV usage datasets, numerous international studies provide valuable insights regarding the substantial shift observed in WFH patterns, as discussed next.

Tables 5 and 6 present compelling evidence showcasing the magnitude of this shift by summarising findings from diverse countries. The summarised studies shed light on the widespread adoption of WFH practices and its consequential implications on commuting patterns and EV charging demands.

Modeling WFH types

Based on the literature survey, we now identify three predominant post-pandemic commuter types that serve as templates for the synthetic trace generation. We identify the distinctive characteristics associated with each of the three types during weekdays and assume that all WFH types follow similar behaviours on weekends. Our three types are based on the EV profiles in reference (Giordano et al. 2020) but

Table 5 Summary of recent publications on changing WFH patterns in Europe

Country	Main findings
Switzerland (Huang et al. 2023)	This study examines the impact of WFH on travel behaviour during the post-lockdown period using GPS tracking data collected in Switzerland from 2019 to 2020. The findings reveal a significant reduction in trip distance, travel time, and travel frequency after the lockdown, irrespective of whether individuals primarily work from home or in office settings. Notably, EVs, regardless of driver type (WFH or non-WFH), spend more time idle at home, averaging 14 h per day for commuters and 16 h per day for WFH users compared to the pre-pandemic average of 13 h. Prior to the pandemic, only 25% of participants were teleworkers, but this number doubled during the initial lockdown period. Furthermore, an estimated 34% of employees express a desire to continue remote work in the post-lockdown period (Deloitte 2023).
Netherlands (van der Koogh et al. 2023; De Haas et al. 2020)	This work analyses electric charging behaviours of different user groups from January 2020 until October 2022. Overall, the study demonstrates how the pandemic has led to a decline in charging, different start times for charging during the day, and longer connection times. Evidence for a persisting effect of WFH was found, with a clear shift in the timing of charging sessions in the evening, showcasing that strict nine-to-five workplace norms are no longer in place. This shows that EVs spend more time plugged in at home and are used less for commuting. Another study from the Netherlands found that 27% of workers planned to continue working from home after the pandemic. During the pandemic, the amount of trips and distance travelled dropped by 55% and 68% respectively (De Haas et al. 2020).
Germany (Kolarova et al. 2021)	An online survey conducted in Germany shows that around 60% of respondants expect to increase their WFH frequency in the future (Kolarova et al. 2021).
Australia (De-Toledo et al. 2023; Pawluk et al. 2023; Currie et al. 2021; Greaves et al. 2024; Beck et al. 2020; Hensher et al. 2022, 2021, 2021)	One study conducted comprehensive stakeholder interviews in the city of Melbourne and discovered evidence indicating that participants perceive a decrease in work-related travel due to enhanced job flexibility and the option to WFH (De-Toledo et al. 2023). Recent research (Pawluk et al. 2023) has identified the emergence of a "hybrid" work model in Melbourne, characterised by working three days in the office and two days at home. This finding aligns with other recent research conducted in Melbourne, which suggests that WFH will lead to a 6% decrease in total peak hour commuter trips and a 20% decrease in commuter trips to downtown areas (Currie et al. 2021). An additional study, gathering data from Sydney, examined the impacts of Covid-19 and remote working on the transport network. It discovered that over 20% of respondents are working from home for 4–5 days weekly, and more than half are engaging in WFH activities for at least one day per week (Greaves et al. 2024). Similarly, findings presented by Beck et al. indicate that 71% of participants express a preference for more frequent remote working (Beck et al. 2020). Likewise, Hensher et al. conducted research in Australia to explore the disruptions to commuting trips caused by Covid-19. Their results indicate that the rise in WFH has significantly influenced travel behaviour and ought to be incorporated into forthcoming updates of transport models (Hensher et al. 2022, 2021, 2021).

Table 6 Summary of recent publications on changing WFH patterns in the United States

Country	Main findings
United States (Javadinasr et al. 2022)	The data collected in the United States between April 2020 and May 2021 highlights the shifts in work and commuting patterns in the US in the post-Covid world. Before the pandemic, 16% of the participants WFH more than once per week and 71.9% commuted to work with their private vehicle. After the pandemic, the percentage of participants who frequently WFH rose to 34%, while the percentage of participants that used their private vehicle to commute to work dropped to 65.6%. Moreover, the mean number of commute days dropped from 4.12 pre-Covid, to 3.42 after the pandemic. The study showcases substantial expansion of frequent telecommuters, who WFH more than once per week.
United States (Kong et al. 2022)	The authors study survey data from Washington to underline how people are gradually shifting from traditional patterns to remote work. The results show that 57% of the participants want to WFH at least one day per week after the pandemic, and 11% want to WFH every weekday. Before Covid, only 27% among them WFH at least one day per week. The biggest increase is observed among the participants who wish to WFH 1-2 days per week, accounting for 17% before the pandemic and 32% after it. This demonstrates that many people have discovered the remote working style during the pandemic (where 82% among the participants WFH at least once per week) and wish to pursue it.
United States (Tan et al. 2023)	This study explores the travel behaviours of tech workers in the San Francisco Bay area, revealing a pronounced shift towards greater remote working and fewer commuting journeys. During the survey period, from November 2021 to March 2022, a mere 3% of participants reported commuting to an office on a daily basis, while 66% were engaging in work entirely from home, and 31% adopted a hybrid working model. This represents a near reversal to pre-pandemic practices, where 74% of respondents indicated they commuted daily and only 3% worked entirely remotely. Furthermore, 47% anticipate maintaining a hybrid work schedule, with 2–3 days of remote work per week, over the long term. The study additionally observed a decline in non-commuting trips for shopping purposes, largely attributed to the growing preference for online grocery shopping and delivery services.
United States (Barrero et al. 2021)	The study surveyed over 30,000 Americans across multiple phases to determine the likelihood of persisting WFH arrangements and the reasons behind this trend. The findings suggest that 20% of all full workdays will be conducted from home following the pandemic, a significant increase from the pre-pandemic figure of just 5%. Five key factors contributing to this notable shift were identifies: better-than-expected WFH experiences, new investments in both physical and human capital facilitating WFH, a substantially reduced stigma surrounding WFH, ongoing concerns about crowded spaces and the risk of contagion, and a surge in technological innovations during the pandemic that support WFH.

modified to reflect the changes in post-pandemic commuting patterns as reflected in our literature survey. We assume that the EV always returns home at night, that it is always fully charged by the morning and that it is only charged at home.

WFH T1: the classic commuter

This corresponds to the typical nine-to-five worker, who commutes to work with their EV every weekday, leaving their residence at around 8:30 and returning home at around 18:00. These EV users have the highest average trip distance and consume the highest amount of energy across all seasons. They spend the least time at home and only recharge from the instantaneous (non-stored) PV production on weekends.

Table 7 Comparison of commute metrics between the three WFH profiles

	T1	T2.2	T3
Average trip distance (km)	26.8	22.3	19.3
Average travel time (min/day)	61	54.4	50
Number of trips per weekday	1	0.7	0.4
Stay at home (hours/day)	14.5	19.6	23

Table 8 Comparison of energy consumption during the week of each of the three WFH profiles across different seasons

	T1	T2.2	T3
$E_{cons}(kWh)$ in Jan	87.8	54.02	31.5
$E_{cons}(kWh)$ in May	56	30.8	14
$E_{cons}(kWh)$ in Jul	65	41.96	26.6
$E_{cons}(kWh)$ in Oct	62.8	46.12	35

WFH T2: the hybrid commuter

These EV users correspond to the newly emerging group of hybrid workers, who commute to work with their EV on some days (typically two or three days) and work from home on the other weekdays. The user therefore mimics T1's behaviour on some days and T3's behaviour on the other days. Due to the nature of this hybrid setup, this group of EV users is characterised by a medium average trip distance, energy consumption and time at home. We use the notations T2.2 and T2.3 to denote a hybrid commuter who work from home on two or three days per week respectively.

WFH T3: the freelancer

This EV user type models the emerging behaviour of EV owners who only WFH or who never use their EV to commute to work. Overall, the EVs belonging to T3 drivers remain idle at home for much longer times, but their usage patterns are a lot more variable and less predictable. We assume that most trips with the EV are conducted to run errands throughout the week and that each trip lasts less than 2 h. This EV user type is characterised by the lowest energy consumption and the highest potential to benefit from the solar energy produced by PV panels.

Comparison of the 3 types

Table 7 summarises key commuting metrics for each WFH type. The results were obtained by combining the findings presented in the section "Evidence for WFH shifts" with the values presented in reference (Mattioli et al. 2019), where T1 corresponds to VDC1 and T3 corresponds to VDC5. As T2.2 is a hybrid model, with 60% of the weekdays corresponding to T3's behaviour and 40% corresponding to T1, we took the weighted average of these two categories to compute T2's metrics.

Table 8 investigates the seasonal differences in the energy consumption of different WFH types, adjusting the results presented in the study (Giordano et al. 2020) to capture the contemporary EV usage patterns of the 3 WFH types. The values for T3 were obtained by reducing EV#3's values by 30% (to model 30% less trips), the values for T1 are computed as a weighted average between EV#1 (70%) and EV#2 (30%). Lastly, the values for T2.2 are obtained by computing a weighted average of T3 (60%) and T1 (40%).

Lastly, Table 9 showcases the seasonal differences in the percentage of time that the EV spends at home during the solar production time window. This metric provides a better understanding of the potential of each WFH type to benefit from the solar energy produced by the PV panels. The results presented in reference (Giordano et al. 2020) are used to compute the values. For T3, we increase EV#3's values by 30% (to model 30% fewer trips). The results for T1 and T2.2 are obtained by computing weighted averages, as described for Table 8.

SPAGHETTI

Tool description

We now define SPAGHETTI, which simulates the daily usage of an EV based on various parameters related to commuting and non-commuting habits, as well as EV characteristics. We use a parametric probabilistic model to generate synthetic samples of EV usage data.

We assume that each session can be described using three parameters: (i) departure time ($dept_C$), (ii) arrival time (arr_C) and (iii) SOC on arrival (SOC_{arr}).

The script generates synthetic daily trip data for an EV over a specified number of days, accounting for commuting trips as well as non-commuting trips. To mimic real-life variability, the script introduces randomness in commute distances and trip timings, simulating a range of possible daily scenarios for an EV owner.

SPAGHETTI is highly personalisable and has the following features:

1. Customisable EV Profile: It allows users to define critical parameters of an EV such as battery size, maximum and minimum SOC, and energy consumption rate.
2. WFH Integration: Users can input specific days of the week as WFH days, affecting the commuting patterns and consequently the EV's charging and discharging cycles.
3. Customisable Commute and Non-Commute Trip Parameters: Users can specify average distances, typical departure and arrival times, and frequency of both commuting and non-commuting trips, allowing for tailored simulations.

The generated trip data, including details like day of the week, departure and arrival times, and SOC at different points, is exported to a CSV file for further analysis.

Table 9 Comparison of X_{pv} during the week (the % of time during which the EV is at home and the PV panels are producing energy) of each of the 3 WFH profiles

	T1	T2.2	T3
X_{pv} (%) in Jan	11.6	28.04	39
X_{pv} (%) in May	17.9	44.6	62.4
X_{pv} (%) in Jul	34.4	52.76	65
X_{pv} (%) in Oct	10.8	26.94	37.7

SPAGHETTI is particularly useful for studies on EV energy consumption patterns, grid load analysis, or for individuals planning EV usage considering various commuting scenarios.

Tool usage

SPAGHETTI takes the input values that are defined in Table 9 in Appendix..

It is possible to adapt SPAGHETTI to specific countries, by replacing the input parameters with typical country-specific default values. Table 10 illustrates this for the UK (Mattioli et al. 2019) and Finland (Iqbal et al. 2021) and provides default values for typical commuting trips in these countries. SPAGHETTI enables the simulation of EV usage patterns across the world, by inputting commuting and non-commuting times and distances relevant to any specific geographical region.

SPAGHETTI offers a broad spectrum of applications and allows to conduct vital research on EV Usage in the future. For instance, it could be used to examine temperature effects on EV SOC and range anxiety, as well as exploring bidirectional EVs' potential in diverse WFH contexts. Alongside these, the SPAGHETTI's applicability extends to optimising EV interaction with smart home systems, assisting urban planning for EV infrastructure, influencing policy-making with targeted incentive schemes, and conducting behavioural studies on driver responses to varying factors. This multifaceted utility highlights the SPAGHETTI's significance in enhancing EV sustainability in both personal and urban environments.

Evaluation

This section presents our experimental results to demonstrate the impact of working from home on EV state of charge. All experiments were carried out using SPAGHETTI for typical households in the United Kingdom and in Finland, according to the parameters defined in Section Tool Usage and modeling the EV as the Tesla Model Y (Best Selling Electric 2023; Electric Vehicle 2022).

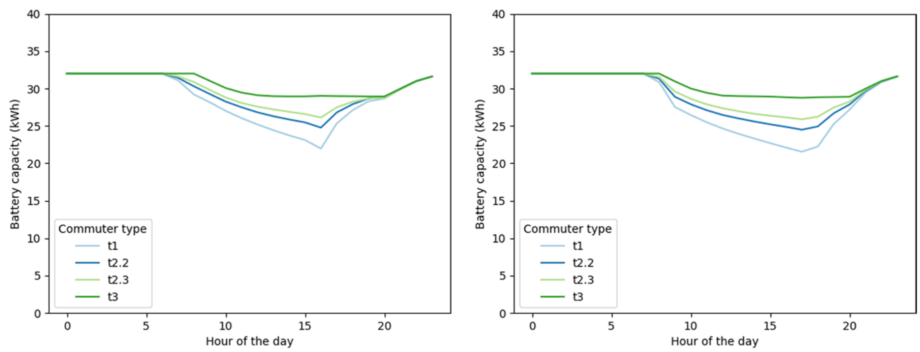
We model a scenario with a 3 kW PV installation that produces electricity during sunlight hours. The typical sunlight hours that we use in our evaluation are WorldData (2024):

1. UK Winter (Dec–Feb): 07h43–16h30
2. Finland Winter (Dec–Feb): 08h46–16h06
3. UK Summer (Jun–Aug): 05h07–21h00
4. Finland Summer (Jun–Aug): 04h33–22h13

We conduct all experiments for the typical WFH types that we defined earlier.

Table 10 Examples of Country-Specific Input Parameters for SPAGHETTI

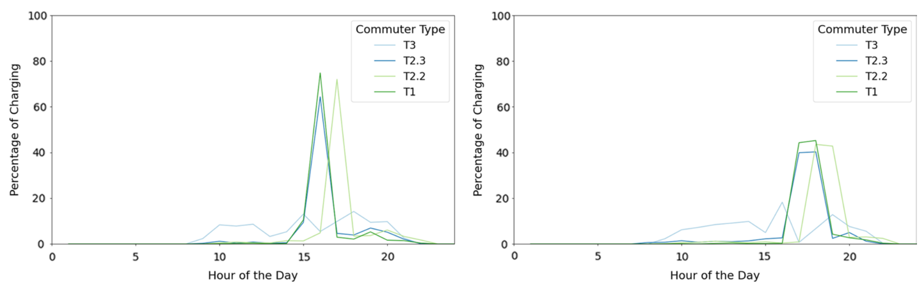
Input	Finland	United Kingdom
Typical commute distance ('-C_dist') (km)	16.00	19.50
Commute departure time ('-C_dept')	7.00	8.00
Commute arrival time ('-C_arr')	16.20	18.00



(a) Average Battery Capacity of an EV in Finland.

(b) Average Battery Capacity of an EV in the UK.

Fig. 1 Average hourly EV battery capacity (*kWh*) for each WFH type on a weekday



(a) Charging Distribution over one Year in Finland.

(b) Charging Distribution over one Year in the UK.

Fig. 2 Hourly residential EV charging distribution for different WFH types over one year

SOC distribution

We study the average EV state of charge (SOC, in kWh) corresponding to the four commuting types in both Finland and the UK, see Fig. 1. We find that the overall SOC pattern is similar between the UK and Finland, with morning and evening commutes being the primary periods of energy use. Hence, the EV owners who commute the most (T1 and T2.2) have the steepest decline in SOC. Both graphs show that EVs improve their SOC at the end of the day, as charging starts as soon as the EV returns home. Commuter type T3 consistently shows the highest average SOC in both countries, demonstrating the impact of working from home on reducing EV usage and the potential for energy savings.

This analysis provides insight into EV usage patterns in relation to battery capacity throughout the day, emphasising the potential benefits of flexible WFH and the need to account for WFH when optimising domestic energy use.

Charging distribution

Next, we study the hourly charging distribution of the different commuter types in both Finland and the UK, see Fig. 2.

We use a conservative charging policy and always start to charge the EV as soon as it returns home at the end of the day. This charging technique is employed by most EV users today. We expect to see a peak in the charging distributions around the return time after commuting trips, for the types T2.3, T2.3 and T1, which have varying frequencies of commuting trips. Furthermore, we anticipate that the overall distribution curves for the two countries look similar but are slightly displaced, due to the difference in the commuting trip timings.

We find that the peaks in the charging distributions are indeed visible around the time at which EVs return home, which aligns with the conservative charging policy. The peaks of the three types that have commuting trips (T2.3, T2.3 and T1) are slightly displaced, which might be due to the randomness associated with the trip generation and especially the non-commuting trips generation. Moreover, the markedly flatter charging curve of T3 commuters exemplifies the significant extent to which increased WFH practices can influence energy demand management.

Additionally, the peaks are more prominent for Finland than for the UK, which is probably due to the higher charging demand in the UK, where charging times take longer and are sometimes spread over more than one hour. Besides, we know that even small variations in the input parameters of SPAGHETTI, and mainly in the typical commuting distances and times, can heavily change the shape of the peaks.

In summary, the analysis of the charging distributions outlines the significant implications that commuting habits can have on grid pressure. Even with a conservative charging policy, the economic and environmental benefits of increasing the WFH frequency of EV drivers become evident. These findings highlight the necessity for future strategies in EV usage and grid management to incorporate flexible WFH policies, aiming to alleviate peak load demands and enhance grid stability. Furthermore, understanding these usage patterns is crucial for the development of smart charging infrastructure and grid-responsive energy systems, ensuring that the growing adoption of EVs contributes positively to the sustainability and efficiency of urban energy networks.

Discussion and conclusion

We presented SPAGHETTI, a tool for the simulation of EV usage which provides a granular and insightful look into the daily energy consumption patterns of EV owners with different commuting types. By considering variables such as battery size, state of charge, consumption rates, and WFH days, SPAGHETTI effectively models the EV usage of typical EV owners in the post-Covid world. SPAGHETTI allows for the simulation of various scenarios, giving valuable data on how commuting patterns influence energy demands.

The evaluation results from the SPAGHETTIS's simulations reveal distinct differences in EV usage patterns between different commuter types and across seasons, but with very similar results in both the UK and Finland. Increased WFH among commuters allows for greater flexibility in home energy management, leading to more efficient optimisation of energy consumption.

This shows that flexible WFH policies can not only reduce energy demand but also carbon emissions. These unexpected benefits of working from home should be taken into account when designing workplace policies.

Our work is not without limitations. Firstly, the absence of post-pandemic real-world EV usage data limits our ability to validate the WFH profiles defined in SPAGHETTI against actual behaviors, as these profiles are based on existing literature rather than empirical evidence. This limitation raises concerns about the model's capacity to accurately represent the diverse and variable nature of EV usage across different regions and demographics. If SPAGHETTI is used primarily to simulate these predefined WFH scenarios, its generalisability may be restricted. However, the tool can incorporate detailed user inputs, which significantly enhances its potential as a versatile generator for post-pandemic EV usage and thereby improves its applicability and effectiveness. Second, the simplifications within SPAGHETTI, though necessary for model feasibility, omit several real-world EV usage scenarios. Assumptions regarding nightly home returns, morning full charges, and exclusive home charging fail to account for the varied charging practices among EV owners. This may not accurately represent the range of real-world charging behaviours, potentially limiting the applicability of our findings in scenarios requiring nuanced understanding of EV charging and usage patterns.

Acknowledging these limitations, future research should prioritise the acquisition and analysis of post-pandemic EV usage data to refine and validate our model. Further investigations should also explore more diverse charging behaviours, potentially through primary data collection or collaborations with EV service providers. A particularly promising direction for future work involves leveraging such data to explore the integration of (bidirectional) EVs into residential microgrids. This research avenue holds significant potential for enhancing energy efficiency, optimising local energy resources, and facilitating the transition towards more sustainable and resilient urban energy systems.

In summary, SPAGHETTI, along with its evaluation outcomes, underscores the pivotal importance of considering commuting and WFH patterns in the wider assimilation of EVs into the energy infrastructure. Policymakers, urban planners, and energy providers can leverage SPAGHETTI to forecast energy demand, plan for adequate charging facilities, and encourage energy-saving practices among EV users. We hope that SPAGHETTI will serve as a valuable resource for future research in this area.

Appendix

Tables 11 and 12 show the input parameters for SPAGHETTI.

For example, to run a simulation for an EV with a 40 kWh battery, 80% max SOC and 20% min SOC, a consumption rate of 164 Wh/km, WFH on Mondays and Wednesdays with a typical commuting distance of 20km, typical commuting times 7:45–17:30 and on average 5 non-commuting trips per week, the input would be:

python ev_simulation.py –output ev_usage_output.csv –days 365 –ev_battery 40 –max_soc 0.8 –min_soc 0.2 –consumption 164 –wfh_monday 1 –wfh_tuesday 0 –wfh_wednesday 1 –wfh_thursday 0 –wfh_friday 0 –C_dist 20.0 –C_dept 7.45 –C_arr 17.30 –N_nc 5

We also published an extended version of SPAGHETTI that gives more fine-grained control over the non-commuting trips. For every day, it is possible to specify the following optional parameters (replace [day] with mon, tue, wed, thu, fri, sat or sun):

- –[day]_nc: Number of non-commuting trips for the day.
- –[day]_dept: Typical departure time for non-commuting trips.
- –[day]_arr: Typical arrival time for non-commuting trips.

Table 11 Input Parameters for SPAGHETTI

Input	Description	Usage	Default value
Output File Name ('-output')	The name of the CSV file where the simulation results will be saved.	Specify a file name to save the output data.	'ev_usage.csv'
Number of Days for Simulation ('-days')	The number of days over which to simulate EV usage.	Set this based on the desired simulation period.	365 days
Battery Size ('-ev_battery')	The capacity of the EV's battery in kilowatt-hours (*kWh*).	Set based on the specific EV model you are simulating.	40 *kWh*.
Maximum State of Charge ('-max_soc')	The maximum state of charge of the battery, expressed as a fraction (0 to 1).	Adjust according to the EV's recommended maximum charge level.	0.8
Minimum State of Charge ('-min_soc')	The minimum state of charge of the battery, also expressed as a fraction.	Set this based on the EV's operational requirements.	0.2
Consumption ('-consumption')	The EV's energy consumption rate in watt-hours per kilometer (*Wh/km*)	Input the average consumption rate of the EV model.	164 *Wh/km*
Work-From-Home Days ('-wfh_[day]')	Binary flags (0 or 1) to indicate whether the user works from home on specific weekdays ('monday', 'tuesday', etc.)	Set to 1 for WFH days and 0 for commuting days. Give an input for each weekday, by replacing 'day' by the corresponding weekday in lowercase.	0 (commuting) for all weekdays

Table 12 Input Parameters for SPAGHETTI

Input	Description	Usage	Default value
Typical Commute Distance ('-C_dist')	The one-way distance of the daily commute in kilometers.	Set this to reflect the typical commuting distance.	20.0 km
Commute Departure Time ('-C_dept')	The usual time of departure for commuting, in hours.	Input the departure time in 24-h format (HH.MM).	7.45 (7:45 AM)
Commute Arrival Time ('-C_arr')	The usual time of arrival back from commuting.	Input the arrival time in 24-h format (HH.MM).	17.30
Number of Non-Commuting Trips ('-N_nc')	The average number of weekly non-commuting trips.	Estimate and input based on typical non-work-related travel.	5

- –[day]_dist: Typical distance for non-commuting trips in kilometers.

If these parameters are not provided for a specific day, random values are used to generate non-commuting trip data for that day.

Abbreviations

WFH	Work-from-home
EV	Electric vehicle
PV	Photovoltaic
SOC	State-of-charge
HEMS	Home energy management system
NC	Non-commuting trips
V2G	Vehicle-to-grid

Author contributions

All authors contributed to the conceptual development of the solution. AB led the implementation and paper writing. SK contributed to the writing. Both authors read and approved the final manuscript.

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Data availibility
The data generator is openly available on Github: https://github.com/amcberkes/SPAGHETTI.git .

Declarations

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