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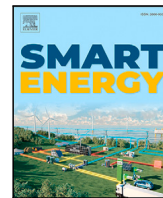
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Quantifying energy transport by electric vehicles: A Monte Carlo and optimization framework for flexible energy communities

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ABSTRACT

Rising grid congestion raises concerns that conventional grid expansion may not keep pace with projected increases in demand and renewable generation. This research proposes a supplementary solution: leveraging the inherent mobility of Electric Vehicles to enable energy transfer within different locations. Through an analytical modelling approach, a stochastic energy transport model using Monte Carlo sampling is developed. This model generates synthetic weekly charging and driving profiles to quantify the energy transport potential of private EV fleets, accounting for battery capacity, mobility patterns, and energy consumption. Building on this concept, the study introduces Flexible Energy Communities (FlexECs), where members share the same living location but commute to different workplaces or vice versa. By enabling electric vehicles to charge at one location and discharge at another during routine daily travels, Flexible Energy Communities exploit private EV mobility as a mechanism for spatial energy transfer, extending Energy Community operation beyond purely grid energy exchange.

Results reveal that approximately 35 kWh, equivalent to 60% of the total energy stored in the EV battery at the time of departure, can be discharged upon arrival. Additionally, when charging patterns are optimized, up to 30 kWh, representing 70% of the energy charged prior to the journey, can be effectively transported and discharged at the destination. By quantifying the impact of EV-imported energy on cost, peak demand, and overall energy consumption reduction, this study underscores the potential of EVs as dynamic energy transporters, providing a technical foundation for energy sharing through private EVs daily travelling patterns.

1. Introduction

The increasing demand for electrical energy transmission, driven by factors such as population growth and the integration of renewable resources, presents a significant challenge, [1]. The demand is further driven by the anticipated increase in electricity consumption due to the decarbonization of the heating, [2], and transport sectors, [3]. As a result, many regions are already experiencing grid congestion, [4], and excess renewable energy, particularly from solar PV, is being curtailed due to insufficient grid capacity, [5]. To prevent such issues and allow for the integration of additional loads and generation, the power grid must be reinforced and expanded, [6]. However, delayed investments in grid infrastructure can significantly hamper the integration of Variable Renewable Energy Sources, as highlighted in [7]. Recent analyses, [8], also raise concerns about whether planned grid

expansions are progressing at a sufficient pace to meet the projected increases in demand and renewable generation.

These studies highlight the need for innovative solutions to meet growing energy transmission demands and support the grid expansion efforts, [9]. The solutions are primarily categorized into two concepts: the use of alternative energy transport sources, such as hydrogen gas grids [10], and the reduction in peak power demand through energy storage, [11], Distributed Energy Resources (DER), [12], and Energy Management Systems, [13], to support the grid.

1.1. Literature review

Electric vehicles have been widely studied as flexible resources for supporting power system operation through controlled charging and discharging strategies. Several studies consider EVs as a means to

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reduce grid expansion needs by optimizing their (dis)charging patterns, particularly in the context of increasing electrification and renewable integration [14]. Within this line of research, EVs are primarily treated as controllable electrical loads or as stationary distributed energy storage assets whose flexibility is exploited over time rather than across space. Smart charging strategies adjust charging times to align with low-demand or low-price periods, while bidirectional charging within the Vehicle-to-Grid (V2G) concept enables EVs to provide grid services such as frequency regulation [15], voltage support and power loss reduction [16], congestion mitigation [17], and improvements in overall grid reliability and safety [18].

A growing body of work demonstrates that coordinated EV charging and discharging can reduce peak demand and support distribution networks, especially when integrated with energy management systems and other distributed energy resources [19,20]. In these approaches, the primary source of flexibility arises from shifting energy consumption or injection in time, typically within a single location such as a household, parking facility, or energy community. As a result, EVs are commonly modelled as stationary assets once connected to a charger, and their mobility is considered mainly to determine availability windows for charging or discharging rather than as an active mechanism for energy redistribution. Consequently, although time-dependent flexibility enabled by EVs is well established, these studies implicitly assume that energy exchange remains confined to the electrical grid and to the locations where EVs are connected.

To overcome the location restrictions, a growing body of literature has examined the spatial distribution of EV charging demand and its impact on distribution networks. In these studies, EV mobility is explicitly considered to determine where and when charging demand arises across urban or regional areas, allowing a more accurate assessment of grid impacts. For example, spatial-temporal EV charging loads have been analysed from the grid perspective to identify congestion risks and network stress in different parts of a city, [21]. In this line of work, mobility patterns are primarily used to map charging demand geographically rather than to model energy redistribution across locations.

Recent contributions have further strengthened this spatial perspective by integrating transportation and power system models. A notable example is the GIS-based framework proposed in [22], which combines graph-theoretic traffic modelling with distribution network data to estimate the additional electrical load imposed by EVs at primary substations. By simulating realistic travel routes and overlaying them with grid service areas, this approach provides high-resolution insight into how electric mobility affects distribution networks in space and time.

While these approaches represent a significant advancement over purely time-based charging models, they remain fundamentally grid-centric. EVs are still treated as mobile loads whose energy demand is ultimately supplied through the electrical network, and the spatial analysis is used to identify where grid reinforcements may be needed. Energy exchange continues to occur exclusively through the grid, and EV mobility is not leveraged as a physical mechanism for transporting energy between locations. Consequently, although the spatial dimension of EV charging demand is explicitly modelled, these studies do not address the potential of private EVs to act as mobile energy carriers that intentionally move energy across geographically separated systems.

Electric vehicle mobility has also been explored as a means to enable direct energy transport between geographically separated locations, giving rise to a set of concepts often referred to as Vehicular or EV-based Energy Networks. One of the earliest formulations is the Electric Vehicle Energy Network, introduced in [23], which leverages EV mobility and V2G capabilities to transmit energy across traffic networks. Building on this idea, subsequent studies examined key technical aspects of such networks. For example, [24] analysed the resilience of EV energy networks under urban traffic congestion, while [25] proposed routing optimization methods to identify efficient energy transfer

paths under congestion constraints. Infrastructure planning aspects were addressed in [26], which focused on optimal charging station placement using city bus networks as energy carriers, and [27] investigated strategies to maintain network functionality during renewable energy shortages.

Closely related to these concepts is the Vehicular Energy Network (VEN) framework introduced in [28], which treats EVs as mobile energy carriers capable of transporting renewable electricity over road networks using dynamic wireless charging and V2G technologies. Follow-up studies expanded this framework by developing mathematical models to assess feasibility [29], optimizing energy routing under traffic uncertainty [30], and applying advanced learning-based methods to jointly optimize routing and energy storage decisions [31]. More recent work has considered multisource-multidestination energy routing problems to improve transmission efficiency in complex VEN configurations [32]. A similar concept is studied in [33], where the authors proposed a vehicle-to-grid mobile energy network in which symmetrical EV mobility is leveraged to balance power demand across locations, demonstrating the potential of EV movement to support demand response without relying on dedicated routing or delivery infrastructure. While these studies demonstrate the technical feasibility of EV-mediated energy transport, they typically rely on engineered energy delivery paths, explicit routing decisions, or dedicated infrastructure, and often assume a level of system coordination that exceeds what can be expected from everyday private vehicle use.

The concept of EV-based energy transport has also been studied in the context of distribution network support through the concept of EV-based Virtual Electricity Networks (EVEN). In [34,35], EVs are coordinated to charge in capacity-rich networks and discharge in capacity-constrained ones, effectively transferring energy across feeders to enhance hosting capacity and mitigate voltage violations. These studies combine inter-network energy delivery optimization, stochastic time-series analysis, and battery degradation modelling, demonstrating that even modest energy shifting can significantly improve grid performance.

Collectively, these studies demonstrate that EVs can be actively coordinated to deliver electricity between locations and provide system-level benefits such as congestion relief, voltage support, and improved renewable energy utilization. However, they share several common characteristics that distinguish them from the focus of this work. First, EV mobility is typically treated as a controllable or optimisable resource, with routing, charging, or state-of-charge targets explicitly designed to achieve energy delivery objectives. Second, the primary goal of these approaches is to optimize grid performance or energy sharing through coordinated control, rather than to quantify the amount of energy that is already transported by EVs as a by-product of routine private mobility. Third, these frameworks often assume dedicated control architectures, partial system-level coordination, or engineered energy delivery mechanisms that go beyond everyday charging behaviour.

In contrast, this study does not aim to design or optimize an EV-based energy network. Instead, it focuses on quantifying the energy transport potential embedded in normal private EV usage, where vehicles follow routine travel patterns and charge opportunistically at locations they naturally visit. Mobility is treated as an exogenous constraint rather than a decision variable, and no additional trips, routing optimization, or behavioural incentives are assumed. By combining stochastic mobility and charging profiles with energy accounting and optimization at the Energy Community level, this work provides a complementary perspective that characterizes how much energy private EV fleets can realistically transport today and how this emergent energy flow can be leveraged within decentralized energy systems.

Energy Communities (ECs) have emerged as a key framework for enabling collective participation in decentralized energy systems, allowing groups of individuals or households to jointly manage generation, storage, and consumption resources [36]. In both regulatory definitions and practical implementations, ECs are typically organized around

shared, location-bound assets such as rooftop photovoltaic systems, stationary batteries, and local loads. Energy exchange within these communities is commonly assumed to occur through the electrical grid, with flexibility provided by time-dependent coordination of locally installed resources.

Beyond technical and regulatory interpretations, ECs are also defined from a socio-organizational perspective. As stated by REScoop.eu, [37], *“An energy community is a way to ‘organize’ citizens that want to cooperate together in an energy-sector related activity based on open and democratic participation and governance, so that the activity can provide services or other benefits to the members or the local community. In this sense, energy communities represent an alternative type of market actor, and a different way/philosophy to do business. The primary purpose of energy communities is to create social innovation and to engage in an economic activity with non-commercial aims”*.

Within this context, electric vehicles are increasingly included as assets in Energy Community models, often treated as Distributed Energy Resources that can provide additional flexibility through smart charging or V2G operation [38,39]. However, in most existing EC implementations, EVs are modelled in a manner similar to stationary storage once connected to a charger, and their role is confined to the location at which they are plugged in. As a result, energy sharing remains implicitly restricted to a single physical site, and the mobility of EVs is primarily used to determine availability windows rather than to enable new modes of energy exchange.

At the same time, prior work has acknowledged that energy communities need not be strictly limited to small, geographically compact areas. As noted in [40], while concrete EC initiatives often involve few participants and limited geographical scope, broader configurations are conceptually possible. In practice, however, geographically distributed energy sharing is typically realized through market mechanisms, aggregation, or grid-based exchanges rather than through the physical movement of energy carriers.

More recently, EV mobility has been explicitly explored as a mechanism for inter-community energy exchange through the Community-to-Vehicle-to-Community (C2V2C) paradigm. Studies such as [41,42] consider EVs as mobile power banks for delivering electricity between different building or community microgrids, developing coordinated charging and discharging control strategies to optimize energy delivery and analysing the robustness of such services under different scenarios. A related spatio-temporal control approach is presented in [43], where coordinated EV charging is optimized across multiple building communities to balance heterogeneous power regulation needs and user preferences. These works demonstrate the potential of EV-mediated energy exchange between communities, but generally rely on explicit coordination mechanisms, centrally optimized control strategies, and predefined inter-community energy delivery objectives.

This highlights a technical gap in how Energy Communities are commonly modelled: existing frameworks do not explicitly account for mobile energy storage assets that transport energy as a by-product of everyday private mobility, without requiring dedicated coordination or energy-delivery-oriented routing. Private electric vehicles represent a unique class of assets in this respect, as they combine energy storage, bidirectional charging capability, and routine mobility across different sites driven by non-energy-related travel behaviour.

Building on this observation, this work considers a configuration in which EV mobility relaxes the implicit spatial constraints of conventional Energy Community models. By enabling energy to be charged at one site and discharged at another as part of normal commuting and daily travel, private EVs can act as mobile links between otherwise independent locations. This motivates the concept of Flexible Energy Communities (FlexECs), in which energy exchange is facilitated not only through the grid but also through the physical movement of private EVs in and out of the community, extending the scope of community-level energy sharing while preserving the core principles of collective resource management.

1.2. Research gaps

Despite extensive research on electric vehicles as flexible assets for grid support, energy management, and energy sharing, the literature reveals several open gaps related to the role of private EV mobility in decentralized energy systems. While prior studies have examined temporal flexibility, spatial charging impacts, and coordinated energy delivery using EVs, important aspects of how everyday private EV mobility can contribute to energy transport and redistribution remain insufficiently understood.

1. Existing studies widely investigate how EV mobility patterns influence charging demand and grid operation, using mobility information to determine when and where EVs charge. In this body of work, EVs are primarily treated as mobile loads or as stationary storage once connected to a charger. Although several studies explore coordinated charging, V2G services, and even EV-mediated energy delivery, there is a limited quantitative understanding of how much energy private EVs can physically transport between locations as a by-product of routine, uncoordinated daily mobility under heterogeneous driving and charging conditions.
2. Prior research has not provided a comprehensive quantification of how key factors such as driving patterns, charging behaviour, vehicle characteristics, and seasonal effects jointly influence the energy transport capability of private EV fleets. As a result, the scale and variability of EV-based energy transport under realistic operating conditions remain unclear, limiting the ability to assess its relevance for decentralized energy systems and peak demand mitigation.
3. While advanced V2G and EV-based energy delivery frameworks incorporate both spatial and temporal dimensions through coordinated control and optimization, these approaches typically assume engineered charging strategies, explicit routing, or system-level coordination. There remains a gap in understanding how spatial energy transport emerges when EV mobility is treated as an exogenous constraint rather than a controllable decision variable, and how this emergent energy flow can be leveraged without altering daily EV usage and travel behaviour.
4. Recent studies have investigated EV electricity delivery between multiple communities through explicitly coordinated control strategies, where electric vehicles are treated as controllable delivery assets providing a dedicated energy-sharing service. In parallel, Energy Community models typically represent EVs as stationary or time-flexible resources operating within a single location. The role of private EV mobility as an intrinsic component of an Energy Community’s configuration, where energy can flow into and out of the community through routine, non-coordinated travel rather than through explicit delivery control, has not been addressed. As a result, existing Energy Community formulations do not capture how everyday EV mobility alters the community’s effective energy boundary and internal energy balance.

1.3. Contributions of the paper

This study focuses on private EVs as dynamic energy transporters, differing from conventional views in the literature, where EVs are considered another stationary DER. Furthermore, it provides quantifiable metrics for potential impacts, such as reductions in peak and overall consumption within residential locations using EV-imported energy. The study also calculates the scale of energy transport achievable by EVs, underscoring the potential of its findings.

Contributions of the paper include:

Table 1
Comparison of EV-based energy transport and energy sharing studies.

Ref	Role of EVs in the energy system	EV mobility representation	Spatial scope of energy exchange	Energy transport quantified	Variability in charging behaviour	Variability in driving behaviour	Analysis scope	Multi-Location context
[39]	Stationary DER	None	Single location		✓		Case-based	✓
[21]	Mobile load	Origin–destination	Urban areas		✓	✓	City-scale	
[22]	Mobile load	GIS-based trips	Substation service areas		✓	✓	Regional-scale	
[33]	Energy carrier	Stochastic trips	Multiple locations	Implicit	✓		Network-level	
[23]	Energy carrier	Traffic flows	Road network				Conceptual	
[24]	Energy carrier	Traffic-aware	Road network			✓	Network-level	
[25]	Energy carrier	Route-based	Road network			Optimized routes	Algorithmic	
[26]	Energy carrier	Fleet mobility	Urban network		✓		Infrastructure planning	
[27]	Energy carrier	Traffic patterns	Network-wide		✓		Network-level	
[28]	Energy carrier	Vehicular flows	Road network				Conceptual	
[29]	Energy carrier	Traffic flows	Road network				Analytical	
[30]	Energy carrier	Opportunistic routing	Road network			✓	Algorithmic	
[31]	Energy carrier	Traffic-aware	Road network		✓	✓	Learning-based	
[32]	Energy carrier	Traffic-aware	Multi-source network		✓	✓	Network-level	
[34]	Energy carrier	Commuting EVs	Inter-network	Explicit	✓		Distribution networks	✓
[35]	Energy carrier	Commuting EVs	Inter-network	Explicit	✓		Distribution networks	✓
[42]	Energy carrier	Daily mobility	Inter-community	Explicit	✓	✓	Community-level	Between ECs
[43]	Energy carrier	Daily mobility	Multi-building	Explicit	✓	✓	Community-level	Between ECs
This work	Energy carrier	Private everyday mobility	Inter-location (physical)	Explicit (fleet-scale)	✓	✓	Top-down + Bottom-up	FlexEC

1. This study proposes a stochastic, mobility-aware framework to quantify the energy transport capability of private electric vehicles under heterogeneous driving and charging patterns. By combining realistic mobility, vehicle characteristics, and energy consumption data, the framework estimates the amount of energy that private EVs can physically transport each day under observed mobility and charging patterns, providing a first-order quantification of the magnitude of EV-based energy transport at the fleet level under different operating conditions.
2. The paper introduces the concept of Flexible Energy Communities (FlexECs), in which private electric vehicles are treated as mobile energy storage assets that are intrinsically embedded in the Energy Community's energy balance. In FlexECs, everyday EV mobility allows energy to enter and leave the community through routine travel rather than through explicit energy delivery services or coordinated inter-community control. This redefines the Energy Community, extending its operation beyond a single fixed location while relying exclusively on routine private EV use".
3. A scalable top-down methodology is developed to estimate the energy transport potential of private EV fleets across different regions, including Europe, the United States, China, and

globally. The top-down results are supported by bottom-up modelling, providing consistent large-scale insights into the role of private EV mobility in energy redistribution and peak demand reduction.

A qualitative comparison with conventional grid-based transmission is also provided in the Discussion section to contextualize the advantages and trade-offs of the proposed approach.

Table 1 presents an overview of previous studies on EV-based energy transport and optimization approaches, highlighting their characteristics and contributions. While several works explore V2G and energy management strategies, most studies focus on predefined trips with EVs or buses, not considering weekly private EV behaviour.

1.4. Structure of the paper

The modelling of charging and mobility patterns is explained in Section 2, which includes the charging demand, Section 2.2.1, the energy used for mobility, Section 2.2.2, and the weekly EV profiles, Section 2.2.3. The Energy Community LP optimization algorithm is modelled in Section 3. Section 4 introduces the use case and the characteristics of the EV fleet and the Decentralized Energy System.

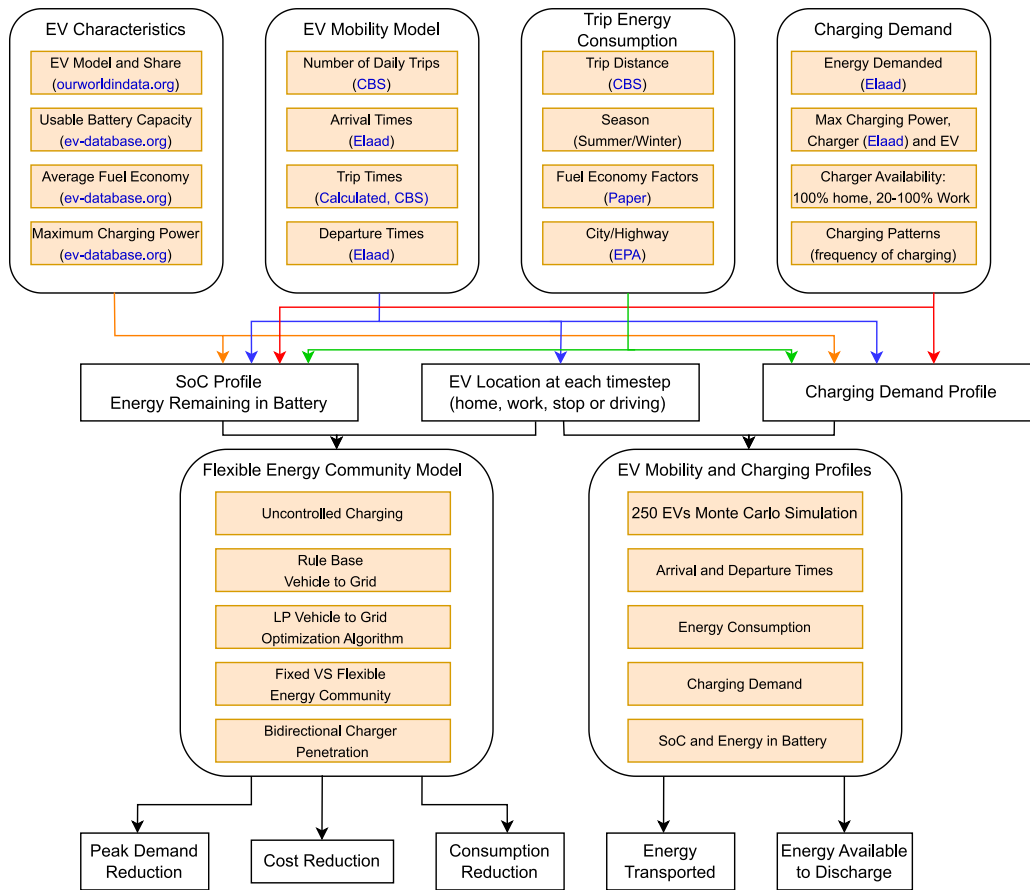


Fig. 1. High-level workflow of the proposed modelling framework, linking EV mobility and charging profiles to the energy community analysis.

Section 5 offers an in-depth examination of the findings, discussing the implications of the data and their relevance to the field. The effect of the mentioned factors, 5.1, and the weather, 5.1.2, on energy transport is explained. The section ends with two Energy Communities’ use case results 5.2. Finally, the key takeaways from the study are reflected in Section 6, and its impact, limitations, and potential future directions for research are discussed in Section 7.

2. EV mobility and charging model

This study quantifies the amount of energy that a private electric vehicle (EV) fleet can transport between different locations by explicitly modelling charging and mobility behaviour. The analysis focuses exclusively on privately owned battery electric vehicles (BEVs) used for non-commercial purposes, including commuting and personal trips such as leisure, family visits, and other activities outside working hours. Both commuting EVs and vehicles remaining at home are considered, allowing the framework to capture the diversity of private mobility patterns.

Since energy can only be transported when vehicles move between locations, trip frequency, timing, and distance are key determinants of energy transport potential. In addition, battery capacity, energy consumption, and charging behaviour influence the amount of energy that can be carried and subsequently discharged. Vehicles used primarily for professional purposes, such as vans or trucks, are excluded due to their higher daily driving distances and reduced parking availability. Plug-in hybrid vehicles and smaller electric vehicles, such as motorbikes, are also not considered, as their battery capacities are generally insufficient for meaningful energy transport.

To represent realistic variability in charging and mobility behaviour, a stochastic simulation model based on Monte Carlo sampling is employed to generate synthetic weekly driving and charging profiles. These profiles reflect heterogeneous arrival and departure times, trip durations, driving distances, charging frequency, and charging power, ensuring that the evaluation of energy transport is not based on fixed or deterministic assumptions. Unlike shared or fleet-based systems, this approach captures the energy transport potential embedded in everyday private travel behaviour.

Fig. 1 provides a high-level overview of the modelling framework. Real-world datasets and assumed parameters are combined to generate stochastic mobility and charging profiles for private EVs. The charging demand module accounts for charger availability at home and work, charging frequency, and seasonal variations. In parallel, the mobility model integrates travel data, including daily trips, arrival and departure times, and trip durations, with vehicle characteristics such as battery capacity, charging power, and energy consumption.

The synthetic mobility and charging profiles generated by this model are used to estimate the energy available for discharge and the amount of energy transported between locations by private EVs. These profiles serve as inputs to the Flexible Energy Community (FlexEC) model, which evaluates different charging and discharging strategies and quantifies their impact on system-level performance indicators such as peak demand, energy consumption, and energy cost.

2.1. Top-down approach

As a preliminary step, a top-down estimation was conducted to assess the large-scale energy transport potential of EVs using publicly

Table 2
EVs stock and characteristics in 2023.

Location	BEV stock	Average capacity (kWh)	Average fuel consumption μ_k , Wh/km	Average daily travelling distance (S_{kr} , km)
Netherlands	703,000	57.67	165	32
Europe	13,000,000	59.75	163	33
China	27,000,000	62	148	34
US	6,000,000	74.6	167	42
World	60,000,000	60	147	15

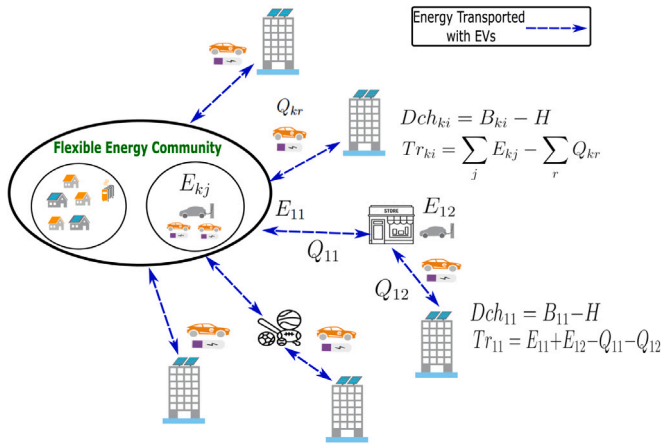


Fig. 2. Energy transported between different locations diagram.

available national-level data. This calculation provides a benchmark for the more detailed bottom-up modelling developed in the following sections and offers insight into the expected scale of energy transport across different regions. Only three discharging days per week were assumed to limit battery degradation due to extra deep cycling. The data used for the calculations is shown in Table 2. Data have been obtained from [44] for the number and share of electric vehicles, [45] for the capacity and average fuel consumption, and [46,47] for the travel distance. The average battery capacity and fuel consumption were calculated with the weighted average of the 10 most common electric vehicles in each study location.

In this study, two different terms are used, energy transported, Tr_{ki} , and energy available for discharging, Dch_{ki} , of each car k at each location i , or used Q_{kr} during each trip r , as illustrated in Fig. 2. The energy available for discharging will be the energy remaining in the EV battery at arrival, B_{ki} , minus a safety margin kept in the battery H .

Energy transported refers to the amount of energy that an EV charges at each location, E_{ki} , minus the energy that it uses during each trip, Q_{kr} , effectively moving energy between these points. For example, energy charged at Location A and discharged at Location B constitutes transported energy. This terminology is selected to avoid double-counting of energy that was already in the battery at Location B at the start of a round trip, as the starting energy is not considered as energy transported.

The average energy a car can discharge has been calculated as explained in Eq. (3). Dch_{ki} is the energy available for discharge, B_{ki} is the energy remaining in the battery obtained by subtracting the initial energy in the battery, I_{ki} , minus the energy used for transport, Q_{kr} (Eq. (2)). The energy used is derived from the daily travelling distance S_{kr} and the average fuel consumption μ_{kr} . H is the safety margin, (1).

$$Q_{kr} = S_{kr} \mu_{kr}, \quad (1)$$

$$B_{ki} = I_{k,i} - Q_{kr}, \quad (2)$$

$$Dch_{k,i} = B_{k,i} - H \quad (3)$$

$$Tr_{k,i} = E_{k,i} - Q_{k,r} \quad (4)$$

Following the defined formulation of energy transported, only the energy that has been charged at any other location can be transported, as shown in Fig. 2. To include this definition in the top-down approach, the energy used for driving has been considered as the charged energy, as without V2G, cars will only charge the energy needed for driving. This accounts for 40% of the battery capacity during the work week. Using that value as the energy charged, we get the daily energy charged and transported following Eq. (4) where Tr is the energy transported and Dch the energy available to discharge.

Table 3 considers only private battery electric vehicles (BEVs). Not all private BEVs are assumed to commute daily. Based on mobility statistics, it is assumed that EVs commute on average three out of seven days per week, reflecting a mix of commuting and non-commuting usage patterns.

The calculation of transported energy assumes an initial state of charge of 80% at the start of a commuting trip, with a safety reserve of 10 kWh remaining in the battery to account for unexpected travel needs. While this represents an optimistic scenario, it is commonly adopted in V2G-related studies to estimate the upper bound of available flexibility. To mitigate this assumption, a second estimation based on typical weekly charging behaviour is included, and both top-down estimates are later compared with bottom-up results in the discussion.

Finally, all EVs are assumed to have access to bidirectional charging infrastructure, as here the maximum potential for energy transport is calculated. This represents a best-case scenario and constitutes a key limitation of the study, which is further discussed in the limitations section.

The table shows the total amount of energy available to discharge and transport for the whole EV fleet and for each car. In Europe, each day, there are 180,694 MWh of energy available to be discharged, and 47,537 MWh have been transported. To put the numbers into perspective, the energy available to discharge can power more than fifteen million houses for a day, while the energy transported can do so with more than 4.3 million houses.

2.2. Bottom up approach

EV models vary in energy consumption, with different usage based on driving conditions, style, and weather. The chosen route also plays a role, as direct routes are more energy-efficient than indirect ones. However, users may deviate from the shortest route for various reasons. These factors highlight the complexity of optimizing energy transport using EVs and the need to consider a broader range of factors beyond distance alone.

To capture these factors, the proposed bottom-up model consists of two stochastic submodels implemented through Monte Carlo sampling. One submodel generates charging demand and patterns by sampling from empirical distributions of arrival times, charging power, and energy demanded. The resulting profiles are used to determine the energy in the car at the arrival and departure times in both locations. The second submodel calculates the mobility patterns and the energy

Table 3
Energy transport potential by EVs in 2023.

Location	Daily energy used for mobility (kWh)	Daily energy transported (<i>Dch</i>)		Daily energy charged and transported (<i>Tr</i>)	
		Total (MWh)	Per car (kWh)	Total (MWh)	Per car (kWh)
Netherlands	5.28	9298	30.86	2348	7.79
Europe	5.37	180,694	32.43	47,537	8.53
China	5.02	400,092	34.58	113,120	9.78
US	7.01	109,713	42.67	32,981	12.83
World	2.21	920,443	35.8	303,300	11.8

use for mobility purposes, drawing from distributions of vehicle energy consumption and trip distances to determine the energy required for each route and the associated travel time. The outputs of the two sub-models are then combined to create synthetic weekly EV charging and mobility profiles. Only weekdays (Monday to Friday) are considered, as commuting trips are not typically undertaken on weekends. This profile-generation approach is conceptually similar to existing open-source tools for creating EV time series from empirical data, such as emobpy, [48], but is here specifically tailored to quantify spatial energy transport enabled by private EV mobility rather than to generate standalone demand profiles.

2.2.1. Charging demand patterns

Since the amount of energy that can be transported depends directly on how much is charged at each location, a model of charging demand is required to capture the variability in key parameters across locations. The charging demand sub-model generates stochastic samples of arrival times, energy demanded, and charging power through Monte Carlo sampling from empirical probability distributions to create the synthetic charging power profiles of each car. The arrival time $A_{k,i}$ of the car k at location i is obtained from the probability density function (PDF) $f_{A_{k,i}}(t)$ and as explained in Eq. (5) where $f_{A_{k,i}}(t)$ is the PDF derived from the empirical data.

$$A_{k,i} \sim f_{A_{k,i}}(t) \quad (5)$$

It has been considered that EVs can only be charged at home or the workspace, either in private/workspace CS or in public ones close to the house/workspace. The trips a car makes each day from/to work and in between the time spent at each stop and in each trip can be accurately modelled. Knowing the arrival time at home and the time it took the car to get there, the departure time from the workplace was calculated.

The following data to be considered is the energy demanded by each charging session. The energy demanded per charging session is modelled as a conditional normal distribution whose parameters depend on the arrival time. The distribution generates random samples via Monte Carlo giving the energy demand $E_{k,i}$ for each of the cars k at location i given the arrival time t , as shown in Eq. (6). Where $\mu_i(t)$ is the mean energy charged at time t , and $\sigma_i^2(t)$ is the variance of energy charged at time t .

$$E_{k,i} | A_{k,i} = t \sim \mathcal{N}(\mu_i(t), \sigma_i^2(t)) \quad (6)$$

The last distribution used is the charging power. Charging power values are obtained by inverse transform sampling from the cumulative distribution function (CDF), ensuring stochastic variability across EVs and sessions, as seen in Eq. (7), where $F_{P_{k,i}}(x)$ is the CDF of the charging power $P_{k,i}$.

$$P_{k,i} = F_{P_{k,i}}^{-1}(u), \quad u \sim \mathcal{U}(0, 1) \quad (7)$$

With charging power and energy charged data, the charging time is also calculated as shown in Eq. (8). Where: $C_{k,i}$ is the charging time, $E_{k,i}$ is the energy demanded, and $P_{k,i}$ and η are the charging power and efficiency, respectively, for car k at charging location i .

$$C_{k,i} = \frac{E_{k,i}}{P_{k,i}\eta} \quad (8)$$

By combining all stochastically sampled parameters (arrival times, energy demanded, charging power, and charging times), each charging session, $CS_{k,i}$, is constructed at a minute scale using Monte Carlo simulation to reflect realistic variability in charging behaviour across vehicles and locations.

$$CS_{k,i}(t) = \begin{cases} P_{k,i}, & A_{k,i} \leq t < A_{k,i} + C_{k,i} \\ 0, & \text{otherwise} \end{cases} \quad \text{s.t.} \quad \int CS_{k,i}(t) \eta dt = E_{k,i} \quad (9)$$

2.2.2. Mobility patterns

To determine the energy available for discharge, the energy used for each trip must be calculated. This requires modelling distance, driving patterns, and consumption factors, which vary across vehicles and routes. The average fuel consumption per kilometre of each vehicle is modelled as a normally distributed random variable, as shown in Eq. (10).

$$M_k \sim \mathcal{N}(\mu_k, \sigma_k^2) \quad (10)$$

To this average fuel consumption, M_k , a deviation factor, $H_{k,r}$ was added to consider how different factors affect the fuel consumption of the car, as shown in Eq. (11). The final fuel consumption per km, $F_{k,r}$, is determined by the average fuel consumption and the deviation factor applied with the use of the binary value $\gamma_{k,r}$, indicating whether the factor affects the vehicle k on the trip r or not.

$$F_{k,r} = M_k(1 + \delta_{k,r}\gamma_{k,r}) \quad \text{s.t.} \quad \gamma_{k,r} \in \{0, 1\}, \quad (11)$$

Once the average fuel consumption (in Wh/km) for each car and trip is determined, the total amount of energy used by each car according to the route is calculated. The energy used by each car, $Q_{k,r}$, is calculated with the fuel consumption per km, $F_{k,r}$, the distance of each trip, $S_{k,r}$ also randomized applying a normal random distribution depending on the trip, and a binary variable, $\beta_{k,r}$, indicating whether car k made trip r , as shown in Eq. (12) and Eq. (13).

$$S_{k,r} \sim \mathcal{N}(\mu_r, \sigma_r^2) \quad (12)$$

$$Q_{k,r} = F_{k,r}S_{k,r}\beta_{k,r} \quad \text{s.t.} \quad \beta_{k,r} \in \{0, 1\}, \quad (13)$$

In this way, Monte Carlo sampling captures stochastic variability in fuel economy, trip distances, and travel choices, producing realistic energy consumption values for mobility across the EV fleet.

2.2.3. Synthetic profile creation

With both the charging and mobility submodels defined, random samples are generated using a Monte Carlo approach. These samples are then combined to construct synthetic weekly profiles for each EV. These profiles reflect the stochastic variability in charging sessions, travel distances, trip times, and stop durations, thereby reproducing realistic, time-varying travel and charging behaviour across the fleet. The combined output is aligned with a timeline of arrival and departure events, where departure times $D_{k,i}$ are obtained as the difference between the arrival time of the next stop and the corresponding travel and stop durations, as shown in Eq. (16). The arrival times $A_{k,i}$, trips

time $G_{k,r}$, and stop times $W_{k,i}$ for car k to location i at trip r are used as follows:

$$W_{k,i} \sim \mathcal{N}(\mu_i, \sigma_i^2) \quad (14)$$

$$G_{k,r} = \frac{S_{k,r}}{V_{k,r}} \quad (15)$$

$$D_{k,i} = A_{k,i} - (G_{k,r} + W_{k,i})\alpha_{k,i} \quad \text{s.t. } \alpha_{k,i} \in \{0, 1\}, \quad (16)$$

Although data on the number of weekly charging sessions or initial SoC was unavailable, the Monte Carlo framework enables the construction of charging and driving profiles for each EV. The obtained distributions are combined to construct the time-dependent charging and driving profile defined as:

$$Z_{k,i}(t) = f(CS_{k,i}, A_{k,i}, D_{k,i}, Q_{k,r}, t) \quad (17)$$

where $Z_{k,i}(t)$ represents the time-dependent charging and driving profiles of each EV k at each location i , considering the charging sessions $CS_{k,i}$, arrival $A_{k,i}$ and departure times $D_{k,i}$, and the energy used in each trip $Q_{k,r}$.

Finally, the State of Charge (SoC) trajectory is calculated dynamically by updating the stored energy after each charging event and subtracting the energy used while driving, expressed as:

$$\text{SoC}_{k,t+1} = \text{SoC}_{k,t} + E_{k,t}^{\text{Ch}}\eta_{\text{Ch}} - E_{k,t}^{\text{Drive}} \quad \forall t \in T, \quad \forall k \in K \quad (18)$$

where $E_{k,t}^{\text{Ch}}$ is the charging energy input, η_{Ch} is the charging efficiency, and $E_{k,t}^{\text{Drive}}$ is the energy used during driving. This formulation ensures that the synthetic profiles capture both stochastic charging behaviour and realistic energy depletion from mobility.

From the obtained time-dependent charging and driving profiles, $Z_{k,i}(t)$, the two metrics used later in the results are calculated. The energy available to discharge is the energy remaining in the EV battery minus the safety margin, as can be seen in Eq. (19), where $Dch_{k,i}$ is the energy available for discharge of car k at location i , $B_{k,i}$ is the energy remaining in the battery at arrival and H is the safety margin.

$$Dch_{k,i} = B_{k,i} - H \quad (19)$$

The energy transported is the energy that has been charged in any other location and discharged at the initial one. The potential energy to be transported can be calculated as the energy charged at each location, which is not the initial one, minus the energy used for mobility. Eq. (20) shows the calculation needed, where $Tr_{k,i}$ is the energy transported by car k to the initial location i , $E_{k,j}$ is the energy charged by that car at the location j and $Q_{k,r}$ is the energy used by the car at trip r .

$$Tr_{k,i} = \sum_{j \neq i} E_{k,j} - \sum_r Q_{k,r} \quad (20)$$

Two other main metrics are used to measure the differences in the simulated scenarios. The percentage of energy available for discharge at home/work, $Pd_{k,i}$ considers the energy in the battery at the departure location, $B_{k,i} + Q_{k,r}$, and the energy available for discharge, $Dch_{k,i}$, to calculate the % of the energy available for discharge by car k to location i as a percentage of the energy at the start of the trip, as shown in Eq. (21).

$$Pd_{k,i} = \frac{Dch_{k,i}}{B_{k,i} + Q_{k,r}} 100 \quad (21)$$

The percentage of energy transported related to the energy charged, $Pc_{k,i}$ considers the energy charged at the departure location, $E_{k,j}$, and the energy transport potential, $Tr_{k,i}$, to calculate how much of the charged energy by car k is transported to location i , as shown in Eq. (22).

$$Pc_{k,i} = \frac{Tr_{k,i}}{E_{k,j}} 100 \quad (22)$$

3. Decentralized energy system

Building on the synthetic mobility and charging profiles generated by the EV model, the framework evaluates how spatial energy transport enabled by private EV mobility affects energy community performance. In addition to temporal energy shifting, energy can be transferred between locations not only through the electrical grid but also via the movement of EVs themselves.

This enables the formulation of Flexible Energy Communities (Flex-ECs), in which EVs charge at one location and discharge at another. Typical examples include charging at the workplace using local generation and discharging at home in the evening, or charging at home during low-price periods and discharging at the workplace the following day. In this configuration, EVs act as mobile energy carriers that physically transport energy across locations as part of their normal mobility.

Fig. 1 illustrates the overall workflow of the proposed methodology. The EV profiles are then used as inputs to the Flexible Energy Community optimization model, which evaluates different charging strategies, including uncontrolled charging, rule-based V2G, and optimization-based V2G. The model determines how much energy is transported between locations, the share of energy available for discharge, and the resulting SoC evolution.

Finally, system-level impacts are quantified, including peak demand reduction, energy cost reduction, and changes in overall energy consumption. This chain of models demonstrates how everyday private EV mobility can be leveraged for spatial energy transport and integrated into Flexible Energy Communities.

3.1. Objective functions

Two objective functions were defined for the linear programming (LP) model to evaluate the impact of different energy management strategies. The first minimizes total system cost based on time-varying electricity prices and considers both energy drawn from and fed into the grid. The second minimizes the peak power drawn from the grid to reduce strain on infrastructure. These objectives are implemented separately to assess trade-offs between economic and grid-oriented performance.

The first objective aims to minimize system costs considering energy prices, shown in Eq. (23). The terms P_t^{feed} and P_t^{draw} are the power feed and drawn to/from the grid, respectively, in each timestep, t . The electricity cost is represented by ϵ_t , and a selling factor, S_c , is applied to indicate that the selling cost is lower than the buying one. Alternatively, the second objective function has been implemented with the main objective of minimizing peak demand at the residential location, shown in Eq. (24). A total of two decision variables have been used, $P_{k,t}^{\text{Ch}}$ and $P_{k,t}^{\text{Dch}}$, that set the charging and discharging power of each EV k over time t , respectively.

$$\min \sum_{t=1}^T \epsilon_t (P_t^{\text{draw}} - S_c P_t^{\text{feed}}) \Delta t \quad (23)$$

$$\min P_{\text{Max}}^{\text{draw}} \quad (24)$$

3.2. Grid constraints

The power balance within the energy community is expressed through a nodal balance equation. Power consumed by residential loads and EV charging must equal the power supplied by PV generation, EV discharging, and grid interaction at each time step:

$$P_t^{\text{L}} - P_t^{\text{PV}} + \sum_{k=1}^K (P_{k,t}^{\text{Ch}} - P_{k,t}^{\text{Dch}}) = P_t^{\text{draw}} - P_t^{\text{feed}} \quad \forall t \in T \quad (25)$$

The load demand is represented by P_t^L while the generated photovoltaic energy is represented by P_t^{PV} . As all the variables are positive, it is important to set the signs correctly in the balance equation. In this case, all power flowing into the building, P_t^{PV} , $P_{k,t}^{Dch}$ and P_t^{feed} have a negative sign, while the power flowing from the building to the loads or the grid, P_t^L , $P_{k,t}^{Ch}$ and P_t^{draw} have a positive sign.

Eq. (26) is used to limit that all drawn power has to be lower than the contracted one, P_{Max}^{draw} , and lower than the installed grid capacity, P_{Max}^{grid} . Eq. (27) states that power fed to the grid must be lower than the grid capacity.

$$P_t^{draw} \leq P_{Max}^{draw} \leq P_{Max}^{grid} \quad \forall t \in T \quad (26)$$

$$P_t^{feed} \leq P_{Max}^{grid} \quad \forall t \in T \quad (27)$$

3.3. Electric vehicle constraints

The state of charge (SoC) of each EV is updated at every time step based on charging, discharging and driving activity:

$$SoC_{k,t+1} = SoC_{k,t} + \frac{P_{k,t}^{Ch} \Delta t}{Q_k} \eta_{Ch} - \frac{P_{k,t}^{Dch} \Delta t}{Q_k \eta_{Dch}} - \frac{E_{k,t}^{Drive}}{Q_k} \quad \forall t \in T, \quad \forall k \in K \quad (28)$$

Where $SoC_{k,t}$ is the state of charge of the Electric Vehicle k at timestep t ; Q_k is the battery capacity of the EV, and η_{Ch} and η_{Dch} are the charging and discharging efficiencies, respectively.

$$Av_{k,t} = \begin{cases} 1, & t \in [t_k^{arr}, t_k^{dep}] \\ 0, & \text{otherwise} \end{cases} \quad (29)$$

$$0 \leq P_{k,t}^{Ch} \leq P_{k,t}^{ChMax} Av_{k,t} \quad \forall t \in T, \quad \forall k \in K \quad (30)$$

$$0 \leq P_{k,t}^{Dch} \leq P_{k,t}^{DchMax} Av_{k,t} \quad \forall t \in T, \quad \forall k \in K \quad (31)$$

Eq. (29) sets the availability of a car connected to the charging station. Eqs. (30) and (31) specify that the vehicle can only charge or discharge if the EV k is connected at time t , if $Av_{k,t} = 1$, and limit the maximum charging and discharging power, $P_{k,t}^{ChMax}$ and $P_{k,t}^{DchMax}$.

4. Evaluation of energy transport potential in The Netherlands

To evaluate the impact of EV-based energy transport within decentralized energy systems, the modelling framework introduced in the previous sections was applied to a representative case study. A fleet of private EVs was simulated using real-world mobility and charging behaviour, and their interaction with a residential Energy Community was analysed under various charging and discharging configurations. This case study quantifies the energy transport potential of EVs and assesses their influence on energy cost, peak demand, and total consumption within the community.

4.1. EV fleet composition

The first step in the case study involves defining the composition and characteristics of the EV fleet, as these directly influence both energy consumption during driving and the energy available for transport and discharge. The fleet used to calculate the energy transport potential consists of 250 electric vehicles representing the market share in the Netherlands in 2020. The share of each EV and its characteristics can be seen in Table 4. Data from [45] of average fuel consumption in Wh/km for winter and summer conditions in city and highway roads were gathered for each EV model as well as the useable battery capacity and the maximum charging power set by the onboard charger. A charging and discharging efficiency of 95% has been considered for all scenarios.

The charging patterns model uses data from the Elaad Open Data repository, [49]. As shown in Fig. 3(a), the peaks in public charging arrival times closely coincide with the arrival times at private homes (in the evening) and workplaces (in the morning). This overlap suggests

that many public charging events occur at or near users' primary locations, home and work, rather than at truly intermediate or transient locations. Therefore, to avoid double-counting and to simplify the model while remaining realistic, only the distributions for private and workplace locations were used. In the model, all EVs that commute are assumed to charge at the workplace rather than public chargers, and similarly, those returning home are assumed to charge at home. This assumption reflects a deliberate simplification to focus the analysis on energy transport between fixed, known locations (home and work), which is central to the concept of Flexible Energy Communities.

To calculate the energy demanded per charging session, a distribution from Elaad is used again, where the average energy charged per arrival time is shown. For the charging power distribution, only the charging power for public CS was used, as private and workspace data are unavailable. The cumulative distribution function (CDF) for the charging power P_{ki} of 2020 was used, as it was the most current data available. Data were generated following the distribution, but it was later fixed to 11, 7.4, and 3.7 kW values, based on the rated power of the onboard EV charger.

The average fuel consumption per km of each car is shown in Table 4. To this average fuel consumption, M_k , a deviation factor, H_{kr} , obtained from [50], and shown in Table 5 is applied. The table shows the factors considered, the deviation, and the number of EVs affected by each factor as a percentage.

The time and distance of each trip according to its purpose and the number of trips each car makes were gathered from [51,52], respectively, and are shown in Table 6. If 0.58 trips are made daily by each car to go shopping, it means that 58% of the fleet cars will go shopping. In this way, each car will make a random number of trips each week following the statistical data retrieved from [52]. To maintain consistency in trip distance and times, the average speed of each trip was used. It is assumed that all trips are made between departure from work and arrival at home, so the commuting EV goes directly to work in the morning, but can go to intermediate stops after work.

All trips have a 55%–45% ratio of highway and city driving distance, based on the EPA weighted average, [53], used to calculate fuel consumption. Self-discharge is not considered here, as typical lithium-ion batteries self-discharge between 2%–3% a month, [54].

Fig. 4 shows example charging and driving patterns for five different EV models over one week. These profiles are illustrative and are used to demonstrate the diversity of synthetic EV behaviours generated by the model. Different EV owners exhibit different patterns, with some charging once per week, others charging twice, and with varying charging powers. The figure also shows the energy consumption during commuting to work and during return trips with intermediate stops. All results in the case study are obtained from the aggregated optimization of the full EV population.

4.2. Energy community configurations

To assess the benefits of location-aware EV energy transport, two Energy Community configurations are modelled. The first corresponds to a conventional Energy Community, as commonly defined in the literature, where energy sharing and flexibility are realized through grid-based exchanges among co-located members. In this work, this configuration is referred to as a Fixed Energy Community (FixedEC) to explicitly denote that EV charging and discharging are restricted to the residential neighbourhood and that energy exchange remains exclusively done through the grid.

The second configuration, named the Flexible Energy Community (FlexEC), extends this conventional framework by allowing EVs to charge and discharge across multiple locations. By exploiting private EV mobility, FlexECs enable energy to be physically transported between sites as part of everyday travel, introducing an additional layer of flexibility beyond traditional, grid energy sharing. This distinction

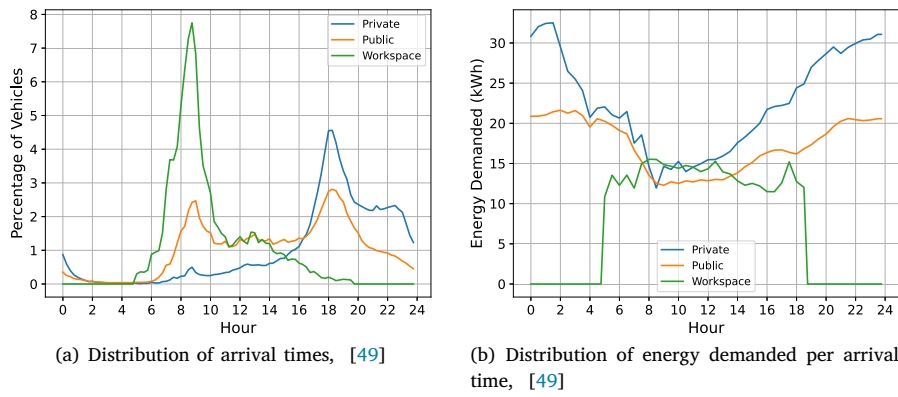


Fig. 3. Elaad distributions.

Table 4
Fleet Electric Vehicle Data.

EV model	Share (%)	Battery (kWh)	Charger (kW)	FC city cold (Wh/km)	FC Hwy cold (Wh/km)	FC city warm (Wh/km)	FC Hwy warm (Wh/km)	WLTP (Wh/km)
Tesla Model 3	25.61	57.5	11	160	209	104	160	144
Kia Niro	11.91	64.8	11	173	240	115	188	164
Volkswagen ID3	10.10	58	11	171	232	113	181	153
Hyundai Kona	10.03	39.2	11	160	224	103	170	143
Renault Zoe	7.93	52	22	168	236	109	182	174
Skoda Enyaq	7.58	58	11	181	247	121	193	157
Nissan Leaf	7.33	39	6.6	166	236	110	181	171
Audi e-Tron	6.95	85	22	210	279	144	218	225
Tesla Model S	6.55	95	11	183	238	123	181	187
Volkswagen Golf	6.02	32	7.4	173	237	114	188	153

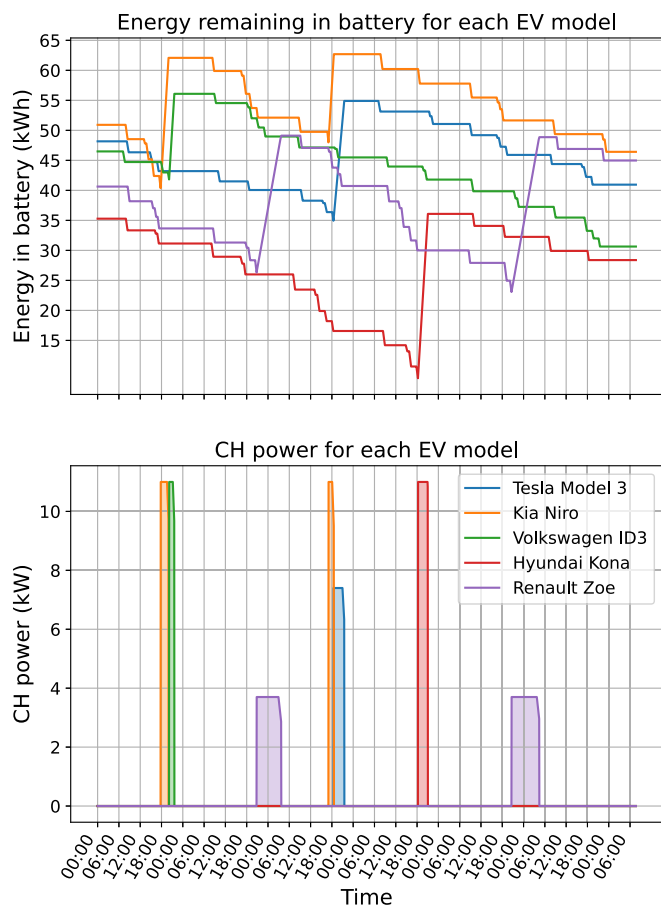


Fig. 4. Energy remaining in the EV battery and charging power for 5 EVs.

Table 5
Factors Impacting EVs Energy Consumption.

Factor	% Deviation (H_{kr})	% EVs affected (y_{kr})
Congestion	20	30
Aggressive Driving	17	20
Eco Driving	-25	20
Mild Headwind (18km/h)	9.5	10
Strong Headwind (50km/h)	23	10
Upwards 3% Inclination	50	0
Downwards 3% Inclination	-65	0
Extra 250 kgs Load	5	15

Table 6
Trip Characteristics.

Purpose of the trip	Distance (S_{kr} , km)	Number of trips per day (β_{kr})	Average speed (km/min)
Commuting	22.78	0.42	0.826
Services/care	11.55	0.09	0.599
Shopping	7.06	0.58	0.508
Education	27.9	0.18	0.774
Visits	27.15	0.26	0.847
Leisure	19.79	0.48	0.687
Other	12.16	0.32	0.660

allows the new role of EVs as mobile energy carriers to be isolated and analysed without redefining the underlying Energy Community concept.

Comparing FixedEC and FlexEC configurations enables a systematic evaluation of how EV-enabled spatial flexibility in charging and discharging affects community-level energy cost, peak demand, and overall consumption.

Fig. 5 illustrates the conceptual spatial boundary of the system. The case study is not defined by a fixed geographical area, but by a set of aggregated residential locations and workplace hubs connected through

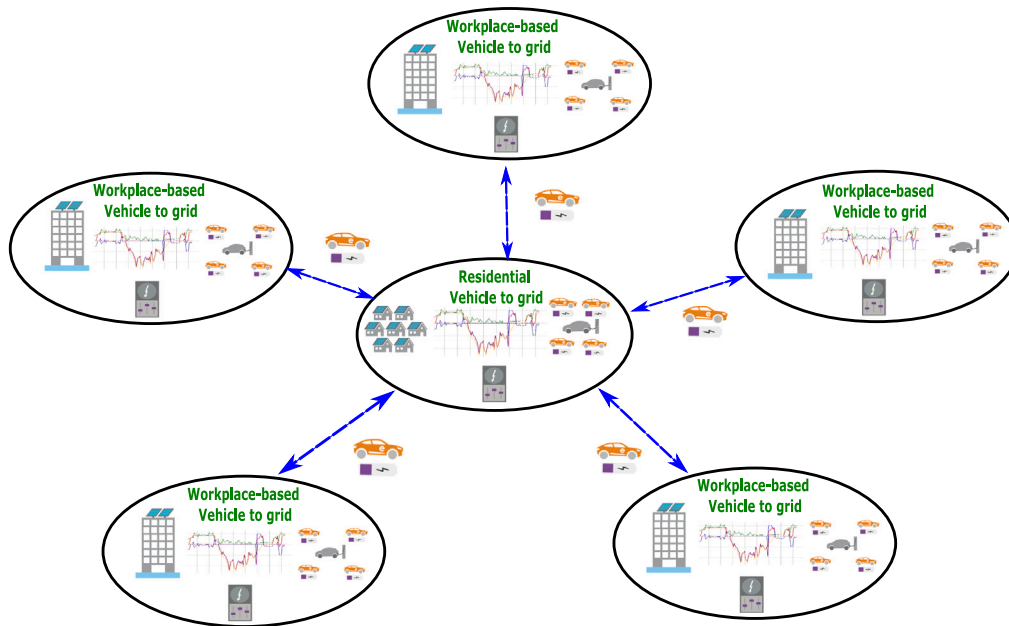


Fig. 5. Example of a Residential FlexEC with 5 different workplace locations.

EV commuting. The residential node represents a neighbourhood-scale aggregation of households, while workplace nodes represent centralized employment locations. This abstraction allows the analysis to focus on mobility-driven energy exchange rather than on explicit spatial layout or distribution grid topology.

Both communities are modelled based on a neighbourhood with residential demand and installed photovoltaic generation with EVs that commute to different workplace locations, as shown in Fig. 5. Both have EVs connected (dis)charging following the explained Energy Community model in Section 3 and the mobility profiles explained in Section 2.2, but only in the FlexEC, the EVs are allowed to (dis)charge in the workplace locations. When discharging energy, a minimum of 10 kWh is always kept in the battery for the return trip or any unexpected trip needed, previously called the safety margin. With that amount of energy, approximately 50 km can be driven, which is considered enough for the daily average use of a car.

An average of one car per household was considered with a 33% penetration of EVs. Accordingly, the residential community consists of 750 households, of which 250 are equipped with a battery electric vehicle. An estimated 20% of the houses have PV installed. Demand and generation profiles were obtained from the Liander Open Dataset in the Netherlands and scaled up afterwards to represent the consumption of 750 homes, [55]. Houses in the dataset were of different characteristics, detached, terraced, and flats, and with different amounts of inhabitants, so the profile resembles as much as possible a real neighbourhood in the Netherlands. The EVs commute to the workplaces following the Montecarlo simulation with commuting data from the Netherlands, with 42% of EVs commuting and driving an average distance of 23 km.

The (dis)charging profiles used in the Energy Community evaluation were obtained using both the LP model described in Section 3 and a rule-based strategy. For the rule-based strategy, an optimistic future scenario with 75% bidirectional charger availability was assumed, while the remaining 25% of commuting EVs follow the stochastic charging behaviour defined in the charging model. To limit excessive battery degradation from deep cycling, EVs are allowed to discharge on only three out of five working days, consistent with the preliminary energy transport analysis and established battery ageing considerations [56].

For the LP-based optimization, three bidirectional charger penetration levels (25%, 50%, and 75%) were evaluated for both Fixed and

Flexible Energy Community configurations. A smart charging scenario, in which EVs are not allowed to discharge, was used as the baseline. In the LP formulation, EVs can charge or discharge at any location and time, subject to charger availability and operational constraints.

In the rule-based strategy, EV behaviour differs between FixedEC and FlexEC configurations. In the FixedEC case, EVs discharge at home at maximum power upon arrival until the safety margin is reached, after which they charge at the minimum power required to reach 90% SoC by the next departure. In the FlexEC case, 75% of EVs transport energy and discharge it at home following the same rule, while the remaining 25% charge at the lowest power necessary to reach 90% SoC by departure.

5. Energy transport results

The results of the simulations are presented in this section, based on the charging and mobility profiles applied to the FixedEC and FlexEC configurations described earlier. Key metrics include the energy available for discharge, the energy transported between locations, and the resulting impacts on cost, peak demand, and overall consumption. The findings are first analysed across a range of driving and charging scenarios to assess the sensitivity of energy transport potential, followed by an evaluation of seasonal effects and Energy Community-level outcomes.

All metrics described in Section 2.2 have been calculated for the whole workweek and the entire fleet. It is important to note that not all car owners drive to work every day, as the data gathered stated that only 42% of owners use their cars to go to their respective workplaces.

The simulation scenarios have been divided into four main categories, namely:

- Charging patterns focus on the differences that the charging behaviour of EV users has on the energy transport capabilities of the fleet. Charging station availability, energy demanded in each charge, and the frequency of charging are studied in this category.
- Driving patterns study how differences in driving behaviour can influence the amount of energy transported. Factors such as trip distance, frequency of trips, and road type are studied.
- Driving conditions focus on how different factors affecting the fuel consumption of the EV can influence energy transport.

- EV model and its characteristics can also greatly influence the amount of energy transported. Bigger battery capacities and lower fuel consumption are studied.

5.1. Energy transport differences

Energy transport scenarios are simulated for winter and summer conditions to study the impact of weather on energy transport, given the variations in average fuel consumption. The results are then calculated for 34 different scenarios, divided into the 4 categories explained. Each of the scenarios includes variations in the factors affecting energy transport, such as frequency of charging, energy use for driving, or battery size. Box plots are used to show how much each factor affects the energy available to discharge and energy transported.

While the absolute values reported in this section depend on the specific mobility and charging assumptions, the purpose of this analysis is to identify general trends and dominant factors governing EV-based energy transport. By systematically varying driving behaviour, charging patterns, vehicle characteristics, and operating conditions, the results reveal which parameters primarily drive energy transport potential and which have a secondary influence, enabling extrapolation to other regions with different mobility and charging characteristics.

5.1.1. Energy transport potential by factor

This section presents a sensitivity analysis of the energy transported and available for discharge across different mobility and charging scenarios. Results are categorized by charging patterns, driving behaviour, driving conditions, and EV model characteristics.

The daily energy available to discharge and the energy transported to work/home are shown in Fig. 6. The percentage values of both metrics are shown in Fig. 7. The box plots include combined values for winter and summer. It can be seen that driving patterns are the factor that has a greater effect on the total energy transported, since more trips mean that more energy is transported, even when the energy per trip remains the same. This behaviour is consistent across all simulated scenarios, indicating that the total amount of energy transported by EVs is primarily governed by mobility intensity, rather than by local charging conditions or vehicle efficiency alone.

On the other hand, charging patterns affect the percentage values of energy transported the most. This makes sense as the energy transported is directly related to the energy charged. Driving conditions show a smaller range of values in both the energy available for discharge and the amount of energy transported, both in total and percentage values, showing that on short trips, factors affecting fuel consumption have a minimal impact on energy transport potential. Charging pattern scenarios have less change in the energy available to discharge than in the energy transported, a difference that is greater in the percentage values.

This also explains the differences in the EV model category, as bigger batteries mean more energy is available to discharge, but the same amount of energy is transported. Despite considerable variations in mobility and charging dynamics across simulations, the percentage of energy available for discharge exhibits a narrower range. On average, approximately 70% of the battery's initial energy is available to discharge at work, while about 60% is available to discharge at home, as shown in Fig. 7. The figure also illustrates that the energy transported to work consistently falls within the range of 60% to 80%, while the energy transported to home averages 60%, demonstrating a consistent trend in all categories. Changes in the EV model battery capacity size increase the energy available for discharge, but not the energy transported.

Not surprisingly, the charging pattern is the factor affecting the most energy transport. On the other hand, driving patterns and conditions present smaller variations in energy transported, as more EVs doing the trip does not mean each of them will carry more energy on average, and the effects of driving conditions in a 20 km trip are not sufficient to

make notable differences. The energy available to discharge at home tells another story, as not all EVs drive directly home after work. Driving patterns especially affect the energy available to discharge, as the number and duration of trips are the biggest factors affecting the energy used by the car.

Importantly, the relatively narrow range of percentage values observed across all categories suggests that the fraction of charged energy that is transported is largely insensitive to regional or technological specifics. This indicates that, once EVs follow regular commuting patterns and have access to charging at multiple locations, similar energy transport ratios can be expected in other regions with different driving distances, charging availability, or EV characteristics.

In conclusion, driving patterns have the strongest influence on the total amount of energy transported, while charging patterns primarily affect the share of charged energy that is ultimately transported. Driving conditions have a comparatively minor impact, as fuel consumption variations over typical commuting distances remain limited. Across all scenarios, consistent average values emerge, with approximately 60%–70% of charged energy being transported and around 70% of the battery energy at the start of the trip remaining available for discharge. These consistent ratios highlight that EV-based energy transport is governed by robust relationships that extend beyond individual case studies.

5.1.2. Seasonal variations

Seasonal weather effects were also evaluated, comparing energy transport and discharge metrics under summer and winter conditions to account for changes in EV efficiency and charging needs. While the magnitude of seasonal effects depends on local climate conditions, the analysis is intended to identify general mechanisms through which changes in vehicle efficiency and charging needs influence EV-based energy transport.

Weather conditions also affect the potential for energy transport, as shown in Fig. 8. In summer, more energy is available to discharge than in winter, while the total energy transported is lower. This behaviour reflects a general mechanism: improved vehicle efficiency reduces charging needs, leading to higher average battery states of charge but lower amounts of energy exchanged through charging. As a result, EVs carry more residual energy that can be discharged locally, while the total amount of energy transported between locations decreases.

Fig. 9 shows the weather differences for the percentage values. Here it can be seen how, even if the total amount of transported energy is higher in winter, the energy transported related to the energy charged is higher in summer. This indicates that relative energy transport metrics are less sensitive to seasonal conditions than absolute energy values, suggesting that similar proportional relationships can be expected in regions with different climates or temperature profiles.

Warm temperatures reduce the energy consumption of EVs, thereby lowering charging demand and total energy transport, while increasing the fraction of energy available for discharge.

Although absolute values vary between summer and winter, the observed trends highlight a consistent relationship between vehicle efficiency, charging intensity, and energy transport. This suggests that seasonal effects primarily shift the magnitude of energy flows rather than altering the underlying transport behaviour.

5.2. Energy community evaluation

The EV (dis)charging profiles have been obtained from the Energy Communities LP and rule-based models defined in Section 4.2. Cost, peak demand, and overall energy consumption reduction differences between Fixed and Flexible Energy Communities have been calculated with the power profiles.

This subsection evaluates the impact of EV-based energy transport on Energy Community performance by comparing Fixed and Flexible

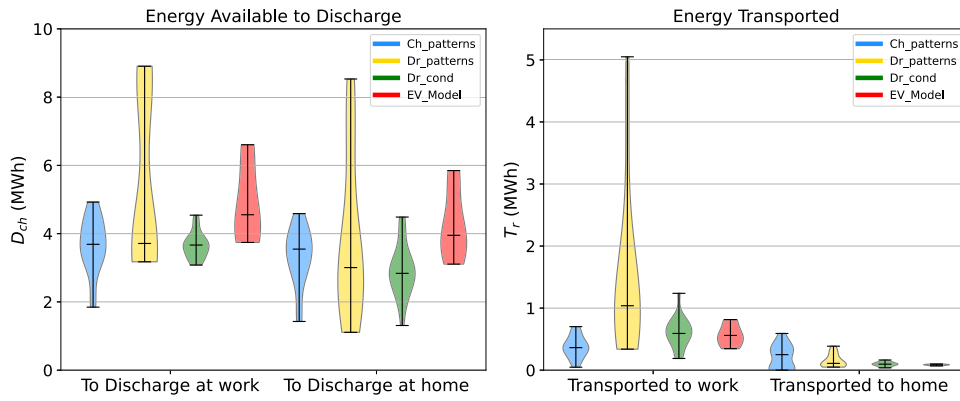


Fig. 6. Energy available to discharge and total energy transported to work/home per scenario.

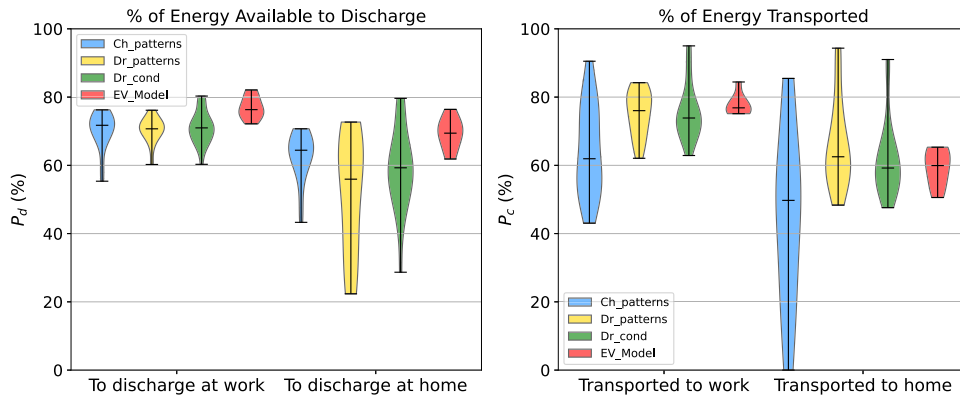


Fig. 7. Percentage of energy available to discharge and energy transported to work/home per scenario.

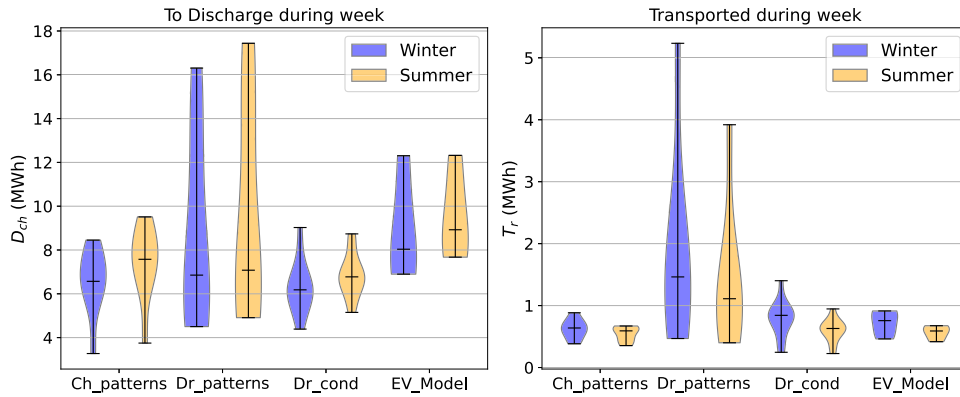


Fig. 8. Seasonal comparison of absolute energy available for discharge and total energy transported.

Energy Community configurations under different control strategies. While numerical results depend on penetration levels and control assumptions, the objective is to identify general effects of allowing EVs to charge and discharge across locations on power profiles, peak demand, and energy costs.

5.2.1. Energy community power profiles

The performance of the FixedEC and FlexEC configurations was evaluated using both rule-based and optimization-based (LP) strategies. The impact on power profiles, peak demand, energy cost, and total consumption is assessed under various levels of bidirectional charger penetration.

Fig. 10 shows the power profile of the rule-based optimization scenarios. Uncontrolled charging increases the peak demand, as the

charging peak coincides with the demand peak. The FixedEC slightly reduces the peak demand, but more importantly, it shifts the peak to nighttime, when the demand is lower, while lowering the demand during peak hours. In the FlexEC scenario, as the energy is charged outside of the community, more cars are charging than are discharging, effectively reducing the peak instead of shifting it to nighttime. This illustrates a general effect of EV-based energy transport: by decoupling charging and discharging locations, local peak demand can be reduced rather than merely shifted in time, even without centralized optimization.

For the LP optimization, the power profiles of the three scenarios, smart charging, FixedEC, and FlexEC, can be seen in Fig. 11(a). Both EC models show the cost minimization objective with 75% bidirectional charger penetration. The main difference between Fixed and Flexible Energy Communities can be spotted in the EV charging curve. While

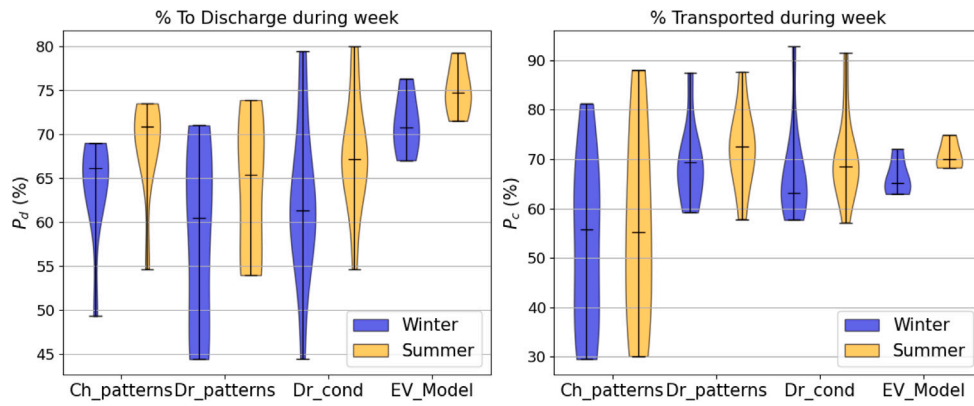


Fig. 9. Seasonal comparison of the percentage of battery energy available for discharge and the share of charged energy transported.

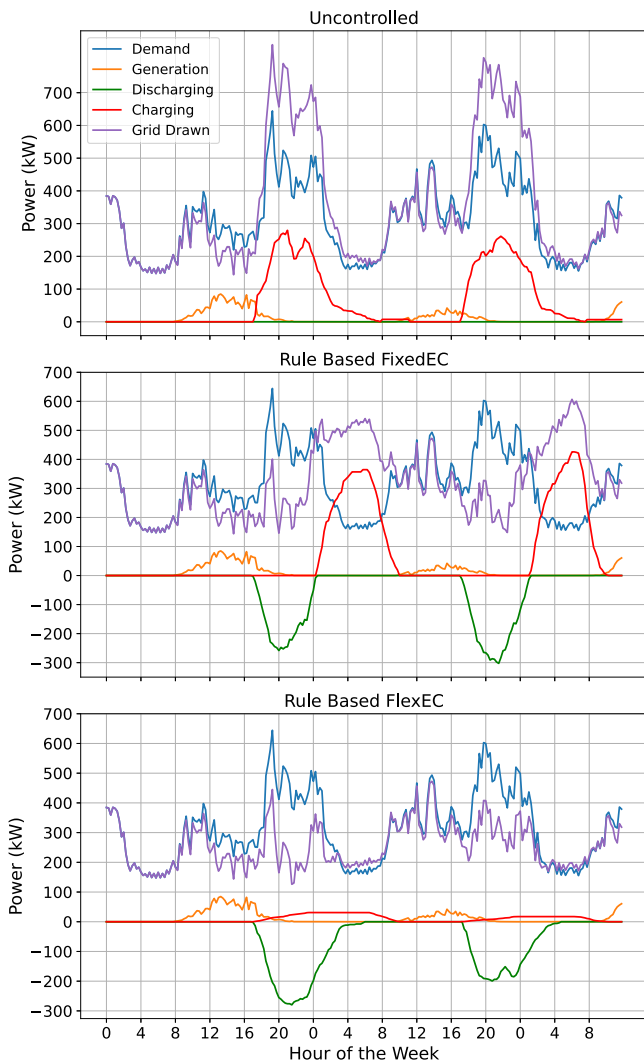


Fig. 10. Rule-based Optimization Power Profiles for Uncontrolled Charging, Fixed Energy Community and Flexible Energy Community.

the discharging is very similar, FlexEC shows overall less charging demand, as some of the needed charging is done at the workplace. More generally, this indicates that location-unconstrained charging reduces the need for local energy intake, as part of the charging demand is displaced to other locations with available capacity.

Fig. 11(b) shows the power profile of the same car for the three different scenarios. Here, it can be better spotted how the FixedEC car profile has more charging demand at home than the FlexEC car profile, where the car can charge outside of home without affecting the EC power profile.

In all scenarios, the power exchange with the grid was topped by the grid capacity when the cost minimization strategy was used. With a 33% EV penetration and 75% bidirectional charger penetration, the discharging power of the EVs is far superior to the peak demand. If EVs (dis)charge following only energy prices, they will do so at full power to take as much advantage as possible of the price differences, increasing the peak at low price points. Even if the peak is increased with the EV charging, this peak occurs now at night and in the central hours of the day, when the prices and demand are lower. This price following strategy is not able to reduce the peak, but it can shift it to low-demand times. This load shifting can potentially benefit the grid as the other loads in it are also low, so there is grid capacity to charge the EVs. The opposite happens with discharging, as the discharging peak occurs at peak price and demand times. Discharged energy can also help the grid as the EVs are feeding energy when most loads are demanding it, reducing the energy the grid needs to import. Across all penetration levels, the qualitative differences between FixedEC and FlexEC remain consistent, suggesting that the observed benefits of EV-based energy transport are robust to different levels of bidirectional charger availability.

Even if these results are promising, these extra deep cycles will age the battery more than if it were used exclusively for driving. As calculated in the top-down approach, the average energy used during the workweek is 40% of the total battery capacity for the Business-as-Usual scenario. For the FlexEC scenario, if the car is transporting energy every day by doing cycles from close to 100% of the battery to the 10 kWh of safety margin, the total equivalent cycles is 417% of battery capacity each week.

Previous studies, [57], are used to provide a simple calculation of the expected battery ageing. In the mentioned study, researchers conducted a year-long experiment where pairs of batteries were cycled, and ageing results were linearly interpolated to approximate the degradation rate as a function of cycles. The authors concluded that cells lose approximately 6.7×10^{-3} % of battery capacity per full equivalent cycle. An EV that only charges the energy used for driving will do around 21 full equivalent cycles throughout the year, which accounts for 0.14% of accumulated ageing or 85 Wh of capacity loss. If the car were used to transport energy, the car would do a total of 221 full equivalent cycles throughout the year. The ageing in this case will be 1.48%, or 885 Wh at the end of the year. In this simple calculation, calendar ageing and all the parameters involved in battery ageing have been overlooked. Ageing is a complex problem that requires a thorough and more in-depth study, which is out of the scope of this paper. A deeper study of the effects of energy transport in battery ageing will be conducted in the following studies to better understand its effect.

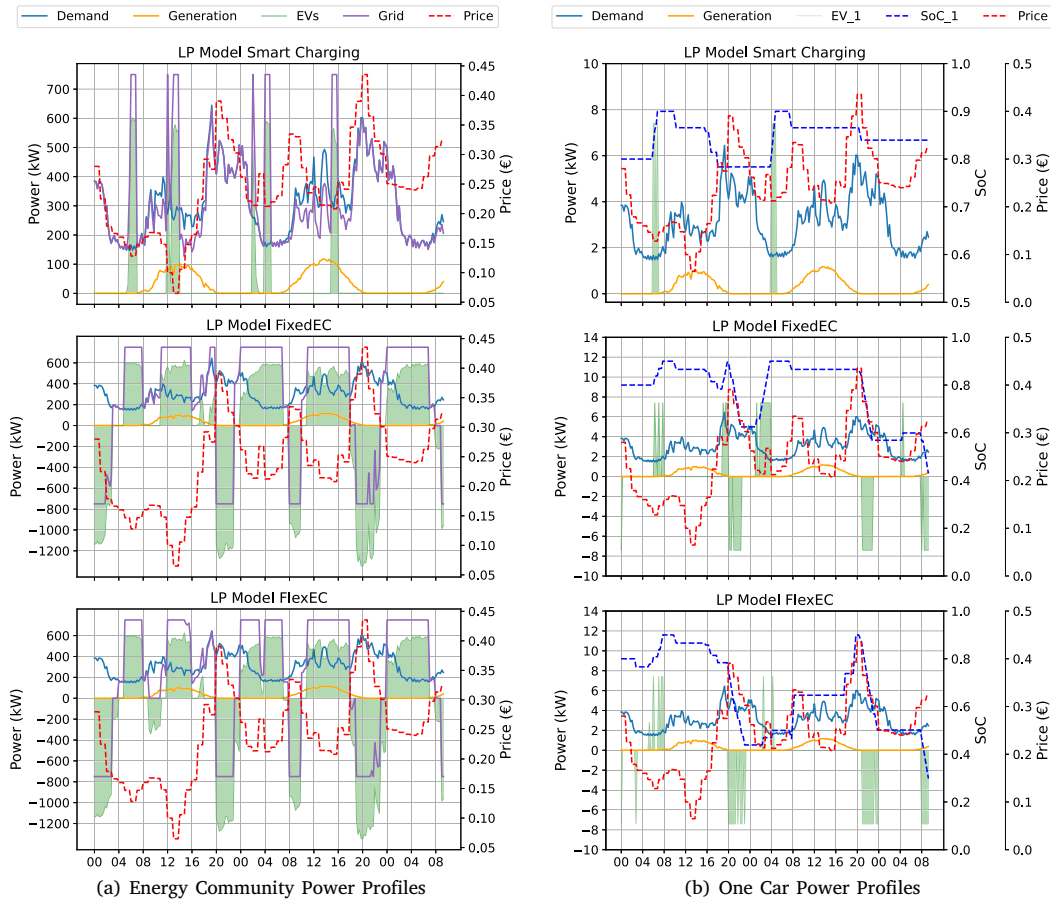


Fig. 11. LP Optimization Power Profiles for different scenarios.

5.2.2. Peak and consumption reduction

To study the reduction in peak demand and total consumption, the peak minimization objective was used. The following equations define the performance indicators used to evaluate peak demand, energy consumption, and cost reductions in the simulated scenarios. The values were calculated for the three scenarios following Eq. (32) and Eq. (33), respectively. Where P_{BaU} and P_{Sc} are the peak demand of Business as Usual and the peak demand of the scenario studied, respectively. The same applies for C_{BaU} and C_{Sc} , but for the overall daily consumption of the building/neighbourhood.

The same approach was used to calculate the reduction in energy costs, but this time the cost minimization objective was used. Eq. (34) was used to calculate the cost reduction.

$$\alpha_{Sc} = \frac{P_{BaU} - P_{Sc}}{P_{BaU}} \times 100 \tag{32}$$

$$\beta_{Sc} = \frac{C_{BaU} - C_{Sc}}{C_{BaU}} \times 100 \tag{33}$$

$$\gamma_{Sc} = \frac{Z_{BaU} - Z_{Sc}}{Z_{BaU}} \times 100 \tag{34}$$

The energy cost, peak demand, and energy consumption of both EC models can be seen in Fig. 12. The study focuses on the energy performance of the residential energy community receiving electricity transported by EVs. In this study, the objective is to isolate and quantify the potential of energy transport enabled by EV mobility and study its benefit within the concept of FlexECs. For this purpose, EVs are assumed to charge at multiple workplace locations, thereby distributing the charging demand across different sites that typically exhibit higher energy demand levels and stronger grid connections than residential

areas, as shown in Fig. 5. This abstraction allows the results to highlight the general impact of EV-based energy transport on local energy performance, independently of the specific characteristics of the supplying locations.

The impacts of EV charging and discharging on the supplying locations are not explicitly analysed in this paper. This represents a deliberate modelling choice aimed at isolating the effect of energy transport on the receiving residential community. The authors acknowledge that a complete system-level assessment would require simultaneous modelling of both the source and destination locations, including their respective power flows and grid constraints. Such an integrated analysis is the focus of the following work, where EVs are allowed to charge and discharge at residential, workplace, and intermediate locations, and the impacts of locational V2G are jointly evaluated across all connected locations.

Results show that when the EVs can charge at work and can transport that energy back home, the energy cost of the Community is reduced further than when EVs can only (dis)charge inside the community itself. This additional cost reduction is primarily driven by a reduction in locally imported energy, as charging is partially displaced to external locations. The FixedEC saw its consumption increase due to the (dis)charging efficiency while trading energy with the grid. Importing energy from outside, the FlexEC can reduce its energy consumption by displacing it to the workplace and thus further the energy cost than the FixedEC.

Peak demand also shows a higher reduction in the FlexEC model, although this time the difference is smaller when the LP optimization model is used. Peak reduction is achieved by discharging energy when the load peak occurs, regardless of where the energy is coming

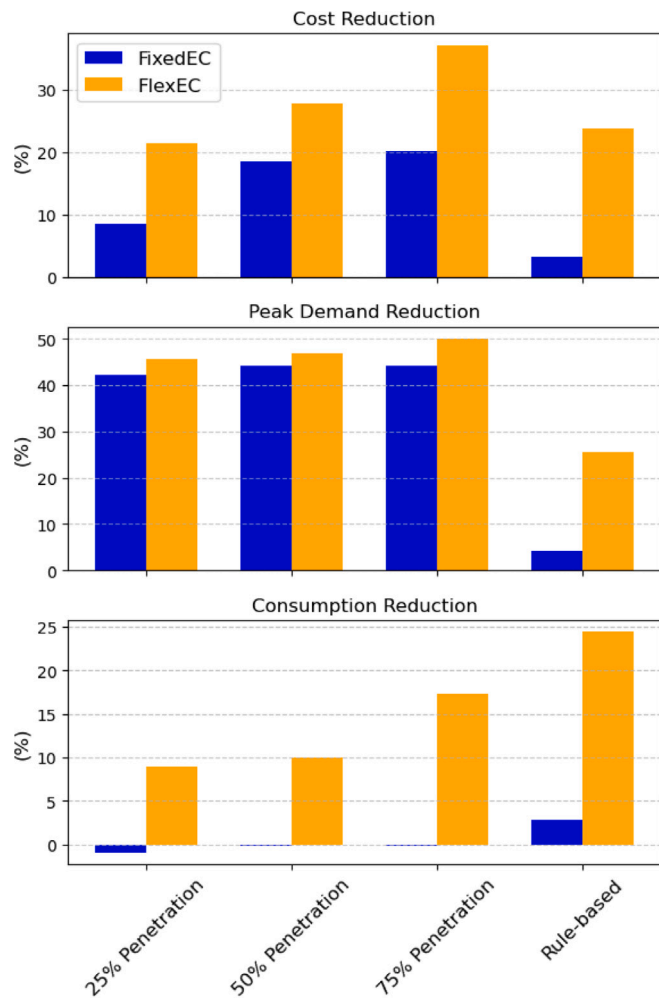


Fig. 12. Energy cost, peak demand, and consumption reductions for FixedEC and FlexEC under different bidirectional charger penetrations.

from. This result highlights the importance of timing in peak reduction. As explained in the introduction, peak reduction can significantly reduce the need for costly grid reinforcement. Grid reinforcement typically involves upgrading cables, transformers, or other infrastructure to handle higher peak loads. By flattening demand peaks, the existing infrastructure can be used more efficiently, reducing the expansion needs.

6. Discussion

This section interprets the key findings from the simulation results in relation to the research objectives and identified literature gaps. The implications of private EV-based energy transport are first discussed at the fleet level, followed by a comparison of its impact within the Fixed and Flexible Energy Community configurations. The discussion also reflects on the scalability and practical considerations of the proposed approach.

6.1. Insights on energy transport

The numerical values discussed in this subsection are used to illustrate orders of magnitude and dominant relationships rather than to characterize a specific national case. While the results are obtained using representative mobility and vehicle statistics, the objective is to extract general insights into how private EV fleets transport energy

under realistic driving and charging conditions, and how this transport scales with battery capacity, charging frequency, and commuting behaviour.

Using representative mobility and vehicle data, the energy transport potential of a fleet of 250 EVs was estimated. When aggregated at the fleet level, several MWh of energy per day were available for discharge at workplaces and residential locations. When expressed per commuting vehicle, this corresponds to several tens of kWh per EV, representing a substantial share of the battery capacity available after a typical trip. Across all simulated scenarios, between approximately 55% and 70% of the battery energy at the start of a trip remained available for discharge, indicating a robust relationship between daily mobility and post-trip energy availability.

Battery capacity was found to scale linearly with energy available for discharge, while the amount of energy transported depends more strongly on charging behaviour than on vehicle efficiency alone. Infrequent charging results in fewer EVs transporting energy, but with each vehicle carrying a significantly larger amount, approaching the energy available for discharge after a trip. Conversely, frequent charging increases the number of transporting vehicles but reduces the energy transported per EV. This trade-off explains the relatively stable fleet-level energy transport observed across a wide range of charging strategies and vehicle characteristics.

Across all scenarios, individual EVs were found to transport on the order of 5–10 kWh per day on average, with values exceeding 25 kWh per vehicle when charging was less frequent. Energy available for discharge was on average 15–20 kWh, with values exceeding 35 kWh when the EV started the trip with a full battery. These magnitudes are comparable to those reported in the top-down approach, with an average of 7.79 kWh of energy transported and 30.86 kWh available for discharge.

The higher values observed in the top-down estimates for energy available for discharge are primarily a consequence of the optimistic assumption of an 80% initial state of charge at the start of each trip. In contrast, the bottom-up simulations explicitly account for stochastic charging behaviour and realistic arrival SoC distributions, which naturally limit the amount of energy remaining in the battery upon arrival. As a result, while the top-down approach represents a theoretical upper bound of energy availability, the bottom-up simulations reflect operational constraints imposed by real-world charging patterns.

The comparison between the top-down and bottom-up approaches shows strong agreement in both order of magnitude and relative trends. This consistency confirms that aggregated mobility and vehicle statistics can provide reliable first-order estimates of EV-based energy transport potential, while detailed bottom-up modelling is required to capture the practical limitations on useable energy transport.

6.2. Flexec vs fixedec effectiveness

The results from the energy community use case highlight the FlexEC model's effectiveness in reducing energy costs and consumption in residential areas compared to both smart charging and the FixedEC model. By importing energy via EVs, the FlexEC not only shifts demand but also actively reduces the peak load. This reduction is crucial for managing energy efficiently in residential areas with high consumption volatility, as it alleviates the strain on the grid during peak hours. The FlexEC model's ability to discharge more energy than it charges during peak times highlights its potential as a robust solution for peak shifting, making it a more effective alternative to traditional Energy Communities. Importantly, these advantages arise from the spatial decoupling of charging and discharging enabled by EV mobility, and are therefore expected to persist across different community sizes, penetration levels, and regional demand profiles.

Additionally, the FlexEC model's scalability to non-residential areas presents considerable potential. Applying this concept to commercial or mixed-use areas, where energy demands are more diverse and fluctuate

more frequently, could result in even greater benefits for grid stability. Additionally, FlexECs could be adapted for other regions with different climates or energy grid structures, offering a flexible and decentralized approach to energy management that could transform how energy is shared and consumed on a larger scale.

It is important to acknowledge the limitations of the study. A high penetration of bidirectional chargers, 75%, was assumed, which played a pivotal role in enabling our proposed energy transport concept. Without such a high penetration, the feasibility of the concept may be constrained. Moreover, the charging and discharging LP model employed is very simple; the implementation of a more sophisticated optimization algorithm could potentially obtain even greater reductions in peak demand, thus representing another opportunity for future work. Finally, the impact of increased battery cycling on battery ageing, resulting from additional charging and discharging cycles, was not thoroughly examined in this paper.

6.3. Qualitative comparison to grid-based distribution

Compared to conventional grid-based transmission, EV-based energy transport has notable limitations but also distinct advantages in specific contexts. The grid remains the most capable and scalable solution for long-distance and high-volume energy transfer, making it essential for reliable system-wide operation. In contrast, EV-based transport is inherently constrained to short distances, and its scalability is limited by EV availability, user participation, and the local need for energy redistribution. However, where such conditions align, EVs can provide a degree of spatial flexibility that grid infrastructure cannot, enabling temporary, localized energy balancing in ways that fixed systems cannot replicate. Losses remain relatively low when energy is transported during routine trips, but would become unaffordable if additional travel were required just for energy delivery. Importantly, while the grid offers centralized control and predictability, EV-based transport introduces significant behavioural uncertainty, making real-time coordination more challenging. Still, when integrated thoughtfully, EV mobility can complement grid operation by offering a flexible, low-cost layer of decentralized support.

EV-based energy transport can complement grid infrastructure by helping reduce local peak demand, as demonstrated in the context of flexible energy communities. Lower peak demand translates into reduced stress on distribution lines, potentially easing congestion and deferring grid reinforcement investments. While grid-based transmission remains more efficient and controllable in the long term, the EV-based approach provides complementary, rapidly deployable flexibility, especially in constrained or underdeveloped areas. However, it is essential to recognize a key operational difference: distribution grids manage energy in real time, addressing instantaneous power flows, while EVs transport energy across time and space, delivering “energy packets” with a delay tied to driving schedules. This temporal disconnect requires accurate forecasting and coordination to ensure EVs are charged and discharged at the right times and locations. As such, EV energy transport should be seen as a supporting layer of flexibility that enhances, but does not replace, the grid’s core function of real-time energy delivery.

7. Conclusions

This study set out to evaluate the role of private Electric Vehicles as mobile energy transporters within Decentralized Energy Systems. The findings support using Private EVs as an alternative method for energy transport, as they demonstrate the potential for EVs to support the grid. EVs can transport substantial amounts of energy between locations, contributing to the overall energy demand and reducing the dependency on traditional energy transport means.

The study shows that the percentage of energy available to discharge and energy transported remains relatively consistent across

different scenarios. In contrast, the total energy available to discharge and the energy transported have greater variations between scenarios. Driving and charging patterns are the primary factors influencing the energy available for discharge and energy transported, respectively.

Furthermore, the study shows a positive correlation between higher battery capacity and increased energy transport in EVs. The study indicates that the influence of improved fuel consumption on energy transport is not significant. Although vehicles with better fuel efficiency consume less energy during trips, the overall impact on energy transport is marginal due to the relatively short trip durations. For longer trips, fuel consumption will have a greater effect and needs to be considered.

Within Energy Communities, EV discharging patterns emerged as a key factor impacting peak demand, cost, and consumption reduction. Notably, the Flexible Energy Community achieved greater reductions in cost and overall consumption as peak demand is highly influenced by timing and not by the origin of the energy. The proposed FlexEC model significantly reduces overall consumption compared to the FixedEC scenario, highlighting its superior potential for cost minimization. Although EV-based energy transport is not a substitute for long-term grid reinforcement, it can serve as a supporting mechanism that helps alleviate short-term flexibility gaps and reduce the scale or urgency of required grid investments. Rather than acting as an alternative, it complements and supports conventional infrastructure, enabling a more efficient and gradual reinforcement process.

Furthermore, the analysis shows pronounced distinctions between summer and winter scenarios, particularly in the scenarios where peak reduction was more substantial. These variations were primarily driven by differences in seasonal load demand patterns, highlighting the importance of seasonality in energy transport considerations.

CRediT authorship contribution statement

Alvaro Menendez-Agudin: Writing – original draft, Software, Resources, Project administration, Methodology, Investigation, Conceptualization. **Gregorio Fernández Aznar:** Supervision, Software. **Pavol Bauer:** Supervision, Funding acquisition. **Gautham Ram Chandra Mouli:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Alvaro Menendez Agudin reports financial support was provided by Dutch Research Council. Alvaro Menendez Agudin reports a relationship with Delft University of Technology that includes: employment. If there are other authors, they 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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Data availability

Data will be made available on request.

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