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Integration of electric vehicles into energy system models: A review

Moritz Raab*, Jonathan Vogl, Tim Signer, Max Kleinebrahm

Institute for Industrial Production, Karlsruhe Institute for Technology, Hertzstr. 16, Karlsruhe, 76187, Germany

HIGHLIGHTS

- We review 58 electric vehicle demand models and 32 integration studies (2010–2025).
- We classify electric vehicle demand models by design and data characteristics.
- We review energy system models from building scale to the international level.
- We compare five electric vehicle aggregation methods and assess their trade-offs.
- We identify a lack of spatially fine-grained, high-fidelity, and diverse models.

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ABSTRACT

The growing adoption of electric vehicles (EVs) presents challenges and opportunities for the energy system, making accurate modeling of EV charging demand and its flexibility essential. EVs create a critical link between the electricity and transport sectors, both requiring models with high temporal resolution. Our review examines methods for modeling EV demand and their integration into energy system models across spatial and temporal scales. We identified 58 EV demand models and 32 integration studies spanning building- to international-scale systems. EV demand models are classified according to their methodological approaches and data sources. Our review highlights that activity-based approaches relying on travel or time use surveys are particularly effective in representing charging flexibility, as they derive empirically based flexibility windows from observed behavior. However, current approaches, mainly based on Markov chains and Monte Carlo simulations, fail to reproduce realistic weekly and seasonal patterns. Advances in generative modeling, especially through deep neural networks, show promise in capturing temporal consistency and variability, as well as integrating complementary data sources. For the integration of EVs into energy system models, we identify diverse aggregation methods, each entailing trade-offs between behavioral realism and computational tractability, yet systematic benchmarking is lacking. Our review reveals a lack of spatially fine-grained, high-fidelity, and diverse models, which are particularly important for analyzing innovative mobility concepts and their impacts on distribution grids. Future high-fidelity EV demand models are essential for anticipating future demand patterns, assessing system flexibility, and guiding infrastructure planning and investment.

1. Introduction

The energy sector is the largest contributor to global greenhouse gas emissions, accounting for more than 75% of total emissions in 2022 [1]. Transitioning to renewable energy sources is essential for significantly reducing greenhouse gas emissions. However, the variable nature of wind and solar power poses challenges for the energy system [2–5]. To reduce system costs, enhance renewable energy utilization, and ensure a stable and reliable energy system, flexibility measures such as battery storage, smart charging, and vehicle-to-grid technology from electric vehicles (EVs) are crucial [6–8].

Simultaneously, decarbonizing the transportation sector, which contributed 24% of global emissions in 2022, is vital [1]. Electrifying the vehicle fleet is a major step in this direction. In 2024, global EV sales reached a record 17 million units, comprising Battery Electric Vehicles and Plug-in Hybrid Electric Vehicles, representing a 25% increase over 2023 [9]. This growth is expected to continue, with projections indicating a global stock of around 235 million electric vehicles by 2030, up from approximately 58 million in 2024 [10].

The growing adoption of EVs introduces both challenges and opportunities for the electricity grid. On the one hand, as more vehicles

* Corresponding author.
Email address: moritz.raab@kit.edu (M. Raab).

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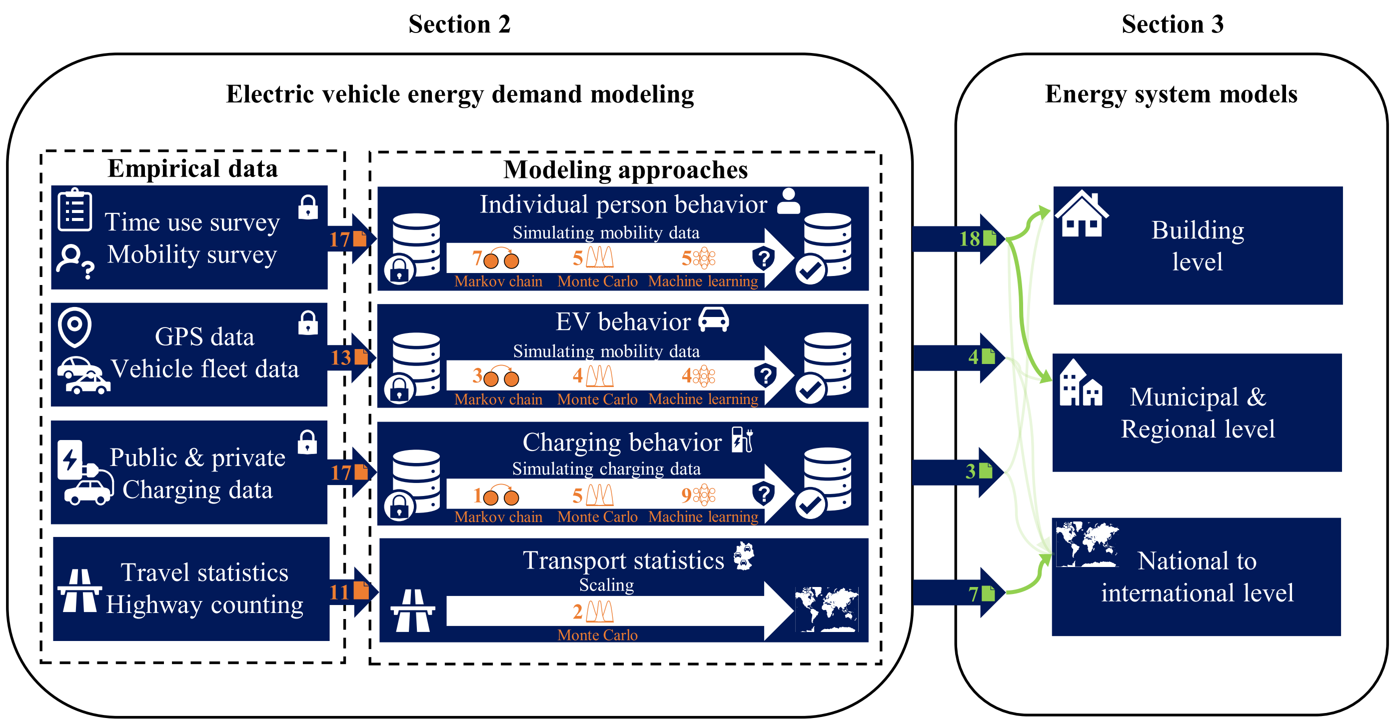


Fig. 1. Two-stage framework of the review. Orange numbers indicate the number of electric vehicle energy demand modeling studies reviewed in each data-source category. Additionally, we indicate how often Markov chains, Monte Carlo, and machine learning are employed within each category. Other methods are not shown. The lock indicates restricted data. Green numbers represent the number of energy system modeling studies integrating EVs at each spatial scale and the corresponding EV input data type. Solid green arrows highlight the dominant data sources at each spatial level of energy system modeling. The reviewed 58 demand-model studies (Section 2) are distinct from those used as inputs to the 32 energy system modeling studies (Section 3).

become electrified, EV charging becomes a major new electricity load and increases overall demand [11,12]. Additionally, uncontrolled EV charging can substantially increase peak load [13–16], particularly in residential distribution grids due to the prevalence of home charging [17], leading to potential overloads even at moderate penetration levels [18,19]. On the other hand, EVs offer significant synergies with the power system, particularly through smart charging and vehicle-to-grid technologies [20,21]. EVs can function as flexible, distributed energy storage, providing crucial services such as peak shaving, voltage and frequency regulation to maintain grid stability [22,23], and improved integration of renewable energies [24–28]. By leveraging smart and bidirectional charging, EVs have the potential to enhance grid resilience and reduce the need for stationary battery storage and grid reinforcement [29,30].

Although a growing body of EV demand forecasting studies predicts short-term charging load [31–33], energy system models typically require year-long demand and flexibility time series. Accordingly, this review focuses on how EV demand and feasible flexibility are modeled and integrated in energy system models, while other system components primarily determine the utilization and value of that flexibility. This charging demand can be incorporated into energy system models along a spectrum: from exogenous, fixed electricity-demand time series representing uncontrolled charging (no flexibility), to exogenous mobility demand with charging scheduled endogenously by the energy system model subject to technical and user constraints, with the latter being the focus of this review.

While the literature on electric vehicle demand modeling and EV integration into energy systems is rapidly growing, a systematic review of the methods used to integrate EVs into energy system models is still absent. Existing reviews on EV-grid integration primarily focus on technical properties [34], data sources for studies on electric vehicle integration [35], optimal charging schedules [36], peak load shaving strategies [37], combined modeling of photovoltaic power generation and EVs [38], machine learning approaches for EV charging [20,39] and overviews of commonly-used EV behavior models [40]. A systematic comparison is lacking regarding the implementation of EVs in energy system models across spatial scales, ranging from individual buildings to international levels. Addressing this gap is important, as both the energy and mobility sectors require highly resolved spatiotemporal representations with appropriately balanced complexity across scales.

Highly granular temporal and spatial data on EV driving behavior are fundamental for accurately representing flexible charging in energy system models. However, unlike weather, technical, or economic data, access to behavioral datasets, such as travel surveys, mobility records, or charging logs, is often restricted due to privacy regulations, posing a major challenge for comprehensive analysis. As a result, many studies rely on EV demand models to generate the required inputs. Additionally, such demand models must meet the requirements of energy system models by introducing assumptions on charging availability, long-term driver behavior, and energy consumption to extrapolate short-term observations into full-year, high-resolution, and flexible demand profiles.

Compared to existing reviews, our contribution is threefold. We structure the review along a two-stage systematic workflow that mirrors the EV modeling pipeline (Fig. 1): (1) generating EV charging demand and feasible flexibility, and (2) energy system integration across spatial scales. These first two parts are explicitly connected by clarifying how demand time series and constraint-consistent flexibility descriptions are translated into tractable model formulations. Third, we synthesize implications of data accessibility and availability for reproducible modeling, highlighting synthetic data generation and emerging generative and privacy-preserving trends as pathways when high-resolution mobility and charging data remain restricted. This review addresses the following research questions:

- **RQ1:** What methods exist for modeling mobility behavior and EV energy demand, and how do they meet the requirements of energy system models?
- **RQ2:** How is EV charging demand integrated into energy system models across different spatiotemporal scales, and how do these models incorporate flexibility in EV charging?
- **RQ3:** What are the limitations of current approaches for generating *synthetic* EV energy demand, and how can they be addressed in future research?

Review methodology

This study follows a systematic review approach to identify literature on EV energy demand models and their integration into energy system models. We applied a systematic search strategy using Scopus by formulating two search strings: one for electric vehicle energy demand models and another for energy system models incorporating electric vehicles.

- **Electric vehicle energy demand models**:
  - "charging demand forecast" OR "charging demand prediction" OR "EV behavior model" OR "electric vehicle charging behavior model" OR "EV charging behavior" OR "EV charging forecast" *AND*
  - "battery electric vehicles" OR "BEV" OR "BEVs" OR "electric vehicles" "EV" OR "EVs" OR "plug-in vehicles" OR "PEV" OR "PEVs"
- **Energy system models incorporating flexible EV demand**:
  - "energy system model" OR "energy system modeling" OR "capacity expansion model" OR "dispatch model" OR "integrated assessment model" OR "sector-coupled energy model" OR "energy systems analysis" *AND*
  - "battery electric vehicles" OR "BEV" OR "BEVs" OR "electric vehicles" "EV" OR "EVs" OR "plug-in vehicles" OR "PEV" OR "PEVs" *AND*
  - "smart charging" OR "controlled charging" OR "vehicle-to-grid" OR "V2G" OR "bidirectional charging"

The two search strings correspond to the two-stage framework of this review: (1) generating EV charging demand and feasible flexibility and (2) representing EV charging demand and flexibility within energy system models across spatial scales. The second search string targets flexible EV representations. Studies that model EVs only as passive fixed demand are not targeted, as their main methodological contribution concerns demand-profile generation (covered in Section 2). The searches were conducted separately to capture both strands comprehensively and then merged and de-duplicated prior to screening. Accordingly, Sections 2 and 3 are structured along this workflow and connected via the demand and flexibility inputs used in energy system models. Importantly, we use this structure to highlight that energy system models often rely on aggregated EV input profiles (primarily for computational tractability), whereas detailed EV demand models provide behavior-based charging demand representations that could improve future EV implementations in energy system models (as summarized in Fig. 1).

Studies were filtered to include mainly peer-reviewed journal articles from Scopus while excluding studies focusing solely on battery chemistry, secondary batteries, or energy management. To ensure completeness, backward and forward citation searches were conducted, which included relevant conference proceedings where appropriate. Articles were identified through title, abstract, and full-text screening, as depicted in Fig. 2.

The remainder of this paper is structured as follows: Section 2 presents a detailed review of electric vehicle energy demand models. Section 3 reviews the representation of EV charging demand in energy system models, covering scales from individual buildings to national and European levels. Finally, we discuss our findings in Section 4 and provide a summary in Section 5.

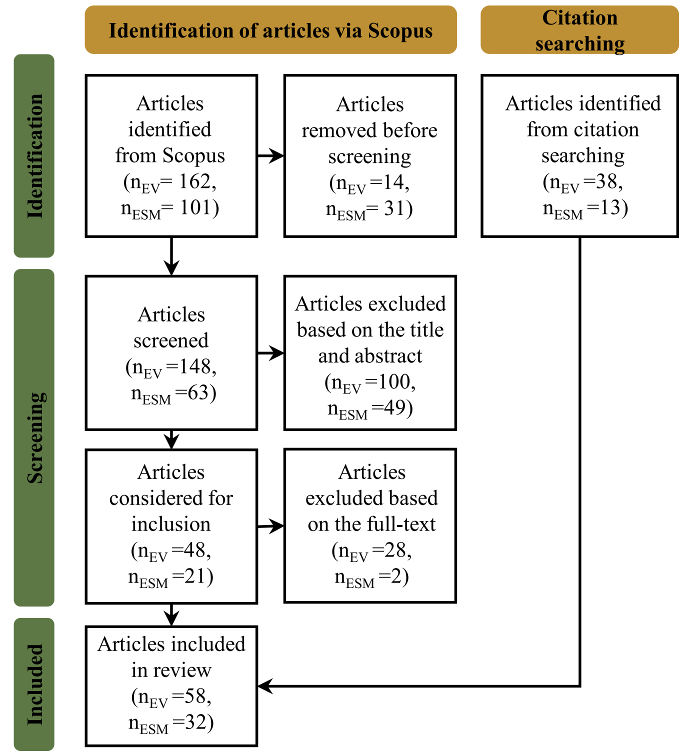


Fig. 2. Flowchart for identifying relevant articles on modeling electric vehicle energy demand (n_{EV}) and on energy system models incorporating electric vehicles (n_{ESM}), based on the PRISMA 2020 Statement [41,42]. Table A.9 summarizes the eligibility criteria applied at the different screening stages.

2. Electric vehicle energy demand modeling

An accurate representation of EV charging demand and associated flexibility potential is crucial for understanding the interaction between EVs and the energy system. This section reviews commonly used methods for modeling EV energy demand, focusing on how different simulation approaches derive charging profiles and charging boundaries. The EV energy demand models are structured based on their underlying data sources, as shown in Fig. 3, and the level of detail in modeling charging demand. All models share the common goal of using the available information in the input data, along with necessary assumptions, to generate energy system–relevant outputs. We classified the models into four categories:

- **Individual person behavior-based** approaches are based on country-specific time use surveys or mobility panel data, which provide detailed information on personal activities, travel patterns, and travel modes.
- **EV behavior-based** approaches utilize datasets on vehicle-level data, such as GPS-based travel data, field trial records, or mobile phone activity data to track vehicle positions.
- **Charging behavior-based** approaches are based on charging session records or operational data from private and public charging stations.
- **Transport statistics-based** approaches rely on aggregated datasets, such as real-world traffic volume data, for example, highway traffic counting data, or other large-scale transport statistics.

The empirical basis behind these four categories is summarized in Table B.10, which lists the main data sources used in the reviewed studies. Complementary technology-oriented approaches to mitigate data scarcity are summarized in Table C.11.

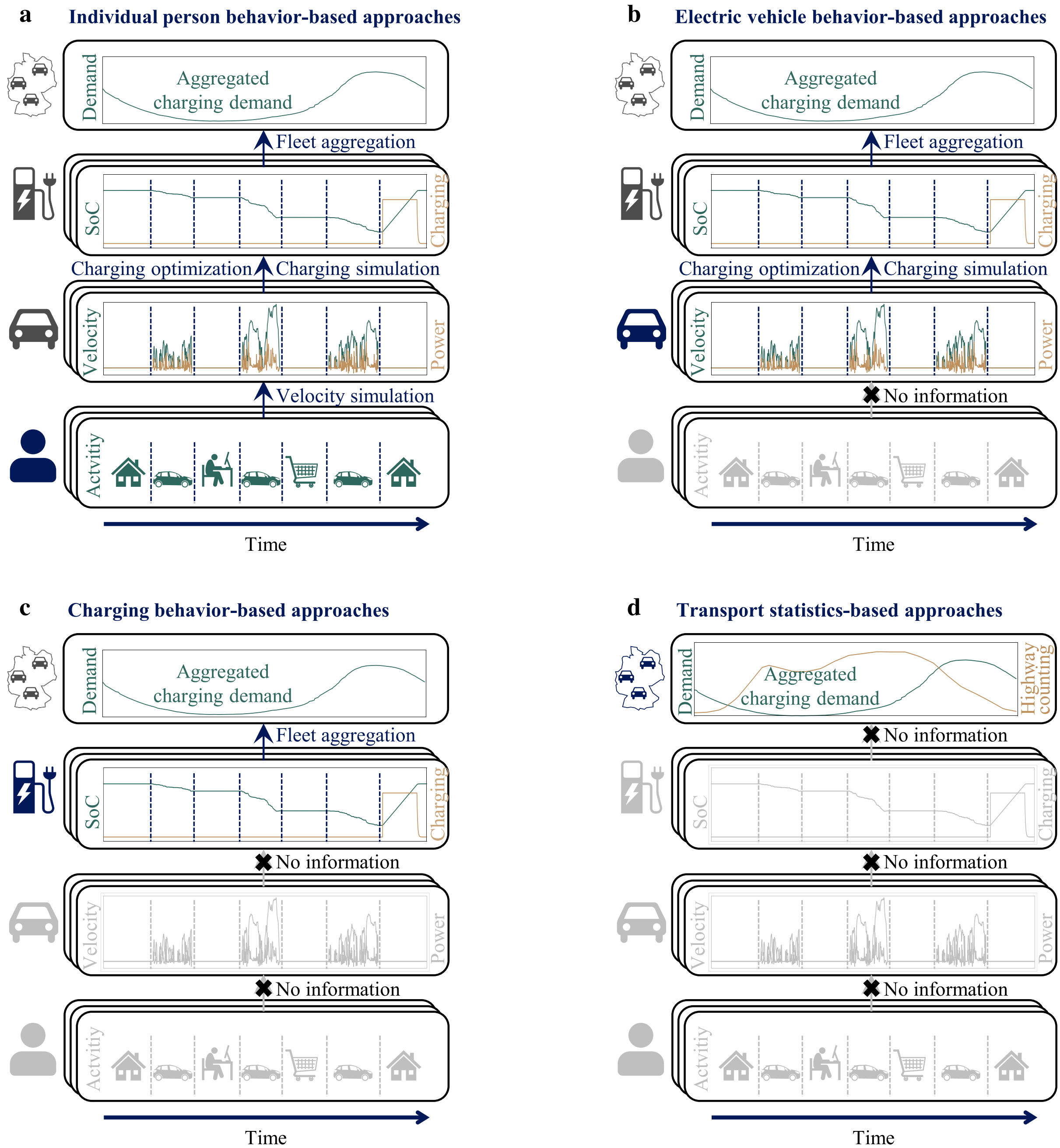


Fig. 3. Simulation starting points for electric vehicle energy demand modeling, structured by underlying data sources: individual person behavior-based (**a**), EV behavior-based (**b**), charging behavior-based (**c**), and transport statistics-based (**d**) approaches. The boxes illustrate typical information available at each stage (observed variables at the starting point (marked with a blue icon) and modeled variables for intermediate modeling steps). The arrows between layers indicate common transformation steps used to derive charging demand and flexibility time series (e.g., for the case of individual person behavior: from activity schedules to trip energy consumption, from trip energy to charging needs, and finally to the corresponding aggregated load). Data basis for the figure: Exemplary individual behavior of a working person who charges exclusively at home, with the state of charge (SoC) decreasing according to the energy consumption of each trip. The velocity and power profiles are derived from the WLTP Class 3 driving cycle [43], while the national charging demand represents aggregated residential level 1 (L1) and level 2 (L2) charging profiles for a typical weekday, as presented by the California energy Commission [44]. Highway counting data are based on hourly vehicle counting statistics from the German Federal Highway Research Institute [45].

Fig. 3 additionally illustrates a common trade-off between scalability and behavioral fidelity. Higher-level abstractions typically contain less information about behavioral attributes such as trip purposes, activity sequences, or heterogeneous charging opportunities. Such attributes can be incorporated by combining complementary data sources or through synthetic activity-based simulations that generate plausible schedules under aggregate constraints. However, these approaches require additional assumptions and calibration, and the resulting uncertainty should be reflected in subsequent energy system analyses. The choice of starting point therefore affects which questions can be answered robustly, particularly with respect to peak demand timing and feasible flexibility potentials.

Tables 1–4 provide an overview of the reviewed papers on EV energy demand modeling. The tables present information on the model and the empirical data, ordered by year of initial publication. Model-related

Table 1
Reviewed papers on electric vehicle energy demand modeling, categorized as **individual person behavior-based models**. The spatial resolution is reported using the NUTS classification: NUTS0 refers to the country level, NUTS1 to federal states, NUTS2 to administrative regions, and NUTS3 to districts. NUTS3+ denotes finer subdivisions below the NUTS3 level. For the empirical data, we report the type of data, the country of origin, and the data size.

Study		Model						Empirical Data		
First author	Year	Methodology	Temporal resolution	Spatial resolution	Energy resolution	Mobility-related states	Study objective	Country	Type	Size
Li [46]	2016	Monte Carlo	1 h	NUTS1	+	0	Renewable energy utilization	NL	TS [47]	30k
Hilgert [48]	2017	Regression	10 min			6	Mobility schedules	DE	TS [49]	20k
Muratori [18]	2018	Markov	10 min		+ +	3	Grid impact	US US US	TUS [50] Others [51] Others [52]	13k 1k 9
Fischer [53]	2019	Semi-Markov	1 min	NUTS3+	+ +	4	Residential load impact, charging load, charging station sizing	DE	TS [54]	40k
Yang [55]	2019	Markov	30 min		+	4	Residential load impact, charging load, charging station sizing	US	TS [56]	300k
Bitencourt [57]	2019	Monte Carlo	15 min	NUTS3+	+	0	Grid impact	US	TS [58]	300k
Crozier [59]	2019	Monte Carlo	30 min	NUTS3	+	0	Grid impact	UK UK	TS [60] Others [61]	16k 213
Yan [62]	2020	Semi-Markov	1 min	NUTS3+	+ + +	3	Renewable energy utilization	US	TS [56]	300k
Zhang [63]	2020	Monte Carlo	1 min		+	4	Residential load impact, charging load, charging station sizing	US	TS [56]	300k
Kleinebrahm [64]	2021	Neural network	10 min			6	Mobility schedules	DE	TS [49]	36k
Fretzen [65]	2021	Markov	1 min	NUTS3	+	4	Renewable energy utilization	SE NL	TS [66] TS [67]	27k 18k
Gaete-Morales [68]†	2021	Monte Carlo	15 min		+ + +	6	Residential load impact, charging load, charging station sizing	DE	TS [69]	300k
Jenkins [70]	2022	Markov	10 min		+	3	Residential load impact, charging load, charging station sizing	UK	TUS [71]	11k
Liu [72]	2022	Regression	1 min	NUTS3	+	3	Residential load impact, charging load, charging station sizing	US	TS [73]	26k
Guo [74]	2023	Semi-Markov	1 min	NUTS3+	+ +	8	Residential load impact, charging load, charging station sizing	US	TS [58]	300k
Charbonnier [75]	2024	Neural network			+	0	Residential load impact, charging load, charging station sizing	UK	TS [76]	330k

Mobility schedules; Grid impact; Residential load impact, charging load, charging station sizing; Renewable energy utilization. (+) fixed average consumption coefficients; (+ +) indicates adjustment for either temperature effects or driving behavior; (+ + +) reflects correction for both temperature and driving behavior or the use of empirical consumption data. TS: Travel survey; TUS: Time use survey; † Open-source implementation available (emobpy).

information includes the methodological approach, the temporal, spatial, and energy resolution, and the study objective.

2.1. Individual person behavior-based approach

Individual person behavior–based approaches utilize a broad range of country-specific travel surveys and time use surveys to model individual mobility activities, as shown in Table 1. Because these surveys typically cover only short observation periods, simulated data play a particularly important role in individual person behavior-based modeling approaches. Although it is widely used in this context, many studies do not explicitly state or justify its use. One underlying reason is the need to generate year-long demand time series that meet the requirements of energy system models [77], particularly to capture seasonal effects such as temperature-related variations in charging demand. Modeling EV usage based on individual activities typically involves three key steps. First, the travel activities are modeled, determining the time and number of trips that occur within a day or a week. Second, the travel distances and durations are determined. Third, the energy consumption for each trip is computed by combining travel data with vehicle-specific energy consumption rates, sometimes incorporating factors like vehicle speed or acceleration, outdoor temperatures, or auxiliary energy use (see, e.g., [18,62,68,74,78,79]).

A widely used method for modeling daily activity sequences is the application of **Markov chains** (see Table 1). Markov chains describe the evolution of activities as transitions between discrete states, with the transition probabilities depending only on the current state (first-order Markov chain). Markov states are typically defined either by location [18,52,53,62,80,81] or by a combination of location and activity type [65,70,82], with Markov chains comprising either three [18,52,62,80,81] or four [53,55,65,82] discrete states. For instance, Muratori [18,52] defined three location states: Home, Work, and Away (see Fig. 4), an approach also adopted in other studies [62,80,81]. Four-state models typically add a driving state [65,82] or another location [53]. Most approaches adopt standard first-order Markov chains [18,52,55,65,70,80–82], while others employ semi-Markov chains [53,62,74], in which state durations are sampled separately from state-differentiated probability density functions. To capture variations in mobility needs throughout the day, time-inhomogeneous Markov chains are employed, where transition probabilities are functions of time [52,53,55,62,65,70,74]. Transition probabilities are further segmented into workdays and weekends to reflect weekly patterns in activity and travel behavior [52,53,62,65,70,74].

An alternative modeling approach is **Monte Carlo** simulation, as shown in Table 1. In this method, departure and arrival times of trips [46,57,59,63,68], and, in some cases, destination types [63,68], are sampled from probability density functions derived from empirical data.

In contrast to Markov chains, which rely on transition probabilities between sequential states, Monte Carlo simulations generate activity schedules without modeling sequential dependencies. However, because Markov chains consider only the current state when predicting the next state, longer-term dependencies beyond a single time step are not captured.

Hilgert et al. [48] tried to address this memory-less property of Markov Chains by a hierarchical, **regression-based** model. The model integrates weekly time budgets for various activities (e.g., work, leisure) to account for long-term dependencies in mobility behavior, such as weekly routines and day-to-day variations. By employing a hierarchical framework, the model operates at multiple levels, including person, day, tour, and activity levels. Logistic regression models combined with weighted random draws determine the types, durations, and sequences of activities at each level.

Kleinebrahm et al. [64] also tried to address the memory-less property of Markov Chains. However, instead of using multiple sequentially

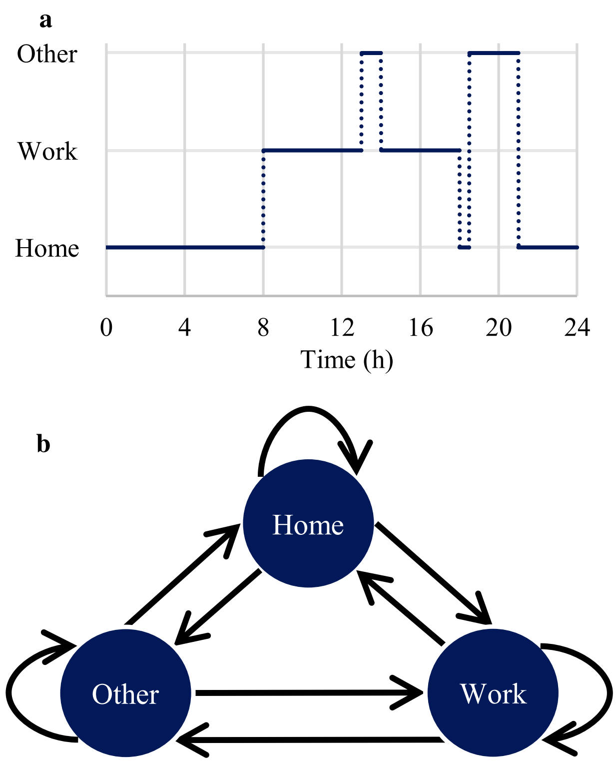


Fig. 4. Example 24-h activity profile (**a**) generated by a Markov chain with three discrete states: Home, Work, and Other (**b**).

executed regression models, which impose strong modeling assumptions, the authors present a deep **neural network-based** approach, using attention-based transformer and Long Short-Term Memory-based (LSTM) architectures. The model represents mobility states, such as "home" or "outside", at a high temporal resolution of 10 min. By training on weekly travel diaries, the model successfully captured both intra-day and inter-day variability in behavior, producing synthetic weekly mobility schedules that reflect temporal patterns and statistical properties observed in real-world data.

More recently, Generative Adversarial Networks (GANs) have been applied to generate synthetic EV demand data. In the current literature, this is mostly done after mobility information has already been translated into electricity-consumption profiles (e.g., from travel-survey diaries), rather than by directly generating detailed mobility behavior itself [75,83,84]. Conceptually, GANs consist of two neural networks trained adversarially: a generator that produces synthetic samples and a discriminator that tries to distinguish synthetic from real data. Through this competition, the generator learns to produce increasingly better synthetic profiles. In contrast, Variational Autoencoders (VAEs) are often discussed as a promising alternative for synthetic load generation, but remain rarely used for EV demand modeling in the reviewed works [85]. A VAE learns a probabilistic latent representation by training an encoder to map observed profiles to a distribution in latent space and a decoder to reconstruct profiles from latent samples, enabling generation by sampling from the latent prior and decoding back to the data space.

Once travel activities and trip timings have been determined at high temporal resolution (see Table 1 for details and Fig. 4 for an example), some studies assign travel distances [18,46,53,57,59,62,63,65,68,70,72,74] and durations [18,46,53,62,63,65,68,70,72] to these trips in a second step.

Monte Carlo simulation is a widely used method for estimating travel distances and durations by sampling from travel survey data [46,52,53,57,59,63,65,68,72]. Several studies further refine this approach by incorporating trip purpose through conditional probabilities when sampling travel attributes [52,53,63,68,72]. Alternatively, clustering techniques have been applied to group mobility profiles with similar travel patterns, from which representative trips are sampled [59,86].

An alternative approach extends the Markov chain by introducing a dedicated "driving" state that determines trip durations. The corresponding travel distances are then derived by assuming either an average travel speed for the entire duration [55,70] or for a fraction thereof (e.g., [52]). Other studies explicitly calculate travel distances or durations by integrating spatial relationships and road network characteristics [62,72,74].

In the third step, the energy consumption of each trip is calculated. Many studies adopt a simplified approach by estimating energy consumption based on the travel distance and specific average energy consumption rates. This straightforward method provides a basic estimate of trip-level energy demand and is widely used [46,53,55,57,59,59,63,65,70,72]. Other studies refine this approach by incorporating environmental factors, particularly temperature, to adjust specific energy consumption rates [53,62,68,74].

More advanced models integrate dynamic driving behavior into energy consumption estimates [18,52,68]. For example, Muratori et al. [52] simulated trips as sequences of velocity and acceleration states using a Markov chain approach, with transition probabilities derived from real-world driving cycles that distinguish between urban and highway driving behaviors.

2.2. EV behavior-based approach

EV behavior-based approaches utilize vehicle-level datasets, such as GPS-based travel data [87,88,93,104,107], field trial records [89,98,100,102,106], or mobile phone activity data [94], to track vehicle positions (see Table 2).

Markov chain models are widely used in this domain to simulate vehicle state transitions over time, enabling the generation of synthetic vehicle activity data [88,94,100]. Unlike individual person behavior-based approaches, which define states by location or activity, EV-focused Markov chain models typically characterize states by vehicle behaviors such as driving, parking, and charging [88], or by discrete state of charge (SoC) levels [100]. To better represent the variability of trip durations, Iversen et al. (2017) extended their Markov model with hidden driving states, which are not directly observed but govern the probabilities of the observable driving behavior. Xu et al. [94] used mobile phone data to model spatiotemporal charging behavior with a time-inhomogeneous semi-Markov chain simulating transitions between home, work, and other destinations.

Monte Carlo simulation is also used to generate synthetic EV travel and charging behavior by sampling from real-world data [87,89,98,106]. Brady and O'Mahony [87] simulate EV travel and charging patterns based on two days of GPS data from a field trial [87]. Key travel variables, including departure times, trip frequencies, and total daily distance for both days, were found to be correlated. These key variables were jointly modeled using a non-parametric copula function, preserving their statistical dependencies. The copula generates synthetic values for the key variables. Next, individual trip distances were assigned using conditional distributions, and journey schedules were synthesized in 5-min intervals. Trip durations and parking times were then iteratively sampled using Bayesian inference, conditioned on previously simulated variables such as departure times, trip lengths, and accumulated parking time. Energy consumption was dynamically tracked by updating the vehicle's state of charge after each trip, based on trip distance and average energy consumption rates.

Vehicle-level datasets are also used to analyze the impact of EV charging demand on charging stations, often in combination with **queuing models** (see Table 2). Yang et al. [93] utilized GPS trajectory data from electric taxis in Changsha, China to identify high-demand charging locations by analyzing dwell events. The arrival rate of EVs at charging stations was modeled using a Poisson distribution, while charging

Table 2
Reviewed papers on electric vehicle energy demand modeling, categorized as **EV behavior-based models**. The spatial resolution is reported using the NUTS classification: NUTS0 refers to the country level, NUTS1 to federal states, NUTS2 to administrative regions, and NUTS3 to districts. NUTS3+ denotes finer subdivisions below the NUTS3 level. For the empirical data, we report the type of data, the country of origin, and the data size.

Study		Model						Empirical Data		
First author	Year	Methodology	Temporal resolution	Spatial resolution	Energy resolution	Mobility-related states	Study objective	Country	Type	Size
Brady [87]	2016	Monte Carlo	5 min		+	0	Residential load impact, charging load, charging station sizing	IE	GPS [87]	15
Iversen [88]	2017	Markov	1 min			6	Mobility schedules	DK	GPS [88]	1
Schäuble [89]	2017	Monte Carlo	15 min		+ + +	4	Residential load impact, charging load, charging station sizing	DE/FR DE	EV data [89] EV data [90,91]	100 400
Kim [92]	2017	Queuing				0	Residential load impact, charging load, charging station sizing			
Yang [93]	2017	Queuing		NUTS3+		0	Residential load impact, charging load, charging station sizing	CN	GPS [93]	8k
Xu [94]	2018	Semi-Markov	15 min	NUTS3+	+	2	Grid impact	US	CDR data [95] Charging data [96] Others [97]	1.4M 580k 2k
Su [98]	2019	Monte Carlo	1 h	NUTS1	+	0	Grid impact	NZ	Vehicle data [99]	400
Ge [79]	2020	Machine learning	1 min	NUTS3+	+ + +	6	Residential load impact, charging load, charging station sizing	CN	EV data [79]	1k
Ma [100]	2021	Markov	1 min	NUTS3+	+	200	Residential load impact, charging load, charging station sizing	CN	EV data [101]	
Li [102]	2023	Machine learning	1 min	NUTS3+	+ + +	0	Residential load impact, charging load, charging station sizing	CN	EV data [103]	1k
Wang [104]	2023	Machine learning	1 h	NUTS3+		0	Residential load impact, charging load, charging station sizing	CN	GPS [105]	76k
Guo [106]	2024	Monte Carlo	1 h	NUTS3+		6	Residential load impact, charging load, charging station sizing	CN	EV data [106]	1
Wang [107]	2025	Machine learning	1 h	NUTS3+		0	Residential load impact, charging load, charging station sizing	CN	GPS [105]	76k

Mobility schedules; Grid impact; Residential load impact, charging load, charging station sizing; Charging sessions. (+) fixed average consumption coefficients; (+ +) indicates adjustment for either temperature effects or driving behavior; (+ + +) reflects correction for both temperature and driving behavior or the use of empirical consumption data. CDR: Call detail records (Mobile phone connection data); PEV: Plug-in electric vehicles.

durations followed an exponential distribution, capturing variations in charging behavior. Similarly, Kim et al. [92] modeled EV charging station demand using a Markov-Modulated Poisson Process, which accounted for time-dependent variations in session arrivals influenced by fluctuating traffic conditions. The charging process was simulated using a Markov chain, incorporating randomized parking durations, requested charging amounts, and system demand constraints, providing a stochastic framework for analyzing station-level charging demand.

Deep learning approaches provide an alternative for simulating charging demand at the station or regional level [79,102,104,107]. For instance, Wang et al. [104] developed an LSTM-based model trained on GPS trajectory data from private EVs in Beijing [105], with charging events identified using a spatial clustering algorithm. The model forecasts short-term EV charging demand, defined as the number of vehicles charging per hour, over a one to five hour horizon.

2.3. Charging behavior-based approach

Charging behavior-based approaches draw on charging session data, either from public charging stations [19,31–33,78,108,111,116,118,120,122,124,126,128,130] or from private residential charging [109,113] (see Table 3).

Monte Carlo simulations are used to generate synthetic charging load profiles that capture the natural variability in user behavior [19,108,122,124,126]. To reduce complexity while preserving dominant behavioral trends, clustering techniques such as k-means [111,126,131] and hierarchical clustering [19,120,122] have been employed. Powell et al. [19,122] applied hierarchical clustering to classify EV drivers based on charging habits, battery size, and session timing, allowing for a more granular and flexible representation of charging behaviors. Instead of assigning users to fixed clusters, the authors developed a graph-based model that probabilistically estimated group memberships, charging location choices, and session parameters (e.g., arrival time, duration, and energy demand), ultimately generating minute-by-minute demand profiles through sampling.

Alternative approaches include Markov chains [78], queuing models [109], and fuzzy logic-based models [111]. Fotouhi et al. [78] proposed a **Markov chain** model that simulates EV charging behavior as transitions between connected and disconnected SoC. Transition probabilities were modeled with logistic functions, reflecting drivers' decisions to connect or disconnect. When connected, EVs charge at a constant rate, while in the disconnected state, the SoC decreases sequentially, with each step determined by an assumed driving speed and an energy consumption coefficient. Zhang and Grijalva [109] used charging data from the Pecan Street Project [110] in Austin, Texas, to simulate residential charging demand. They derived an empirical distribution for charging durations and modeled arrivals with a Poisson process. A queuing model with 15-min resolution was then applied to simulate temporal demand fluctuations, which was validated against real-world charging data. Xydas et al. [111] used **fuzzy logic** to capture uncertainty in charging demand and its impacts on the grid. Daily charging profiles from UK charging stations were clustered into typical behavioral groups. Correlation analysis revealed that air temperature strongly influences charging behavior through effects on battery efficiency and energy use. Finally, a fuzzy logic–based risk index was introduced, integrating charging profiles, weather sensitivity, and long-term demand growth to assess grid vulnerability.

Recently, **machine learning** approaches have gained popularity for analyzing and optimizing EV charging demand, supporting applications such as pricing strategies, station occupancy prediction, and energy consumption forecasting [31–33,113,116,118,128,130]. Methods range from classical algorithms such as decision trees, random forests, and support vector machines [33,116], to deep learning techniques [118,128,130], and more recently, physics-informed neural networks that embed domain knowledge to improve interpretability [31–33]. As shown in Table 3, these approaches are primarily applied to short-term forecasting of charging demand.

2.4. Transport statistics-based approach

Transport statistics-based approaches utilize traffic data [30,134,136,138,152], fleet-level information [144,148,150], and aggregated energy demand projections [132,140,146] (see Table 4). These approaches are particularly well-suited for long-term energy system

Table 3
Reviewed papers on electric vehicle energy demand modeling, categorized as **charging behavior-based models**. The spatial resolution is reported using the NUTS classification: NUTS0 refers to the country level, NUTS1 to federal states, NUTS2 to administrative regions, and NUTS3 to districts. NUTS3 + denotes finer subdivisions below the NUTS3 level. For the empirical data, we report the type of data, the country of origin, and the data size.

Study		Model						Empirical Data		
First author	Year	Methodology	Temporal resolution	Spatial resolution	Energy resolution	Time horizon	Study objective	Country	Type	Size
Leou [108]	2015	Monte Carlo	30 min		+ + +	4 d	[Charging load, charging station sizing]	TW	Public CS [108]	17 [Charging stations]
Zhang [109]	2015	Queuing	15 min		+ + +	1 d	[Charging load, charging station sizing]	US	Private CS [110]	7 [Unique EVs]
Xydas [111]	2016	Fuzzy logic	1 h	NUTS3+	+ + +	1 m	[Grid impact]	UK	Public CS [112]	255 [Charging stations]
Amini [113]	2016	Machine learning	1 h	NUTS3+	+ + +	1 d	[Charging load, charging station sizing]	US	Private CS [113]	12k [Unique EVs]
Fotouhi [78]	2019	Markov	1 h		+		[Charging load, charging station sizing]	US UK	Public CS [114] Public CS [115]	6k [Charging sessions] 14k [Charging sessions]
Shahriar [116]	2021	Machine learning	1 h		+ + +	1 y	[Charging load, charging station sizing]	US	Public CS [117]	
Eddine [118]	2022	Machine learning	1 h		+ + +	1 d	[Charging load, charging station sizing]	CN	Public CS [118]	
Jeon [33]	2022	Machine learning	1 h		+ + +	1 d	[Charging load, charging station sizing]	KR	Public CS [119]	30k [Charging sessions]
Yi [120]	2022	Machine learning	≥1 d	NUTS3		5 m	[Charging load, charging station sizing]	US	Public CS [121]	1.2k [Charging stations]
Powell [19,122]	2022	Monte Carlo	1 min	NUTS1	+ + +	1 y	[Grid impact]	US	Public CS [123]	2.8M [Charging sessions]
Nespoli [124]	2023	Monte Carlo	1 min		+ + +	7 d	[Charging load, charging station sizing]	US	Public CS [125]	21k [Charging sessions]
Van Kriekinge [126]	2023	Monte Carlo	15 min		+ + +	1 y	[Charging load, charging station sizing]	BE	Public CS [127]	10k [Charging sessions]
Koohfar [128]	2024	Machine learning	≥1 d		+ + +	90 d	[Charging load, charging station sizing]	US	Public CS [129]	1.4k [Charging sessions]
Kuang [32]	2024	Machine learning	5 min	NUTS3+	+ + +	1 h	[Charging load, charging station sizing]	CN	Public CS [32]	18k [Charging stations]
Kumar [130]	2024	Machine learning	1 h		+ + +		[Charging load, charging station sizing]	US	Public CS [117]	16 [Charging stations]
Qu [31]	2024	Machine learning	5 min	NUTS3+	+ + +	1 h	[Charging load, charging station sizing]	CN	Public CS [31]	18k [Charging stations]

[Grid impact] Grid impact; [Charging load, charging station sizing] Charging load, charging station sizing; [Charging stations] Charging stations; [Unique EVs] Unique EVs; [Charging sessions] Charging sessions; CS: Charging station data. (+) fixed average consumption coefficients; (+ +) indicates adjustment for either temperature effects or driving behavior; (+ + +) reflects correction for both temperature and driving behavior or the use of empirical consumption data.

planning, as they allow researchers to account for transport electrification in a computationally feasible way without relying on high-resolution, agent-based mobility modeling.

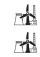
Monte Carlo simulation is commonly used to estimate charging demand. Arias and Bae [138] linked traffic volumes to weather variables through grey relational analysis and applied decision trees for mapping weather forecasts to expected traffic conditions. Charging profiles were generated from Gaussian distributions, with charging events allocated to home, work, or bus station locations according to traffic context and SoC. Mu et al. [134] constructed hourly trip flows from origin–destination matrices based on transportation statistics [135], simulating charging loads that were spatially assigned to busbars in proportion to local non-EV demand, while temporal variation was captured via hourly matrices to enable detailed grid impact analysis.

Liang et al. (2014) developed a **queueing network model** to estimate EV charging demand across interconnected charging stations. Each station is modeled as a service center, with EVs acting as customers who make probabilistic charging decisions in response to price signals and congestion. Station-level demand is then derived as a function of vehicle arrival rates and behavioral routing choices.

Most studies in this domain directly rely on empirical data, scaling it as needed for their analyses [30,132,140,144,146,148,150,152]; these approaches are included in this chapter because they are commonly used to represent aggregated EV fleets in large-scale systems, such as at the national level. Rottoli et al. [140] employed the EDGE-T transport model [154] to simulate EV adoption and energy demand under long-term global scenarios. Vehicle fleet composition is estimated using a Weibull-based discrete choice model that accounts for technology costs, consumer preferences, and policy incentives. Charging demand is then derived at the country level from projected transport activity [141–143] and powertrain efficiencies, but without consideration of charging flexibility or system interactions. Kendziorski et al. [146] disaggregate Germany's national transport electrification demand to the NUTS2 level, weighted by gross domestic product and population shares. Hourly EV demand is derived from standardized load profiles [147] for the residential, commercial, and industrial sectors, while a four-hour flexibility window is introduced to shift charging in response to renewable generation availability and grid constraints. Sánchez Diéguez et al. [144] estimate EV electricity consumption from national transport projections [145], incorporating flexibility through archetypes that impose intra-day energy balance, battery saturation, and charging/discharging constraints. Franken et al. [30] simulate electric transport by using a weekly vehicle usage profile derived from hourly highway counting statistics [45]. This profile is applied uniformly across European countries, with adjustments for time zones and climate conditions. Country-specific profiles are then scaled to annual road and rail transport energy demand and corrected for EV efficiency as well as temperature-dependent heating and cooling requirements. Wang et al. [152] model EV charging demand using spatially detailed commuter flows from the Swiss Commuter Transport Matrix [153], which reports inter-municipality trip volumes for 2169 regions, weighted by private car usage from the national Mobility and Transport Microcensus. Empirical hourly charging profiles from 2.6 million real-world charging sessions [131] are incorporated to reflect user behavior at home and workplace locations. Charging is dynamically allocated between these two locations in response to grid congestion, renewable generation availability, and system cost optimization, allowing direct comparison of home- and workplace-based charging as flexibility strategies within the power system.

Across the reviewed literature, the choice of EV demand model starting point (Section 2) is closely mirrored in the EV representation chosen in energy system models (Section 3). EV demand models primarily provide charging demand time series and flexibility descriptions (e.g., availability windows), which must be translated into tractable formulations at the spatial and temporal scale of the energy system model. High-detail activity-based approaches can capture heterogeneous charging opportunities and mobility constraints, but are rarely used directly at the national scale. Instead, their outputs are typically compressed into representative profiles or fleet availability series. Conversely, approaches that start from transport statistics can be integrated more

Table 4
Reviewed papers on electric vehicle energy demand modeling, categorized as **transport statistics-based models**. The spatial resolution is reported using the NUTS classification: NUTS0 refers to the country level, NUTS1 to federal states, NUTS2 to administrative regions, and NUTS3 to districts. NUTS3 + denotes finer subdivisions below the NUTS3 level. For the empirical data, we report the type of data, the country of origin, and the data size. No methodology indicates the direct use of empirical data.

Study		Model					Empirical Data	
First author	Year	Methodology	Temporal resolution	Spatial resolution	Energy resolution	Study objective	Country	Type
Masuta [132]	2014		1 h		+		JP	Energy data [133]
Mu [134]	2014	Monte Carlo	1 h	NUTS3+	+		US	Traffic data [135]
Liang [136]	2014	Queuing model	1 h	NUTS3+	+ +		US	Traffic data [137]
Arias[138]	2016	Monte Carlo	1 h	NUTS3+	+ + +		KR	Traffic data [139]
Rottoli [140]	2021		≥1 d	NUTS0	+		World	Energy data [141–143]
Sánchez Diéguez [144]	2021		1 h	NUTS0	+		EU	Vehicle kilometer [145]
Kendziorski [146]	2022		1 h	NUTS2	+		DE	Load profiles [147]
Zafeiratou [148]	2022		1 h	NUTS2	+		GR	Vehicle kilometer [149]
Meha [150]	2024		1 h		+ +		XK	Vehicle kilometer [151]
Franken [30]	2025		1 h	NUTS0	+ +		DE	Traffic data [45]
Wang [152]	2025		≥1 h	NUTS3	+		CH DE	Traffic data [153] Charging data [131]

 Grid impact;  Charging load, charging station sizing;  Impact on generation;  Impact on emissions, (+) fixed average consumption coefficients; (+ +) indicates adjustment for either temperature effects or driving behavior; (+ + +) reflects correction for both temperature and driving behavior or the use of empirical consumption data.

directly, but may underrepresent heterogeneity that drives peak timing and realistic flexibility limits.

3. Representation of electric mobility in energy system models

Electric vehicles introduce a new dynamic element to the energy system, necessitating their integration into energy system models. EVs serve as a critical link between electricity and road transport infrastructure, providing not only mobility but also potential flexibility services [22–24]. The role of EVs involves a wide range of stakeholders, including private car owners [155–158], households [18,159,160], companies [161–167], charging hub operators [94,168–172], distribution grid operators [173–175], fleet operators [93,176,177], system planners [178–180], and policymakers [181–184]. As EV adoption continues to increase [9,185], it becomes increasingly important for energy system models to represent not only the additional electricity demand from EVs but also their capacity to provide flexibility. The integration of EVs can influence multiple aspects of the energy system, including generation capacity expansion [186–188], grid planning [189,190], system operation and dispatch [191–193], renewable energy integration [194,195], CO_2 emissions [196–200], and electricity market dynamics [201–203]. This underscores the central role of EVs for the electricity market, grid operation, and energy system transformation. A comprehensive assessment of the technical, social, and regulatory barriers to V2G implementation from a multi-stakeholder perspective is beyond the scope of this review and has been addressed in dedicated V2X implementation reviews, such as Gschwendtner et al. [204]. In this section, we review the existing literature on how EVs are represented in energy system planning models.

A key distinction in EV modeling lies in the assumptions about charging behavior. Charging demand can be modeled either as a fixed, exogenous profile [18,140] or as a flexible, endogenous load that can be optimized within the model. This review focuses on the latter approach, specifically on smart charging [132,146,152,194,205–213] and Vehicle-to-Grid (V2G) charging [144,178–180,214–224]. Incorporating flexible charging is important for capturing sector coupling effects within the energy system, where EVs interact with electricity generation, heating, and other demand sectors [30,179,225–229].

In the following, we present an overview of the reviewed energy system models, classified into three categories: **building-level** (Table 5), **municipal-level** (Table 6), and **national, European, or international-level** models (Table 7). Each table summarizes the key characteristics of the models, including how EV charging demand is represented and which types of charging flexibility and associated constraints are incorporated. Flexibility constraints are defined as the *availability window*, which indicates the time periods during which the vehicle is available for charging or discharging, and the *travel energy requirement*, which specifies the energy needed for the next trip.

3.1. Building level

At the building scale, energy system models can capture detailed representations of individual electric vehicles by accounting for their charging behavior, travel patterns, and potential flexibility (see Table 5). The literature offers a range of modeling strategies that vary in data requirements and complexity. Broadly, these can be classified into rule-based approaches, which rely on simplified assumptions, and empirical approaches, which draw on observed data.

Rule-based modeling approaches rely on predefined assumptions about vehicle availability and energy demand, thereby avoiding the need for empirical travel data [205,206,208,209]. Charging availability is typically represented through time blocks of “available” and “unavailable” periods [205,206,208,209]. Momber et al. [205] integrated EVs into a building-level energy management framework designed to minimize electricity costs and CO_2 emissions. Vehicles were assumed to be available for charging during weekday working hours (e.g., in office parking lots). Flexibility was incorporated by enabling discharging during peak price periods, while ensuring a minimum SoC to meet mobility needs. Igualada et al. [206] adopted a slightly different strategy, modeling residential microgrid EV charging using a single representative profile from the VERDE project [206]. Such simplified approaches are computationally efficient, making them well-suited for scenario analysis, system sizing, or identifying general trends. However, the realism of their results depends on the validity of the assumed EV availability patterns and energy demand.

Empirical approaches determine EV availability and usage profiles from mobility survey data [194,207,210,211,214]. Kaschub et al. [194] co-optimize household electricity consumption, PV and battery system dimensioning, and EV charging by sampling weekly mobility schedules from survey data [49] and replicating them across the modeling horizon. Charging flexibility was defined by comparing two extreme cases: immediate charging upon arrival versus delayed charging that ensured only the minimum SoC required for the next departure. This approach

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Table 5
Reviewed **building-level energy system models** incorporating electric vehicles. Building-level models typically represent individual EVs and therefore do not require an aggregation method, as indicated by the empty column.

Study		Model						EV charging				Flexibility	
First author	Year	Name	Optimization	Dispatch	System design	Temporal resolution	Temporal horizon	Uncontrolled charging	Smart charging	Vehicle-to-Home	Vehicle aggregation	Availability window	Travel energy requirement
Momber [205]	2010	DER-CAM [230]	✓	✓		1 h	1 y	✓	✓	✓		(✓)	(✓)
Igualada [206]	2014		✓	✓		<1 h	1 d	✓	✓	✓		(✓)	✓
Nguyen [214]	2014		✓	✓		1 h	1 d	✓	✓	✓		✓	✓
Kaschub [194]	2016	SpeicherOpt [194]	✓	✓	✓	<1 h	1 y	✓	✓	✓		✓	✓
Doroudchi [207]	2018		✓	✓		1 h	1 y		✓	✓		✓	✓
Bracco [208]	2019		✓	✓	✓	1 h	1 y	✓	✓	✓		(✓)	✓
Chakir [209]	2022		✓	✓		1 h	1 d		✓	✓		(✓)	
Zhang [210]	2023		✓	✓		1 h	1 d		✓	✓		✓	✓
Lerbinger [211]	2024	MANGOever [231]	✓	✓	✓	<1 h	25 y	✓	✓			✓	✓

Flexibility: (✓) denotes assumption-based constraints; ✓ denotes empirical-based constraints.

enabled the quantification of self-consumption improvements achieved under controlled charging relative to baseline conditions. Similar approaches have been applied to different objectives, such as enhancing on-site PV utilization [211], jointly scheduling EVs and heating, ventilation, and air conditioning systems for cost and comfort [214], facilitating neighborhood-level energy trading [210], and reducing dependency on the grid [207].

All of these studies integrate electric vehicles as a flexible component within the building energy system. Most studies consider vehicle-to-home applications [194,205–210], while Nguyen et al. (2014) extend the scope to coordinated charging/discharging across multiple buildings at the neighborhood scale [214]. Flexibility is typically constrained by factors such as SoC limits and charging rates [194,205–209,214], battery efficiency [109,194,205,214], battery degradation [194], and vehicle availability [194,207,210,211,214]. V2H is often considered a more immediate entry point for behind-the-meter flexibility (e.g., self-consumption optimization and household peak shaving) and typically requires detailed modeling of household/building demand and local boundary conditions (e.g., meter connection limits and on-site generation). In contrast, system-wide V2G typically requires additional grid and market integration arrangements and is commonly represented via aggregated fleets subject to system-level constraints (e.g., supply–demand balance and network congestion).

3.2. Municipal and regional level

Municipal-, city-, and regional-scale energy system models consider substantially larger EV populations than building-level models, which typically necessitate aggregating EVs into flexible loads or storage units to preserve computational tractability (see Table 6). The aggregation methods used in the reviewed studies can be broadly categorized into Dynamic EV fleet, Postponed charging, and Virtual storage, with the terminology of the first two following Wang et al. [232].

The **dynamic EV fleet** aggregation [215–219,233] represents the EV fleet as a single, time-dependent energy storage unit. Instead of modeling each vehicle individually, the fleet is simplified into an aggregated battery whose energy and power capacities vary over time according to vehicle availability. Availability profiles are derived either from assumptions [219] or from empirical mobility data [215–218], reflecting the fraction of EVs connected to the grid (e.g., parked at home) during each time step. As vehicles connect to or disconnect from the grid due to arrival and departure patterns, the available storage and power capacities adjust accordingly. This enables the model to schedule charging and, in some cases, discharging decisions across the fleet within realistic constraints. Aggregation is typically performed at the regional or city scale [215,219], and may be further disaggregated into sub-fleets by vehicle category [216,218] or by location [217]. Charging efficiency, power limits, and other technical parameters specific to vehicle or charger types are incorporated to represent diverse vehicle fleets [178,215–219]. While this aggregation method omits individual vehicle-level constraints, it retains the essential collective flexibility of the fleet, defined as the ability to shift charging or discharging across time. The method is widely adopted because it captures critical system-level flexibility while maintaining computational feasibility, particularly in optimization-based energy system models [232]. Reviewed studies include Heinisch et al. [216], demonstrating how smart and V2G charging in a city context can reduce stationary storage investments and enhance photovoltaic utilization. Owens et al. [217], assessing the long-term value of V2G for decarbonization. Falkoni et al. [219], modeling a fully renewable urban energy system. Fattori et al. [215], investigating the integration of PV generation and EVs under different charging strategies, and Rotondo et al. [233], who generate synthetic hourly charging profiles with the open-source emobpy tool and integrate them into the multi-node regional energy system model oemof [234] to evaluate smart charging and V2G impacts on peaks and imports.

Building on the dynamic EV fleet approach, recent research by Brodnicke et al. [220], based on the aggregation framework of Muessel et al. [235], introduced a more advanced method for representing fleet flexibility in optimization models via **virtual storages**. Instead of directly optimizing an aggregated fleet battery, the approach defines a reference charging scenario that reflects inflexible baseline behavior, typically immediate charging upon arrival. Deviations from this reference are captured through two virtual storages: one representing time-shifted charging and another enabling bi-directional charging. For smart charging, only the first storage is available, whereas for V2G both are accessible. The flexibility provided by these virtual storages is constrained by the underlying fleet's energy and power limits. At each time step, the available capacity is derived from empirical mobility data, which determines vehicle connection times and thereby the feasible charging or discharging potential. The method is implemented in two stages: first, a pre-processing step establishes the time-dependent upper and lower energy bounds of the aggregated fleet by comparing the reference charging trajectory with the set of feasible charging profiles for all vehicles; second, these bounds are used to represent EV charging in the main optimization model through the virtual storages.

An alternative and computationally lighter approach is **postponed charging** aggregation, in which EV demand is modeled as a time-shiftable load within predefined time windows rather than through detailed arrival and departure constraints. Mascherbauer et al. [212] applied this method by assuming that charging could be shifted to off-peak hours with lower electricity tariffs. Future distribution grid investment needs in two urban areas were analyzed by simulating individual residential buildings and their corresponding energy demand, considering the electrification of heating alongside the integration of photovoltaics, batteries, EVs, and home energy management systems.

Table 6

Reviewed **municipal- and regional-level energy system models** incorporating electric vehicles. The spatial resolution is reported using the NUTS classification: NUTS0 (0) refers to the country level, NUTS1 (1) to federal states, NUTS2 (2) to administrative regions, and NUTS3 (3) to districts. NUTS3 + (3 +) denotes finer subdivisions below the NUTS3 level. A spatial resolution down to the building level is indicated by "B".

Study		Model							EV charging				Flexibility	
First author	Year	Name	Optimization	Dispatch	System design	Temporal resolution	Temporal horizon	Spatial resolution (NUTS)	Uncontrolled charging	Smart charging	Vehicle-to-Grid	Vehicle aggregation	Availability window	Travel energy requirement
Fattori [215]	2014	EVLS [215]	✓	✓		1 h	1 d		✓	✓	✓	🚗	✓	
Heinisch [216]	2021		✓	✓	✓	1 h	1 y		✓	✓	✓	🚗	✓	
Owens [217]	2022	GenX [236]†	✓	✓	✓	1 h	1 y		✓	✓	✓	🚗	✓	
Straub [178]	2023			✓		1 d	2 d	3+	✓	✓	✓		✓	✓
Babonneau [218]	2024	ETEM-SG [237]	✓	✓	✓	1 h	10 y	3+	✓	✓	✓	🚗	✓	
Falkoni [219]	2024	Calliope [238]†	✓	✓		1 h	1 y	3+	✓	✓	✓	🚗	(✓)	
Rotondo [233]	2024	oemof [234]†	✓	✓		1 h	1 y	3+	✓	✓	✓	🚗	✓	✓
Brodnicke [220]	2025	REASON [239]	✓	✓	✓	1 h	28 y	3+	✓	✓	✓	🔋	✓	✓
Mascherbauer [212]	2025		✓	✓	✓	1 h	30 y	B	✓	✓		🔌	✓	✓

🚗 Dynamic EV fleet; 🔋 Virtual storage; 🔌 Postponed charging. Flexibility: (✓) denotes assumption-based constraints; ✓ denotes empirical-based constraints; † Open source model.

Table 7

Reviewed **national to international-level energy system models** incorporating electric vehicles. The spatial resolution is reported using the NUTS classification: NUTS0 (0) refers to the country level, NUTS1 (1) to federal states, NUTS2 (2) to administrative regions, and NUTS3 (3) to districts.

Study		Model							EV charging				Flexibility	
First author	Year	Name	Optimization	Dispatch	System design	Temporal resolution	Temporal horizon	Spatial resolution (NUTS)	Uncontrolled charging	Smart charging	Vehicle-to-Grid	Vehicle aggregation	Availability window	Travel energy requirement
Hedegaard [221]	2012	Balmorel [240]†	✓	✓	✓	1 h	15 y	0		✓	✓	🚗	✓	(✓)
Masuta [132]	2014	MARKAL [241]	✓		✓	1 h	60 y		✓	✓		🔌		
Schill [213]	2015		✓	✓		1 h	2 y		✓	✓		∿	✓	✓
Tarroja[191]	2016	HiGRID[242]	✓	✓		1 h	1 y	0	✓	✓	✓		✓	✓
Brown [179]	2018	PyPSA [243]†	✓	✓	✓	1 h	1 y	0	✓	✓	✓	🚗	✓	(✓)
de Tena [222]	2018	REMix [244]†	✓	✓	✓	1 h	2 y	1	✓	✓	✓	≈		✓
Taljegard [223]	2019	E&E [245,246]	✓	✓	✓	1 h	30 y	1		✓	✓	∿	✓	
Rottoli [140]	2021	REMIND [247]†	✓		✓	>1 y	110 y	0	✓					
S. Diéguez[144]	2021	IESA-OPT [144]†	✓	✓	✓	1 h	30 y	0		✓	✓	🔌		
Kendziorski [146]	2022	AnyMOD [248]†	✓	✓	✓	1 h	1 y	2		✓		🔌		
Luh [224]	2023	Swiss TIMES [224]†	✓		✓	1 h	30 y	0	✓	✓		∿	✓	
Guéret [180]	2024	DIETER [249]†	✓	✓	✓	1 h	1 y		✓	✓	✓	∿	✓	
Meha [150]	2024	EnergyPLAN [250]		✓		1 h	1 y			✓	✓	🔌		
Wang[152]	2025	EXPANSE [251]	✓	✓	✓	>1 h	1 y	3	✓	✓				

🚗 Dynamic EV fleet; 🔌 Postponed charging; ∿ Representative profiles; ≈ Aggregated boundary. Flexibility: (✓) denotes assumption-based constraints; ✓ denotes empirical-based constraints; † Open source model.

3.3. National to international level

National- to global-scale energy system models face even greater complexity due to larger EV fleets, spatial heterogeneity, and long-term infrastructure planning horizons. Consequently, a broad range of fleet aggregation methods is employed to capture EV energy demand and flexibility to ensure computational feasibility (see Table 7).

The **dynamic EV fleet** approach, as previously described, models an aggregated fleet as a flexible, time-varying storage system [179,221]. In a European context, Brown et al. [179] implemented this approach in the PyPSA-Eur-Sec-30 model [243], which optimizes investment and dispatch decisions across the electricity, heating, and transport sectors for Europe at hourly resolution. Fleet availability for charging or discharging in each hour was derived from national-scale traffic statistics [45]. For both smart and V2G charging, a minimum SoC was imposed at a specified time each day to reflect mobility requirements. Within these constraints, charging and discharging were optimized in response to renewable availability and system costs. Similarly, Hedegaard et al. [221] examined EV integration in Northern Europe using the Balmorel model [240]. The EV availability was determined from average values obtained from national transport surveys. A key assumption is that all EVs must leave the grid fully charged, imposing a lower bound on daily energy requirements. Both studies [179,221] demonstrate the scalability of the dynamic EV fleet approach to large-scale systems, using simplified assumptions for spatial and behavioral diversity, but nevertheless capturing essential aspects of aggregated charging flexibility.

The **postponed charging** approach is frequently employed in large-scale energy system models [132,144,146,150], where EV flexibility is represented by allowing energy demand to be satisfied within a predefined time window. Masuta et al. (2014) employed an extended MARKAL model [241] to compare nighttime and smart charging, assuming that EV demand could be shifted within the day. Similarly, Kendziorski et al. [146] implemented postponed charging in the AnyMOD framework [248], assuming that EV demand had to be met within four-hour blocks. Sánchez Diéguez et al. [144] extended this formulation by integrating V2G functionality into the IESA-Opt model [144], constraining flexibility through daily energy balances and hourly charging and discharging limits. In contrast, Meha et al. [150] modeled EVs in EnergyPLAN [250] as fully flexible demand-response units with both smart and V2G charging, but without explicit intra-day constraints; in this case, EV demand was balanced only on an annual basis, which may overstate actual flexibility.

The **aggregated boundary** approach (terminology from Wang et al. [232]) constrains EV charging and discharging within a feasible flexibility range defined by the maximum and minimum cumulative energy trajectories of the fleet. Individual vehicle profiles are first aggregated by arrival time to compute upper and lower bounds on cumulative SoC. The upper bound corresponds to vehicles charging immediately upon arrival to their maximum allowed SoC, while the lower bound reflects maximum discharging followed by the latest feasible charging to meet the minimum SoC at departure. Aggregating these individual bounds across all vehicles yields a time-dependent flexibility band for the entire fleet. Within these limits, the energy system model can optimally schedule charging and discharging while ensuring mobility requirements are met. De Tena and Pregger [222] applied this method in the REMix model [244] to assess the role of controlled charging and V2G in a future renewable-based German and European power system. Using empirically observed travel profiles, they generated statistical SoC trajectories for representative vehicles and constructed fleet-level SoC boundaries based on a confidence interval. This enabled hourly optimization of EV charging scenarios at the national scale while maintaining computational feasibility.

A widely used strategy for reducing complexity in large-scale EV integration studies is the use of **representative profiles** [180,213,223,224]. Instead of modeling individual driving behavior, these approaches rely on a limited set of typical charging or driving patterns, usually obtained by clustering empirical mobility data. Such profiles capture essential behavioral heterogeneity while keeping model size tractable. The resulting time series are scaled to the national or regional level and subsequently used as inputs to energy system models. Schill and Gerbaulet [213] derived charging profiles from mobility data across 28 vehicle categories to simulate EV demand in a German electricity dispatch model and assessed the impact of charging strategies on system operation and CO_2 emissions. Taljegard et al. [223] processed GPS-based travel data, clustered them into 200 representative daily driving profiles, and integrated these into the ELIN capacity expansion model [245] and the EPOD dispatch model [246] to evaluate investment and operation of the Scandinavian–German power system under different charging and V2G scenarios. Guéret et al. [180] employed travel surveys [69] to generate synthetic hourly mobility profiles across location-based clusters (metropolis, large city, medium-sized city, small city, and rural area) using the emobpy tool [68]. These profiles were scaled to the national fleet and applied in the DIETER power sector model [249] to investigate the implications of shifting from private to shared EV fleets under different charging strategies.

While most large-scale energy system models capture EV flexibility primarily in the temporal dimension, Wang et al. [107] introduced an alternative approach that emphasizes the spatio-temporal flexibility of EV charging. They explicitly modeled commuting EVs as being able to shift their charging location between home and workplace municipalities, with each location providing specific charging windows. This approach was implemented in the spatially resolved optimization model EXPANSE [251], which covers 2169 Swiss municipalities, combined with a detailed commuter transport matrix derived from national survey data [153]. The formulation enables endogenous optimization of charging locations, allowing the system to exploit synergies such as workplace charging aligning with midday solar generation, while home charging contributes to evening demand peaks.

Finally, some large-scale studies reduce complexity by coupling an external EV charging model to the energy system model, rather than representing EVs endogenously within the system optimization. For example, Tarroja et al. [191] couple an EV charging-dispatch model to a detailed electricity dispatch model to assess the system value of V2G and its equivalence to stationary storage, showing that mobility-constrained availability can limit balancing provision relative to stationary batteries.

4. Discussion

In the following, we critically evaluate the findings of our literature review, structured around the three research questions introduced in Section 1. Table 8 summarizes the key limitations, challenges, and future research directions identified across the reviewed literature and serves as an overview for the discussion below.

4.1. Electric vehicle energy demand modeling approaches

As the electrification of the transport sector advances [9,10], assessing the impacts of electric vehicles on the energy system, particularly their demand and flexibility potential, becomes increasingly important. The data requirements of energy system models depend strongly on the study's objective. Investment decisions evaluated at the household level require high-fidelity individual profiles, while higher-level analyses allow for greater aggregation. Across spatial scales, the temporal resolution must be sufficient to capture the variability of renewable energy availability, and the temporal horizon should cover at least one year to represent seasonal dynamics, extending further for robust system designs [77]. Spatial requirements range from national resolution for electricity market studies to very high, GPS-exact spatial resolution for distribution grid analyses. The reviewed literature reveals a wide variety of modeling approaches that differ considerably in their data sources and methodological assumptions, which are discussed in the following.

Individual person behavior-based modeling approaches utilize data that provide detailed and representative insights into mobility

Table 8
Summary of key limitations, challenges, and future research directions of the reviewed literature.

Theme	Limitations in current literature	Key challenges	Future directions
EV demand modeling	• Empirical datasets often cover only a few days (travel surveys) [49,50,69] or weeks (vehicle/charging data) [89,90,123]. • Many surveys are based on conventional vehicles (travel surveys, vehicle data) [69, 99]. • Limited population representativeness beyond specific regions or early-adopter samples (vehicle and charging data) [99,121]. • Limited interpretability for purely data-driven models trained on vehicle/charging data [78,79]. • Aggregated inputs limit temporal resolution and behavioral diversity [144,152].	• Extrapolating short observation periods to year-long time series [48]. • Capturing long-term behavioral stability and variability [48,52]. • Early-adopter bias [89,123]. • Data scarcity and restricted access to high-resolution mobility/charging data [69,89]. • Transferability across regions and user groups [129]. • Tractability of the resulting EV profiles for downstream energy system models.	• Utilize surveys with higher EV shares and richer charging context [254]. • Combine complementary datasets to improve fidelity and coverage. • Use vehicle and charging data for calibration/validation where feasible. • Leverage generative AI to improve diversity and fidelity of behavioral profiles [64].
Integration into energy system models	• Charging availability is commonly tied to parking times. • Coarse spatial resolution at larger scales limits the assessment of local peak loads. • Tractability typically requires temporal, spatial, and fleet aggregation, which can smooth peaks and mask heterogeneity [77, 232,255].	• Limited availability of consistent, high-resolution demand and flexibility inputs. • Representing uncertainty in charging flexibility (mobility variability, weather, behavior). • Distribution grid analyses require very high spatial resolution. • Trade-offs between aggregation approaches and their impact on feasible flexibility due to computational effort.	• Synthetic data to counteract data scarcity. • Use empirical evidence for temporally varying SoC requirements and minimum reserves. • Generate high-fidelity and diverse behavioral/charging profiles via advanced generative models. • Systematically benchmark aggregation methods.
Synthetic data for EV modeling	• Synthetic data quality is bounded by the quality/coverage of training data. • Current model limitations (e.g., instability for GANs, over-smoothing for VAEs) [85, 258].	• Ensuring privacy protection of input data for sharing synthetic mobility, vehicle, and charging data. • Capturing long-term stability (weekly/seasonal patterns). • Preserving cross-correlations between activities in household profiles. • Capturing inter-person dependencies within households (e.g., synchronization and car sharing).	• Develop generative models that capture long-term stability, cross-correlations, and inter-person dependencies. • Combine datasets to improve representativeness, diversity, and fidelity of generated profiles. • Combine synthetic data generation with differential privacy to strengthen privacy guarantees and reproducibility [259].

patterns [49,58,60,69,71], making them particularly suitable for assessing charging flexibility. Furthermore, these approaches offer high interpretability and flexibility, as they explicitly model the dependencies between individual behavior and travel energy demand, making it easier to incorporate changes such as technological innovations [13,53,252,253]. However, the underlying datasets typically cover only a few days [49,50,69], meaning that information about long-term behavioral stability is limited. Even when such dependencies are present in the data, Markov chain and Monte Carlo simulations often fail to capture them, making these methods less suitable for applications that require high-fidelity behavioral data, such as joint household-level analyses of photovoltaic and EV investments. Moreover, most mobility surveys are based on internal combustion engine vehicles and therefore do not reflect potential changes in driving behavior associated with EVs (e.g., the absence of trips to fuel stations) and generally lack information on charging availability, requiring additional assumptions in modeling. New surveys with higher shares of EV drivers, such as the latest edition of Mobility in Germany [254], should be utilized in future research to better capture structural differences between internal combustion and battery electric vehicles. Current studies often rely on single national surveys [58,69,71] with limited sample sizes, which makes detailed analyses of diverse subgroups difficult. Future work should integrate multiple, complementary datasets and leverage big data and generative AI approaches to enhance both the diversity and fidelity of individual mobility profiles [64]. For example, combining datasets with different temporal or household coverage can improve simulated data quality if the assumption of similar temporal consistency and intrahousehold dependencies across datasets holds, which is probably more realistic than assuming no behavioral stability or inter-person dependencies within households.

Overall, individual person behavior-based approaches provide a robust foundation for long-term explanatory studies, such as assessing the future impacts of emerging mobility concepts like autonomous driving, where understanding fundamental mobility needs is crucial. However, these approaches will always remain limited, as the impact of novel technologies on behavior can only be assessed once relevant data become available. They are also particularly valuable for household-level studies, such as those on investment decisions [194] or residential demand [18], where high-fidelity behavioral data are essential for consistently simulating energy demand for EVs, space heating, and other household appliances.

EV behavior-based approaches rely on data providing high-resolution information on driving distances and durations [93,105], and in some cases velocity profiles or SoC evolution [89–91]. These datasets typically span several weeks or months, offering longer time horizons than most survey data [87,88,95] thereby providing greater temporal robustness. However, these data often lack population representativeness beyond the specific context in which they were collected, making transferability difficult due to missing contextual information. Moreover, many datasets are based on internal combustion engine vehicles [99], implicitly assuming comparable driver behavior, or on small EV trial fleets [79,89–91], which introduces early-adopter bias. In addition, these approaches offer limited interpretability due to a lack of behavioral context, particularly regarding trip purposes, which results in implicit behavioral dependencies, and they are less adaptable to scenario changes because key relationships are not explicitly modeled. Despite these limitations, the technical granularity of vehicle-level data makes it valuable for analyzing charging behavior and energy consumption in specific locations or scenarios. Future research could employ such datasets to calibrate behavior-based models for specific applications and contextual conditions, thereby improving the understanding of actual charging behavior.

Charging behavior-based approaches utilize empirical data from charging infrastructure offering precise information on charging times, durations, power levels, and energy per session [113,123]. However, such datasets mostly lack contextual behavioral insights, such as trip purposes or underlying mobility patterns, and are biased toward early adopters. Moreover, as most datasets reflect historical, uncontrolled charging behavior, they cannot capture interactions with the energy system, such as smart charging or V2G strategies. Consequently, these approaches are best suited for analyzing demand at specific locations, short-term forecasting, or peak load prediction [32,109,111].

Transport statistics-based approaches draw on macroscopic datasets such as highway traffic counts, commuting statistics, or aggregated indicators from national travel surveys to estimate EV charging demand. These datasets are particularly suited for large-scale, long-term energy system models, where the objective is to generate representative load profiles rather than capture individual mobility behavior [30,152,179]. Although such approaches often lack fine temporal resolution and behavioral diversity, they offer strong spatial and demographic representativeness [144,152]. As a result, they inform an aggregated representation of national transport that requires comparatively low computational resources in energy system modeling, which is particularly important for national- or continental-scale analyses where scalability and tractability are critical.

Some studies combine different approaches by leveraging the complementary strengths of multiple datasets [52,59,64,94], for instance, by integrating person activity data with vehicle-level data [18]. Such combined approaches should be applied in future research due to their strong potential to improve the robustness and accuracy of EV demand modeling.

4.2. Integration of EVs into energy system models

The integration of EV charging demand and flexibility into energy system models depends on the underlying demand and flexibility representations generated by EV demand models, as well as on spatial scale and the research question being addressed. At the building level, models can simulate individual EVs in detail, incorporating explicit mobility-driven constraints (see Table 5). Charging availability is typically tied to parking times, with models ensuring that sufficient battery levels are reached before departure. Nevertheless, the modeling of individual EVs remains limited by both data availability and model capabilities (see Section 4.1). Moreover, many models are purely techno-economic, neglecting social factors (such as range anxiety or the unequal availability of charging infrastructure across income groups and housing types) and political factors (such as subsidies or incentives for V2G participation), and they often fail to account for uncertainties in charging flexibility, which arise from variations in mobility demand, weather conditions, or technological failures, by assuming perfect foresight over the entire modeling horizon [194]. The limitation of uncertainty in mobility demand could be mitigated by introducing empirically derived ranges of temporally varying minimum states of charge that must be maintained, which may be higher than the energy required for the next trip. To assess interactions with local renewables such as photovoltaics or wind, building-scale studies often simulate an entire year at hourly or sub-hourly resolution [194,205,208]. While this granularity is computationally feasible for small systems, it becomes intractable at larger scales.

At municipal, regional, and national scales, models often exhibit poor spatial resolution, typically lacking spatial differentiation and only rarely providing municipal-level detail, likely due to high modeling complexity and data protection constraints. Nevertheless, particularly for distribution grid analyses at the municipal level, very high spatial resolution is essential to understand where and when peak loads occur. Modeling at building-level resolution remains rare and, when conducted, often relies on low-fidelity individual profiles [212], which limits the evaluation of individual-level flexibility potentials, for example those arising from temporally consistent simulations of EV and heat pump dispatch. Furthermore, future innovative mobility concepts, such as autonomous vehicles, probably have their strongest impacts on the distribution grid. Future research should therefore assess the implications of innovative mobility concepts using spatially fine-grained models combined with high-fidelity and diverse behavioral profiles, which are essential for capturing realistic mobility needs.

Energy system models often adopt an hourly resolution to reduce computational complexity (see Tables 5–7). EV energy demand models, in contrast, are frequently calibrated on much finer-grained data (e.g., 1–10 min travel or charging records; see Tables 1–4). For integration into energy system models, these high-resolution outputs are typically aggregated to match the hourly time step, either by generating sub-hourly profiles and aggregating them, or by formulating the demand model directly at an hourly time step where feasible. More generally, temporal aggregation in energy system modeling can be achieved by directly reducing the number of time steps (downsampling), segmenting the time series, or using representative periods (e.g., clustered typical days or weeks). Similarly, spatial aggregation reduces the number of modeled regions, often via administrative zoning or clustering of nodes, which improves tractability but may smooth local peaks and conceal spatial heterogeneity relevant for EV charging and flexibility [77,255]. This limitation is particularly relevant for distribution grid analyses, where overloads may be triggered by a relatively small number of households with coincident charging peaks [256,257]. Spatial aggregation above the household level can smooth these local coincidences and thereby mask congestion risks that would be visible at finer spatial resolution. Conversely, when EV demand is modeled at an aggregated level, disaggregation into spatially resolved model regions is typically performed by allocating aggregated profiles using proxies (e.g., population, car ownership, or commuting patterns) [146]. Maintaining behavioral integrity under such scaling requires preserving key distributions and correlations (e.g., arrival/departure times and the timing of charging), not just annual energy demand.

Simulating thousands or even millions of individual EVs is often impractical, making aggregation necessary (see Tables 6 and 7). Our review identifies five prominent aggregation methods: postponed charging, dynamic EV fleet, virtual storage, aggregated boundary, and representative profiles. These approaches differ in their data requirements, the degree of behavioral diversity captured, computational complexity, and accuracy in representing charging demand and flexibility (see Fig. 5). Future research should benchmark these aggregation methods more systematically to identify their respective strengths and limitations with regard to accuracy and computational effort.

- **Postponed charging** simplifies flexibility by allowing aggregated EV demand to shift within a predefined window. Its advantages are low data requirements and minimal computational complexity. However, it often overestimates flexibility by ignoring mobility constraints and behavioral diversity. Moreover, the defined window is rarely empirically grounded [132,144,146]. Despite its low accuracy, it remains a practical option for large-scale scenario studies [232].
- **Dynamic EV fleet** aggregates all EVs into a single virtual fleet with time-varying energy and power capacities that reflect vehicle availability. This method balances accuracy and computational complexity [232] and has been widely applied in large-scale models using survey-based travel statistics. Its limitations are the lack of behavioral detail and the need for availability and daily travel demand data.
- **Virtual storage** defines a reference charging profile and models flexibility as deviations from this baseline. Since the reference profile already ensures feasibility, optimized deviations remain realistic by design. Muessel et al. [235] demonstrated that this

approach is both accurate and scalable, providing reliable flexibility estimates with manageable complexity, though it requires detailed behavioral data for calibration.

- **Aggregated boundary** tries to preserve individual-level detail by grouping EVs by arrival times and computing cumulative upper and lower SoC bounds. Charging is optimized within these bounds, ensuring that individual constraints are respected. This approach achieves high fidelity and flexibility accuracy, particularly when boundaries are finely constructed. The drawbacks are significant computational overhead and the need for detailed mobility data, which restricts its use to smaller-scale or computationally robust studies [232].
- **Representative profiles** reduce data requirements and computational effort by clustering empirical mobility data into typical usage patterns, which are then scaled to regional EV demand. This method is practical and widely applicable, but its accuracy depends heavily on the number and quality of clusters [86]. Behavioral diversity within clusters is lost, and outliers or extreme usage patterns are often excluded, which may lead to underrepresentation of flexibility in heterogeneous fleets.

4.3. Potential and limitations of synthetic mobility data

As stated before, individual person behavior-based approaches are particularly suited for assessing representative EV charging flexibility, which is essential for accurately capturing demand-side dynamics in energy system models. However, these approaches rely on behavioral datasets that are often restricted by privacy regulations and limited accessibility, posing a significant barrier to open and reproducible analysis. This includes high-resolution travel and mobility records as well as charging data, which are frequently unavailable publicly due to privacy regulations and proprietary data ownership (see Table B.10). Synthetic data generated by simulation models offer a promising solution by reproducing the statistical properties of empirical datasets and thereby providing high-resolution inputs for energy system analysis without the need for extensive data collection. Despite this potential, synthetic mobility data generated by the models described in Section 2 are still rarely used in energy system models (see Section 3), where empirical data sources remain the preferred choice [132,152,179,194], likely due to limitations in the quality of synthetic datasets.

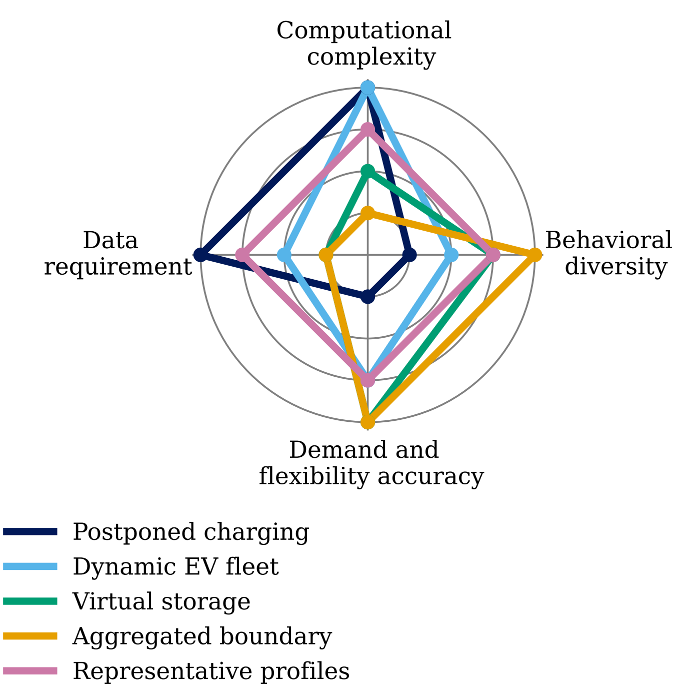

Fig. 5. Comparison of aggregation methods, evaluated based on computational complexity, behavioral diversity, demand and flexibility accuracy, and data requirements. Relative performance increases with distance from the center.

When synthetic data is generated, its purpose and justification are often insufficiently addressed. A key motivation is the temporal mismatch between available empirical travel data and the needs of energy system models, which require year-long time series to capture seasonal charging demand and broader system dynamics [77].

To bridge this gap, synthetic mobility profiles are often generated by extending short-term datasets using probabilistic methods such as Markov Chains or Monte Carlo simulations. However, these approaches fail to reproduce realistic weekly and seasonal variations in behavior [64], which limits their suitability for energy system modeling where long-term temporal consistency is essential. Hilgert et al. [48] proposed a hierarchical model with weekly time budgets, but this comes at the cost of additional assumptions due to the large number of regression models. Deep learning methods such as LSTM networks and attention-based transformers have shown strong potential for capturing intrapersonal consistency and variability [64]. AI-driven generative models can preserve cross-correlations between household activities, a common limitation of Monte Carlo-based methods, by learning joint multivariate distributions, which typically require sufficiently large and representative training datasets. However, when modeling households using this approach, future research should also account for interpersonal dependencies, such as the synchronization of activities between household members (for example, car sharing), to generate high-fidelity behavioral profiles. More recently, transformer-based deep neural networks, including emerging Large Language Model (LLM)-based approaches, represent a promising direction for mobility behavior modeling, since mobility behavior can be represented as discrete sequential data, for example as ordered sequences of activities or locations over time, and can therefore be treated as tokenized sequential data. Such models may combine multi-source datasets, such as different travel surveys (e.g., German MiD [69] and MOP [260]), weather data, and other contextual information, to learn higher-dimensional and longer-range dependencies [261,262]. This may improve the temporal consistency of simulated data and help capture not only weekly and seasonal patterns, but also interpersonal dependencies within households, provided that sufficiently large and diverse training datasets are available.

For continuous-valued time series, GANs and VAEs have emerged as alternative tools for generating privacy-preserving synthetic data [75,83,84,263]. However, time-series GANs still face well-known challenges including vanishing gradients and mode collapse, where important variability can be missed [258]. VAEs are often considered a promising and comparatively stable alternative, but in the reviewed literature they are still rarely applied to EV demand modeling. Moreover, VAEs can lead to over-smoothed profiles that underrepresent sharp peaks relevant for EV demand and flexibility assessment [85]. Diffusion models have recently gained traction for continuous time-series synthesis and are a promising candidate for future EV charging profile generation [264].

Another critical challenge is to ensure that synthetic mobility data are adequately protected so that underlying patterns cannot be reverse-engineered, preventing both the re-identification of individuals and the reconstruction of original datasets, which is especially important for mobility data with fine-grained spatial resolution. Otherwise, this undermines a central promise of synthetic data: enabling privacy-preserving data sharing to support transparency, reproducibility, and accessibility. Advanced generative models, such as deep neural networks, offer the potential to enhance privacy protection by producing high-fidelity datasets that retain key statistical properties while minimizing re-identification risks [265]. Once trained, such models can be released as open-source tools, facilitating broader use in research and education. Future research should systematically evaluate the extent to which current approaches protect sensitive information and explore methods to strengthen privacy guarantees. A promising methodological trend is to combine synthetic data generation with formal privacy guarantees via differential privacy.

Differential privacy introduces carefully calibrated randomness during model training or data release to ensure that the released outputs are only weakly influenced by any single individual record, thereby limiting the risk of re-identification or dataset reconstruction [259]. This enables reusable benchmarks and cumulative modeling progress even when raw mobility and charging data cannot be shared.

Furthermore, synthetic data enables the simulation of large and diverse datasets, rebalancing underrepresented groups, imputing missing values, generating scenario-specific profiles, and mitigating statistical biases [266]. An often underutilized strength of synthetic data is its ability to integrate heterogeneous datasets. However, realizing this potential requires advanced techniques capable of harmonizing diverse data inputs without introducing inconsistencies.

Finally, future research should systematically validate synthetic data used in energy system analyses. High-quality synthetic profiles must not only resemble empirical data, but also preserve the variability, temporal structure, and behavioral diversity relevant for downstream modeling. Otherwise, synthetic inputs may introduce artifacts, for example by distorting peak loads, underrepresenting flexibility potentials, oversmoothing charging behavior, or leaking highly sensitive information such as individual driving patterns. An overview of key validation dimensions for synthetic data generation, including their implications for downstream energy system modeling, is provided in Appendix Table C.12.

5. Conclusion

The increasing penetration of electric vehicles (EVs) will affect a wide range of stakeholders, including distribution grid operators and system planners, thereby necessitating their integration into energy system models. We systematically review 58 EV energy demand models and 32 energy system integration studies. The EV demand models are categorized according to their underlying data characteristics: (i) individual person behavior-based models, which utilize individual-level behavioral data such as time-use surveys; (ii) EV behavior-based models, which employ vehicle-level data; (iii) charging behavior-based models, which rely on charging station data; and (iv) transport statistics-based models, which use aggregated transport statistics such as traffic volume data. Furthermore, the models are classified according to their methodological approach, temporal, spatial, and energy resolution, as well as their study objectives. The energy system models are structured by spatial scale, ranging from building-level to international-level analyses, including additional information on temporal and spatial resolution and the implementation of EVs.

Our review reveals that individual person behavior-based approaches are often based on a single national survey. Moreover, Markov chain and Monte Carlo simulations exhibit limited temporal consistency and should therefore be avoided when high-fidelity data are required. Energy system models at the building level require high-fidelity data to produce realistic conclusions. However, these models are constrained by the quality and availability of current EV demand models and behavioral datasets. At municipal, regional, and national scales, models often exhibit poor spatial resolution, likely due to high modeling complexity and data protection constraints. This limitation is particularly critical for distribution grid analyses at the municipal level, which require fine spatial resolution. Such spatially fine-grained studies are rare, and when conducted, the behavioral profiles of individual occupants at the building level are of low fidelity. EV aggregation is essential when simulating large EV fleets. We identified five aggregation methods that vary in computational complexity and accuracy. Future research should conduct systematic benchmarking studies to evaluate their trade-offs and limitations.

Future mobility concepts, such as autonomous driving, are expected to have their most pronounced impacts on the distribution grid. Therefore, future research should assess the effects of innovative mobility concepts using spatially fine-grained models combined with high-fidelity and diverse behavioral profiles, which are essential for capturing realistic mobility needs. New surveys with higher shares of EV users should be utilized, and the combination of multiple datasets with advanced generative approaches, such as deep neural networks, should be employed to generate diverse, high-fidelity behavioral data. Additionally, EV and charging data should be used to calibrate these behavioral profiles for specific contexts whenever possible.

Future research should systematically benchmark synthetic datasets using comparable validation metrics. In this context, Large Language Models, diffusion models, and physics-informed neural networks represent particularly promising methodological directions for next-generation EV demand modeling. LLM-based approaches may, for example, support the generation of travel diaries by integrating heterogeneous mobility inputs, such as travel surveys, weather information, and other contextual data. Diffusion models appear especially promising for generating continuous charging and load profiles, including non-Gaussian charging patterns, while avoiding some of the training-instability issues associated with GANs. Physics-informed neural networks could help embed battery, charging power, and network constraints directly into learned charging demand models, thereby improving physical plausibility. At the same time, such methods may help generate high-fidelity and diverse datasets while strengthening privacy protection. A related future direction is the coupling of such demand models with agent-based reinforcement-learning frameworks, in which individual EV agents learn adaptive charging decisions under dynamic prices, congestion signals, or local renewable availability.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT in order to improve the readability and language of the manuscript. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declaration of competing interest

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

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Appendix A. Literature screening

Table A.9
Eligibility criteria applied during the screening process for the two literature strands of this review.

Screening stage	EV energy demand models	Energy system models incorporating EVs
Removed before screening	Records not matching the targeted publication types were removed before screening. The review focused primarily on peer-reviewed journal articles. Relevant conference papers were only considered when identified through backward or forward citation searching and when they provided a clear methodological contribution.	Records not matching the targeted publication types were removed before screening. The review focused primarily on peer-reviewed journal articles. Relevant conference papers were only considered when identified through backward or forward citation searching and when they provided a clear methodological contribution.
Excluded based on title/abstract	Studies were excluded if they focused primarily on battery chemistry, secondary batteries, or other topics outside the scope of EV demand modeling and charging-flexibility representation.	Studies were excluded if they focused primarily on energy management topics without a substantive methodological contribution to the representation of EV charging demand or flexibility in energy system models.
Excluded based on full text	Studies were excluded if they focused purely on charging-station operation without contributing to EV demand modeling, if they lacked sufficient methodological detail, or if they did not provide sufficient additional methodological insight for the purposes of this review.	Studies were excluded if they lacked sufficient methodological detail to assess how EV charging demand or flexibility was represented in the energy system model.

Appendix B. Electric vehicle–related data sources and accessibility

Table B.10
Summary of EV-related data used in the reviewed studies.

Data type	Country	Data references	Data access
Travel survey	Germany	[49,54,69,254]	Restricted
	Netherlands	[47,67]	Restricted
	Sweden	[66]	Restricted
	United Kingdom	[60]	Restricted
	USA	[56,58,73]	Open
Time use survey	United Kingdom	[71]	Restricted
	USA	[50]	Open
Cell phone data	USA	[95]	Restricted
EV data	China	[79,101,103,106]	Restricted
	Denmark	[88]	Restricted
	Germany	[90,91]	Restricted
	Germany & France	[89]	Restricted
	Ireland	[87]	Restricted
GPS & Vehicle data	China	[93,105]	Restricted
	New Zealand	[99]	Restricted
Charging data	Belgium	[127]	Restricted
	China	[31,32,118]	Restricted
	Germany	[131]	Open
	South Korea	[119]	Restricted
	Taiwan	[108]	Restricted
	United Kingdom	[112,115]	Restricted
	USA	[96,110,113,114,121,123,125]	Restricted
	USA	[117,129]	Open
Synthetic charging data	USA	[52]	Open
Energy data	Japan	[133]	Restricted
	World	[141–143]	Open
Load profiles	Germany	[147]	Open
Traffic data	Switzerland	[153]	Open
	Germany	[45]	Open
	South Korea	[139]	Open
	USA	[135,136]	Restricted
Vehicle kilometers	Europe	[145]	Open
	Greece	[149]	Open
	Kosovo	[151]	Open

Open denotes publicly accessible data (possibly requiring registration/terms-of-use); Restricted denotes access-controlled, proprietary, or non-public datasets.

Appendix C. Data-scarcity mitigation and privacy-preserving data generation

Table C.11
Technology-oriented approaches to mitigate data availability constraints and enable reusable EV demand and flexibility inputs.

Technique family	Description
Markov chains, Monte Carlo [46,52,53,87,100]	Extend short observation windows (e.g., travel diaries) into longer synthetic sequences. May struggle with realistic weekly/seasonal structure and long-term temporal consistency [52,64].
Hierarchical/time-budget regression models [48]	Combine weekly activity time budgets (e.g., work, leisure) with a hierarchical, regression-based generation of activity types, durations, and sequences. This comes at the cost of additional assumptions and calibration effort due to the large number of regression sub-models [48].
Machine learning [31–33,113,116,118,128,130]	Learn from historical charging data for charger occupancy prediction and charging load/energy forecasting. Methods range from decision trees, random forests, and support vector machines to deep learning and physics-informed neural networks.
Long Short-Term Memory/Transformers [64]	Learn sequence dynamics from behavioral records to generate temporally consistent mobility/activity profiles. Can capture intra-personal consistency and variability over time, while household-level realism requires capturing inter-person dependencies (e.g., car sharing).
Generative Adversarial Networks [75,83,84]	Generate synthetic charging/load profiles. Training instability and mode collapse can miss important variability [258].
Variational Autoencoders [263]	Latent-variable generation of synthetic profiles. May over-smooth profiles and underrepresent sharp peaks relevant for EV demand/flexibility [85].
Synthetic data for augmentation/scarcity mitigation [266]	Increase sample size, rebalance underrepresented groups, impute missing values, and generate scenario-specific profiles, but requires careful validation.
Differential privacy [259]	Combine synthetic generation with differential privacy mechanisms when raw mobility/charging data remain inaccessible. Limits re-identification and dataset reconstruction risks by bounding single-record influence.
Open-source generators [68]	Open-source tools (e.g., emobpy) for reproducible profile generation and standardized integration workflows, enabling transparency, reuse, and community benchmarking.

Table C.12
Validation dimensions for synthetic data generation, following Alaa et al. [267], including implications for downstream energy system modeling.

Validation dimension	Primary validation target	Representative validation metrics[a]	Main limitation/trade-off with other dimensions	Implication for energy system modeling
Fidelity	Sample-level realism, i.e., whether individual synthetic profiles are plausible with respect to the real distribution and preserve key temporal characteristics.	α-Precision [267], Precision [268].	Strong fidelity alone does not guarantee adequate coverage of the real behavioral space and may increase generalization/privacy risk when synthetic profiles become too similar to real samples.	Poor fidelity may distort peak loads, charging magnitudes, and other temporally relevant demand characteristics.
Diversity	Distributional coverage, i.e., whether synthetic profiles span the variability and support regions of the real data rather than collapsing onto a limited subset of modes.	β-Recall [267], Recall [268].	Higher diversity can come at the expense of fidelity if broader coverage is achieved by generating samples in sparse or weakly supported regions; diversity also does not by itself ensure generalization/privacy.	Poor diversity may underrepresent flexibility potentials as well as rare but system-relevant behavioral patterns.
Generalization /privacy	Non-memorization, i.e., whether synthetic profiles are sufficiently distinct from training data and do not reproduce real individuals too closely.	Authenticity [267], data-copying (overfitting) detection [269].	Stronger privacy protection can reduce fidelity, since pushing samples farther from the training data may also move them away from the real distribution; high generalization alone does not ensure sufficient diversity.	Poor generalization may indicate memorization of training data, while overly strong privacy protection may smooth profiles and reduce behavioral realism.

[a] Metrics are illustrative examples and are not intended to be a complete inventory of all possible validation metrics. For open source synthetic data generators and evaluation tools, see, for example, [270,271].

Data availability

No data was used for the research described in the article.

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