A Review of Challenges and Opportunities in Occupant Modeling for Future Residential Energy Demand

Jonathan Vogl, Max Kleinebrahm, Moritz Raab, Russell McKenna, Wolf Fichtner

No. 76 | MARCH 2026

WORKING PAPER SERIES IN PRODUCTION AND ENERGY

A Review of Challenges and Opportunities in Occupant Modeling for Future Residential Energy Demand

Jonathan Vogl [*,1], Max Kleinebrahm[1], Moritz Raab[1], Russell McKenna[2], Wolf Fichtner[1]

[1] Chair of Energy Economics, Institute for Industrial Production, Karlsruhe Institute for Technology, Hertzstraße 16, 76187 Karlsruhe, Germany
[2] Chair of Energy Systems Analysis, Institute of Energy and Process Engineering,
Department of Mechanical and Process Engineering, ETH Zurich, Clausiusstrasse
33, 8092 Zurich, Switzerland
[*] Corresponding author: Jonathan Vogl, jonathan.vogl@kit.edu, +49 721 608 44591

Abstract

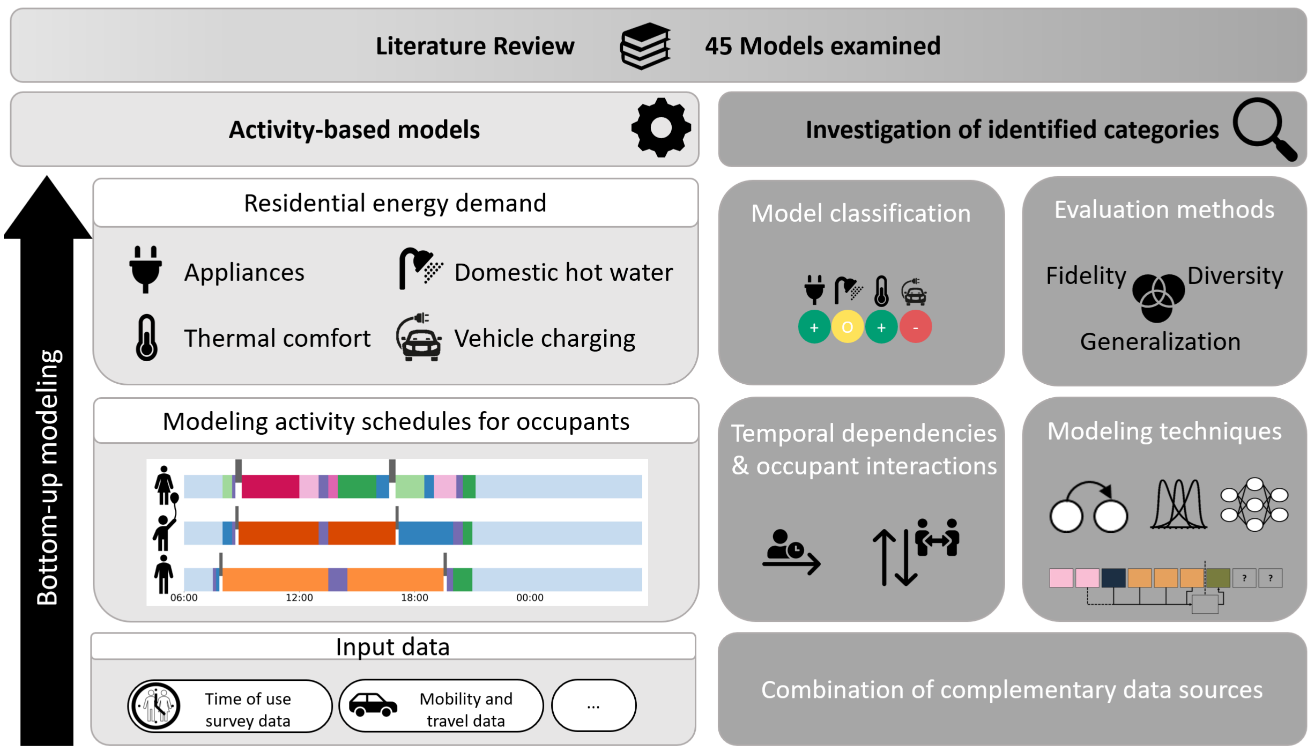
Electrified heating and electric mobility are increasing residential electricity demand and, together with distributed energy resources, reshaping load profiles, necessitating substantial investment in distribution grids and flexibility measures. Yet key behavioral factors that drive present and future residential demand remain poorly captured in many demand models. Activity-based, bottom-up models make dependencies explicit, better informing flexible operation and investment in low-carbon technologies.

We review 45 activity-based, bottom-up models and assess coverage of appliances, domestic hot water, space heating and cooling, and electric vehicle charging, which are rarely considered jointly in one integrated model. To our knowledge, this is the first review to include activity-based mobility modeling, thereby identifying methodological gaps in consistent behavior modeling across residential energy services: First, most studies simulate single occupants and overlook interdependencies among household members. Second, predominant approaches are structurally limited in producing temporally consistent activity schedules. Together, these shortcomings hinder a consistent, cross-service representation of household demand and can bias estimates of coincident peaks and residential flexibility. We provide guidelines to overcome these shortcomings and to support high-quality behavioral foundations for future bottom-up demand modeling. Future studies should combine complementary behavioral datasets with sophisticated models (e.g., deep neural networks). Such models can capture complex dependencies to generate high-quality synthetic behavioral data as a basis for future bottom-up residential energy demand modeling. In order to ensure consistent progress in this field, reproducible validation frameworks based on open datasets are needed to enable the benchmarking and comparison of activity-based models.

Graphical Abstract

A Review of Challenges and Opportunities in Occupant Modeling for Future Residential Energy Demand

Jonathan Vogl, Max Kleinebrahm, Moritz Raab, Russell McKenna, Wolf Fichtner



Highlights

A Review of Challenges and Opportunities in Occupant Modeling for Future Residential Energy Demand

Jonathan Vogl, Max Kleinebrahm, Moritz Raab, Russell McKenna, Wolf Fichtner

- Reviews activity-based, bottom-up models for residential energy-demand profiles.
- Spans all energy service demands: appliances, hot water, thermal comfort, mobility.
- Examines modeled activity schedules: intrapersonal and intrahousehold dependencies.
- Reviews validation methods for activity schedule and demand profile generation.
- Identifies limits in occupant modeling and weak linkages to energy service demands.

A Review of Challenges and Opportunities in Occupant Modeling for Future Residential Energy Demand

Jonathan Vogl[a,*], Max Kleinebrahm[a], Moritz Raab[a], Russell McKenna[b] and Wolf Fichtner[a]

[a] *Karlsruhe Institute of Technology (KIT), Institute for Industrial Production (IIP), Karlsruhe, Germany*
[b] *ETH Zürich, Institute of Energy and Process Engineering (IEPE), Zürich, Switzerland*

ARTICLE INFO

Keywords:
household energy demand
activity schedules
occupancy behavior
activity modeling
mobility behavior
bottom-up demand modeling

ABSTRACT

Electrified heating and electric mobility are increasing residential electricity demand and, together with distributed energy resources, reshaping load profiles, necessitating substantial investment in distribution grids and flexibility measures. Yet key behavioral factors that drive present and future residential demand remain poorly captured in many demand models. Activity-based, bottom-up models make dependencies explicit, better informing flexible operation and investment in low-carbon technologies.

We review 45 activity-based, bottom-up models and assess coverage of appliances, domestic hot water, space heating and cooling, and electric vehicle charging, which are rarely considered jointly in one integrated model. To our knowledge, this is the first review to include activity-based mobility modeling, thereby identifying methodological gaps in consistent behavior modeling across residential energy services: First, most studies simulate single occupants and overlook interdependencies among household members. Second, predominant approaches are structurally limited in producing temporally consistent activity schedules. Together, these shortcomings hinder a consistent, cross-service representation of household demand and can bias estimates of coincident peaks and residential flexibility. We provide guidelines to overcome these shortcomings and to support high-quality behavioral foundations for future bottom-up demand modeling. Future studies should combine complementary behavioral datasets with sophisticated models (e.g., deep neural networks). Such models can capture complex dependencies to generate high-quality synthetic behavioral data as a basis for future bottom-up residential energy demand modeling. In order to ensure consistent progress in this field, reproducible validation frameworks based on open datasets are needed to enable the benchmarking and comparison of activity-based models.

1. Introduction

The residential sector accounted for 21% of final energy consumption and 17% of CO_2 emissions in 2022 globally, originating from the operation of heating, cooling, and other household appliances [1]. Decarbonising heating in the buildings sector is widely expected to rely on heat pumps as the primary technology, with scenarios assuming them to be dominant by mid-century [2–4]. The uptake of private electric vehicles will add another major electric load to the residential sector. Home charging is currently the dominant practice [5, 6] and also a key driver for EV adoption [7], adding a substantial new load to residential grids (see Figure 1) [8]. The increased uptake of heat pumps and electric vehicles will not only contribute to an expected doubling of overall electricity demand by mid-century in Europe [9–11], but will also amplify daily and seasonal peaks and steepen ramp rates, stressing networks and driving costly upgrades [12–15]. Flexibility is needed to prevent grid congestion and costly grid expansions [15], particularly as simultaneous peaks in heating and home charging coincide with cold weather, as well as the already present "evening peak".

Since balancing electricity demand and supply will be more difficult in the future [16], changes on the supply side will also impact the residential sector. Households are becoming prosumers, installing more photovoltaics and batteries as costs fall [11, 13, 17, 18]. In parallel, the renewable share of the energy system will rise [18–20]. Consequently, the system will become more weather-dependent [14, 21]. This calls for a paradigm shift: instead of supply following inflexible demand, demand must adapt to variable supply [20, 22]. High-potential residential flexibility includes smart electric vehicle charging, behind-the-meter batteries, and thermal storage with heat pumps, enabling households to adapt demand to variable supply [23–25].

Opposed to dynamic factors, static factors influencing residential energy demand are well-studied [26]. Sociodemographic characteristics of occupants shape the overall energy consumption, in particular demand for heating, cooling and domestic hot water [27, 28] and influencing electricity peaks [29]. These characteristics are also associated with dwelling characteristics and appliance ownership [26, 29]. Within sociodemographic groups, individual thermal preferences and perceived comfort vary [30, 31], as well as showering duration responsible for the majority of hot water consumption in urban areas [32]. However, the dynamic drivers of household energy demand are currently largely unknown [33]. With improvements in appliance efficiency and the electrification of heating and transportation, the role of occupant behavior becomes even more significant. As a result, conventional standard load profiles are unable to

*Corresponding author
jonathan.vogl@kit.edu (J. Vogl)
ORCID(s): 0009-0007-5396-2085 (J. Vogl)

capture the diversity of household configurations and behavioral impacts [33]. A fundamental understanding of the underlying factors that shape residential demand dynamics is lacking.

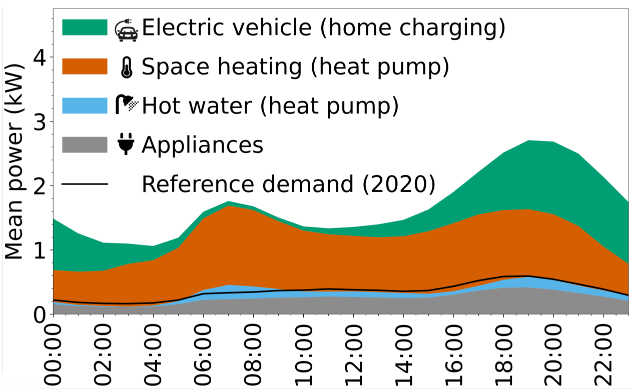


Figure 1: Average winter-day electricity demand of a median German household in 2045, divided by energy service, compared with reference electricity demand in 2020. See [34] for data and methodology.

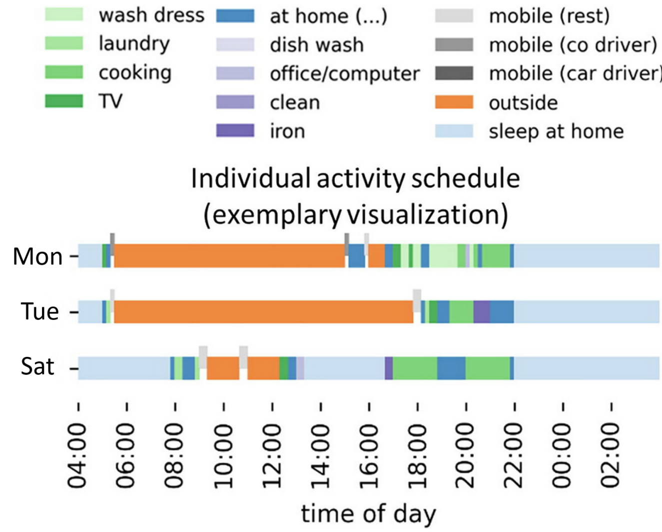


Figure 2: Example of an activity schedule constructed from a synthetic time-use survey sample (image based on [57]). The activity schedule specifies the start time, duration, and type of activities for an occupant at each point in time during the day.

Such granular understanding of residential energy demand can be achieved through bottom-up models that can create temporally-resolved household energy demand. Data-driven bottom-up approaches rely on smart meter data and have been used in numerous studies [33, 35–41]. However, smart meter data are not always available or accessible due to privacy restrictions, often lack household meta information, and only provide aggregate demand instead of device-specific load profiles hindering explanation of the temporal composition of residential demand. More detailed sub-metering data come with additional costs and are not yet widely available [42].

These shortcomings can be addressed with activity-based, bottom-up models which are grounded in the temporal dependence between occupants' activities and energy service demands (e.g. in energy consumption [43], cooling [44], and space heating [44, 45]). Specifically, occupant behavior can cause variations in space heating up to 30% [46] (less in energy efficient or passive houses [47, 48]), water consumption can vary by a factor of about 6 [49], and overall energy demand can vary by up to 50% [50, 51], whereas homes with similar occupancy patterns tend to experience coincident peak loads [52]. An example of an activity schedule is illustrated in Figure 2. Based on the behavior of household occupants as foundational component, activity-based models simulate energy service demand, technology operation, and final energy carrier demand of a dwelling unit (see Figure 3). A dwelling unit is thereby defined as a self-contained residential space that houses one or more occupants and includes the physical structure, appliances, and energy-relevant systems necessary for providing heating, cooling, mobility, and other household services. Activity-based, bottom-up models enable the study, understanding, and forecasting of dependencies between sociodemographic household determinants, technical and environmental parameters, occupant behavior, behavioral shifts and associated energy demands [42, 53–55]. Compared to data-driven approaches [33], which implicitly represent underlying dependencies by learning patterns between and within demand profiles, activity-based, bottom-up approaches provide explicit dependencies and high interpretability. Their relationships are easy to adjust, for example in response to behavioral changes [54] or technological innovations, and to support system design [56].

To address future challenges, it is crucial to gain a more detailed understanding of demand and its potential flexibility. To estimate future flexibility potential in the residential sector, it is necessary to have a deep understanding of the temporal and spatial uptake of flexible demand-side technologies and their socio-techno-economic constraints in providing system services while meeting household demand [24]. With such detailed information, distribution system operators can implement targeted grid expansions proactively, avoiding congestion and voltage-band violations that occur when critical peaks go unaddressed, such as with uncontrolled charging [58]. Furthermore, electricity retailers can provide targeted dynamic tariffs to enhance flexibility while mitigating potential distributional effects [59–61].

No existing review study has consistently addressed all household energy service demand categories, with mobility-related demand for electric vehicles being particularly underrepresented (Table 1). Existing reviews that cover multiple demand categories typically treat them in isolation rather than examining interconnections. To the best of our knowledge this study is the first to integrate modeling approaches of all energy service demand categories within a single review, providing a comprehensive perspective on household

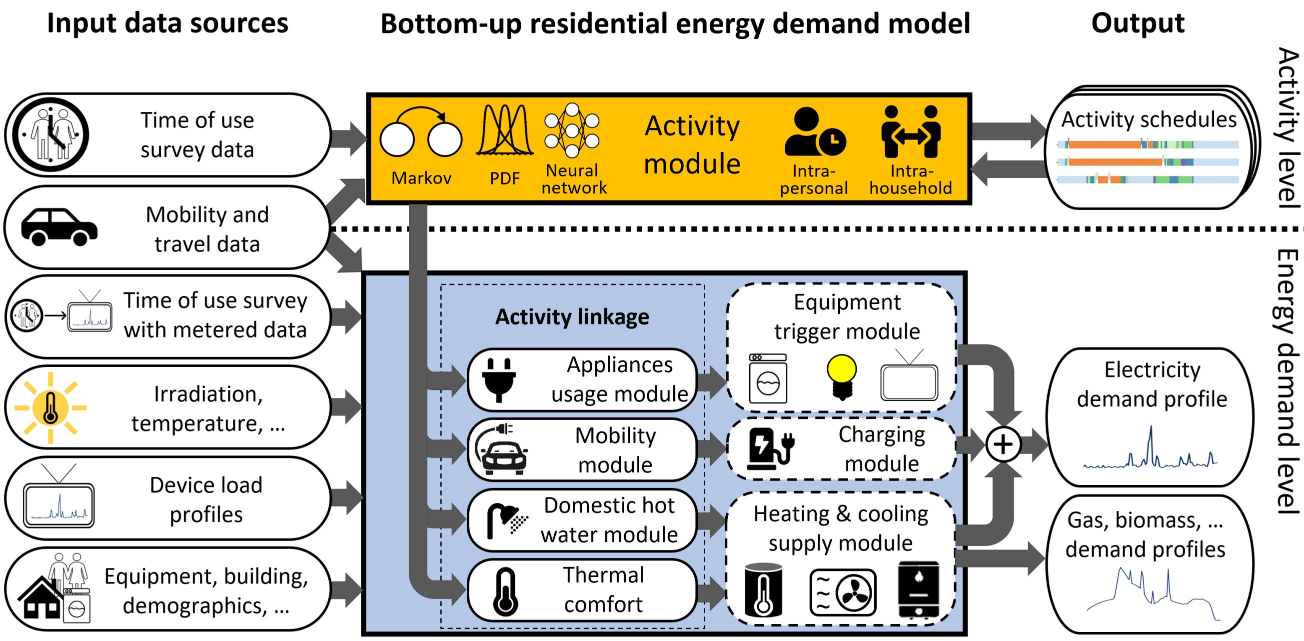


Figure 3: Components and information flow in bottom-up activity-based load profile modeling.

energy demand modeling and, on this basis, guiding the following research questions:

(RQ1) How well do current residential activity-based energy demand models consistently represent demand for energy services involving hot water, thermal comfort, mobility, and other household appliances?

(RQ2) Which requirements must activity-based energy demand models fulfill to support future sector-coupled energy systems? What best-practice guidance and future research needs follow from these requirements?

(RQ3) How should evaluation criteria for activity schedules and energy demand profiles be defined to ensure consistent progress in energy demand modeling?

The paper is structured as follows: Section 2 outlines data sources for an activity-based, bottom-up load profile model, explains the need for synthetic activity schedules, and describes how to model residential energy demand based on activities. Section 3 reviews activity-based, bottom-up models for residential energy demand, while Section 4 discusses commonly used validation metrics. Section 5 presents and discusses the central findings, before Section 6 concludes the paper.

2. The concept of activity-based, bottom-up modeling

This section introduces the input data (Section 2.1), explains why activity schedules are modeled (Section 2.2), and describes how activities are mapped to residential energy demand (Section 2.3).

2.1. Input data

Temporally resolved behavioral data are essential for developing models capable of generating activity-based load profiles. The most prominent data sources used in the reviewed studies in Section 3 are time-use surveys (TUS) (see Table 2 and Table 9 in the Appendix). Time-use surveys contain occupant diaries, recording their household activities usually at ten-minute or fifteen-minute intervals over one or a few days [80, 88, 89]. Only a few surveys offer longer observation periods, including Dutch seven-day diaries [90] and Swiss 28-day diaries [91]. Time-use surveys contain sociodemographic information about the occupants as well as data on household affiliation. Time-use surveys exist in over 65 countries [89], many of which are included in the Multinational Time Use Study (MTUS) [92] or the Harmonised European Time Use Survey (HETUS) [93]. Collection frequency varies from annual intervals to five- to ten-year intervals, and some countries have only a single wave [89]. Although most time-use survey datasets are subject to data protection, a few are openly accessible, notably the Spanish time-use survey [94] and the American time-use survey [95].

Beyond time-use surveys, national mobility surveys provide representative travel-behavior data. These surveys are conducted repeatedly over multiple years, see Table 9 in the Appendix. One-day travel diaries come from the Mobility in Germany survey (MiD; *Mobilität in Deutschland*) in repeated cross-sections [96], London's Travel Demand Survey (LTDS) [97], and the U.S. National Household Travel Survey (NHTS) [98]. The Deutsches Mobilitätspanel (MOP) provides seven-day panel data [99].

Table 1
Overview on reviews considering occupancy- and activity-based residential energy demand models.

Review paper	Year	Reviewed energy service demands			
		Appliances	Hot water	Thermal comfort	Mobility
Swan and Ugursal [42]	2009		✓	✓	
Grandjean et al. [62]	2012	✓	✓	✓	
Torriti [63]	2014				
Yan et al. [64]	2015			✓	
Gaetani et al.[65]	2016	✓	✓	✓	
Stazi et al. [66]	2017			✓	
Delzendeh et al. [67]	2017		✓	✓	
Fuentes et al. [68]	2018		✓		
Yamaguchi et al. [69]	2018	✓			
Hong et al. [70]	2018			✓	
Zhang et al. [71]	2018			✓	
Balvedi et al. [72]	2018			✓	
Happle et al. [73]	2018	✓	✓	✓	
Dong et al. [74]	2018	✓		✓	
Li et al. [75]	2019	✓	✓	✓	
Carlucci et al. [76]	2020			✓	
Torriti [77]	2020	✓			
Proedrou et al. [53]	2021	✓			
Rezvany et al. [78]	2021	✓			✓
Chen et al. [79]	2021		✓	✓	
Osman and Ouf [80]	2021	✓	✓	✓	
Li et al. [81]	2022				
Dabirian et al. [82]	2022	✓	✓	✓	
Kang et al. [56]	2023	✓	✓		
Kewo et al. [83]	2023	✓			
Vosoughkhosravi et al. [84]	2023	✓	✓	✓	
Ahmed et al. [85]	2023		✓	✓	
Mylonas et al. [86]	2024	✓	✓	✓	
Banfi et al. [87]	2024	✓	✓	✓	
Present work	**2025**	✓	✓	✓	✓

Multiple alternative data sources may provide additional value but are mostly not representative, limiting their generalizability. Charging-only data (e.g., wallbox measurements) lack behavioral context unless paired with activity information. The METER dataset [100, 101], which combines time-use survey data with high-resolution smart meter data collected simultaneously in the same households, enables inference from reported activities to appliance-related demand patterns [102–104]. Data on load profiles for individual appliances (e.g., [105, 106]) can help link modeled appliances to their corresponding electrical loads. Sensor-based measurements, e.g., CO_2 concentration, window-opening states, thermostat datasets [107], or Wi-Fi usage [108], typically rely on small, purpose-specific samples.

2.2. On the need for activity modeling

There is a need to model activity data, rather than rely on it directly, for residential energy demand analysis. Having presented the empirical datasets in the previous subsection, we now focus on the gap between available data and the requirements for consistent activity-based energy-demand modeling. An optimal behavioral dataset would include:

(1) **Openness:** fully accessible and shareable data.

(2) **Temporal structure:** an annual time horizon with regular, homogeneous time steps.

(3) **Resolution:** high-resolution temporal records of household and mobility activities with consistent locations.

(4) **Metadata:** rich sociodemographic attributes, regional granularity, multi-country scope, and possible future pathways for scenario analysis.

(5) **Dependencies:** should capture the following structures:

   (a) **Intrapersonal:** temporal consistency in an individual's activity schedule, excluding implausible sequences (e.g., drying before washing), limiting excessive activity changes, and reflecting longer-term regularities (e.g., stable wake-up times and recurring work hours).

   (b) **Intrahousehold:** joint activities (e.g., shared meals), resource/blocking constraints (e.g., access to laundry), and more complex interactions whereby household members influence one another's schedules.

   (c) **Calendar-year factors:** weather, seasons, holidays, and major events (e.g., sports).

Such a dataset would provide a common foundation for consistent modeling of all energy service demands.

However, such an idealized dataset does not exist and is unlikely to be available soon due to privacy constraints and survey costs. This absence leads to several challenges. First, because activity schedules are protected by strict privacy rules, the underlying microdata cannot be shared openly, which restricts its direct use (1). Consequently, models that use data directly (e.g., [46, 109–112]) or derive activity schedules (e.g., [51, 113–118]) can publish only aggregated results, hindering open-source application toolchains. Second, most empirical surveys span only a few days per household, whereas system planning and investment studies require continuous annual or even longer profiles (2) [13, 119].

Synthesizing activity data by modeling can tackle these shortcomings by deriving statistical properties such as the time-dependent distributions of activities and dependencies among them. Activity schedules sampled from these distributions preserve the essential statistical structure of the original time-use survey data while obscuring links to individual diaries. This enables fully shareable bottom-up models and supports long simulation horizons with effectively unlimited synthetic samples.

The use of models instead of direct data can be motivated by further reasons. No dataset includes both activity and mobility data (3) [120] and none covers all regions, sociodemographic segments, and future scenarios (4). It is therefore necessary to combine datasets with different survey objectives, leveraging complementary strengths to generate a holistic dataset. Unlike the former case of synthesizing activity data, this integration requires additional steps: appropriately combining sources, imputing missing or irregular values, addressing underrepresented subgroups, and extrapolating into the future.

When simulating, the dependencies (5) must also be captured. Modeling from a single dataset should reproduce intrapersonal and intrahousehold dependencies present in behavioral data. Achieving longer-term consistency may require additional assumptions or the combination of additional datasets. This also applies to additional dependencies, such as calendar-year factors, but we do not consider them further in this review.

2.3. Residential energy demand

Activity-based bottom-up models link activity schedules to household energy demand. Because the degree of linkage can vary across demand modules, stronger linkage not only aligns each module more closely with the activity schedule but also supports cross-service consistency by maintaining a shared behavioral basis (see Figure 4).

Modeling **appliances** involves assigning each energy-related activity to one or more appliances. For example, “cooking” may involve several appliances or one sampled at random. Non-energy activities do not invoke appliances directly but still support internal consistency in the activity schedule (e.g., “sleeping”, “reading”). A more coherent, fine-grained activity model strengthens schedule linkage and enables more direct, robust appliance mapping. Models that capture only occupant-presence states or inconsistent activity states cannot map appliances directly and therefore rely on stochastic methods or follow-up corrections (see Table 6 in the Appendix). Lighting use follows occupant-presence rather than specific activities, though room-differentiated occupancy schedules can refine lighting-demand estimates (e.g., using room-level occupancy models [118, 121–130]). Occupant-independent constant or cyclic demands (e.g., modems, refrigerators) should also be represented in the model.

Appliance-specific modeled demand must be met by an installed household appliance (see Figure 3). Appliance presence (equipment) and variants (model type) determine electricity demand and may involve different operating programs (e.g., washing-machine cycles, dishwasher programs). Resulting loads can be represented as a constant over the activity duration or as an appliance-specific load profile (see Table 6 in the Appendix). In multi-occupant households, appliances may be used simultaneously across multiple activity schedules, leading to **appliance sharing**

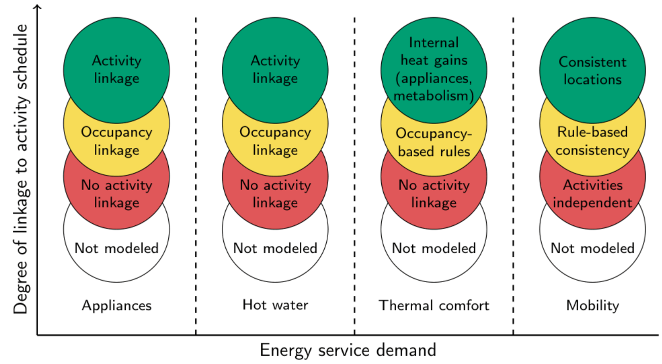


Figure 4: Qualitative categories used to classify the linkage between an activity schedule and the different energy service demands. For **appliances** and **domestic hot water**, linkage is coded as (i) no activity linkage (demand generated independently of the activity schedule), (ii) occupancy linkage (demand conditioned only on presence/absence), and (iii) activity linkage (explicit activity-to-demand mapping). For **thermal comfort**, linkage ranges from (i) no activity linkage (independent/setpoint-driven demand), to (ii) occupancy-based rules, to (iii) models including activity-conditioned internal heat gains (metabolism and appliance/process gains). For **mobility**, linkage is characterized via schedule integration and spatial consistency: from (i) activities independent, to (ii) rule-based consistency/conflict resolution, to (iii) consistent locations. Not all aspects are always included in the model or described, so in these cases a heuristic assessment had to be made in addition to the rules based on the available criteria. Further model-specific attributes that form the basis for any required additional heuristic assessments are listed in Tables 6-D in the Appendix.

through direct interaction or coincidental overlap (e.g., cooking or watching TV together). The model should incorporate assumptions about sharing because simply adding appliance demand across occupants is inappropriate. Modeling can also account for saturation effects and within-period operating frequency, for example, a cooker cycling during one cooking activity.

Domestic hot water demand modeling is conceptually similar to appliance modeling, with related activities generating specific hot-water demand. The same activity (e.g., bathing, hygiene) may require different amounts of hot water. Hot-water demand from appliances can vary across countries because some devices include built-in water heating.

Thermal comfort-related heat demand is often setpoint-driven and occupancy-independent. Accounting for occupant influence can progress from presence-based HVAC control to deeper coupling that includes activity-driven metabolic heat and appliance heat gains.

Domestic hot water and space heating (possibly also cooling) can be supplied by different systems (e.g., heat pumps, district heating, gas boilers, electric water heaters). As the demand layer is system- and supply-independent, the framework supports analyses of system replacements and shifts between energy carriers (e.g., electricity vs. gas). Operating these systems depends on additional inputs for weather (solar irradiation, outdoor temperature) and building characteristics (insulation, orientation, thermal mass).

Mobility demand for electric vehicles translates into household electricity demand for home charging. 75% of charging occurs at home [5], and for households with access to home charging this share may be even higher. Charging demand can be modeled from vehicle energy use during mobility activities. During trips, the state-of-charge reduction of the electric vehicle battery can be estimated from trip distance or duration, or from detailed energy-consumption profiles reflecting driving conditions (urban, rural, highway) (see Table D in the Appendix). Assuming a fixed commute distance can improve model consistency. Within the activity schedule, mobility behavior must align with consistent locations to avoid conflicts, since absence due to travel precludes simultaneous household activities or home charging. A detailed mobility-demand model enables comparative analysis of charging power and strategy. The model should be able to represent charging strategies (direct, delayed, smart charging) and vehicle-to-grid (V2G) interactions.

3. Review of activity-based energy demand models

This section reviews activity-based energy demand models. Section 3.1 outlines the review methodology. Section 3.2 compares activity-modeling approaches and their defining characteristics, and Section 3.3 describes simulation objects and states. We then examine the modeled energy service demands, accounting for appliances, hot water, thermal comfort, and mobility, and the extent to which they are linked to activity schedules in Section 3.4. The structure follows the characteristics of the reviewed models, summarized in the comparative overview in Table 2.

3.1. Review procedure

We searched Web of Science and Scopus and expanded the set via backward- and forward-citation chaining, seeding the search with prior reviews (Table 1).[1] Inclusion required residential, activity-based demand models explicitly linked to at least one energy service. If multiple papers by the same authors described the same model, we selected the most comprehensive paper. We excluded studies limited to occupancy status without detailed activities or energy-service demands, studies focusing solely on lighting (e.g., [131–133]), or on window-opening within building performance simulation (e.g., [134–137]), pure country transfers without substantive methodological changes (e.g., [138]), and non-residential contexts such as offices or schools (e.g., [139–145]). We screened cross-references from included works and ran forward searches for each table (Table 1 and Table 2), anchoring them on publications from 2020 onward to capture recent models and also used Research Rabbit to verify inclusion of prominent, field-relevant publications.

[1]The main word patterns used were: load modeling, load profile energy demand, household/residential/domestic energy demand/use; behavior/occupant/occupancy/activity modeling/schedules, occupant/activity behavior; electric vehicle, consumption profile, time use survey.

Table 2 summarizes the literature review. The "Activity model" section lists data sources, the method used to generate activity schedules, and differentiates between an individual occupant or a household as the simulation object. "Number of activity states" reports the number of distinct, interdependent states. Data sources are not discussed here but are listed in Appendix Table 9. "Energy service demands" cover appliances, hot water, thermal comfort, and mobility, indicating whether each demand and its load are explicitly modeled. A three-color scale denotes the strength of coupling to the activity schedule, as explained in Section 2.2 and visualized in Figure 4. Empty circles denote services not captured by the model. In the case of mobility, an empty circle is also used for models that simulate mobility activities but do not convert them into corresponding energy demand. The "Dependency" section distinguishes activity-related and demand-related dependencies. Activity dependencies include intrapersonal and intrahousehold dependencies, as detailed in Section 2.2. Intrapersonal continuity is visualized as horizontal bars, with fill level indicating the temporal connection. Intrahousehold dependencies capture joint behavior during schedule generation. "Appliance sharing" indicates concurrent use of shared appliances is handled to avoid double counting.

3.2. Activity modeling approaches

The choice of activity modeling approach represents a central component in the overall model design. Three model types are present in the literature for generating activity schedules, namely Markov chains, probability density functions (PDFs) and neural networks. These three, along with additional variants, are discussed in the following sections. Table 3 provides a concise comparison of the main activity modeling approaches discussed below.

First-order Markov chains. Markov chains are among the most widely used techniques for modeling activity schedules. In a Markov chain approach, discrete states are defined, each representing a specific activity. At each time step, exactly one activity is selected by sampling a state transition based on predefined transition probabilities. The first-order variant operates under the Markov property, meaning that the next activity state depends solely on the current activity and not on earlier states or external factors (Figure 5(a)). Transition probabilities are computed from the relative frequencies of observed state transitions, differentiated by time of day, in a time-inhomogeneous Markov chain. Each transition determines the probability density function used at the next time step. Apart from this, state-specific probability density functions are assumed to be independent across time steps and activity states. An initial state is typically sampled from empirical data.

A prominent line of work starts with Richardson et al. [146], who introduce a two-state occupancy model (present vs. absent) for multiple occupants. McKenna et al. [149]

Table 2
Overview of reviewed activity-based, bottom-up models for residential energy demand, grouped by research streams.

Model (first author)	Year	Activity model: Data source (see Table 9): Activity data	Mobility data	Markov (order)	PDF sampling	Neural network	Simulation object	Number of activity states	Energy service demand: Appliances	Hot water	Thermal comfort	Mobility	Dependencies: Activities: Intrapersonal	Intrahousehold	Demand: Appliance sharing
Richardson [146]	2008	TUS UK		1^{st}			👥	2	○	○	○	○	▯▯▯▯	✓	✓
Richardson [147]	2010	TUS UK		1^{st}			👥	2	∘	○	○	○	▯▯▯▯	✓	✓
Good [148]	2015	TUS UK		1^{st}			👥	2	∘	∘	+	○	▯▯▯▯	✓	✓
McKenna [149]	2015	TUS UK		1^{st}			👥	4	○	○	○	○	▯▯▯▯	✓	
McKenna [150]	2016	TUS UK		1^{st}			👥	4	∘	∘	+	○	▯▯▯▯	✓	✓
Buttitta [151]	2020	TUS UK		1^{st}			👤	3	○	○	∘	○	▮▯▯▯		
Widén [152]	2010	TUS SE		1^{st}			👤	9	+	○	○	○	▮▯▯▯		✓
Widén [121]	2012	TUS SE		1^{st}			👤	9	+	+	+	○	▮▯▯▯		✓
Grahn [153]	2013	TUS SE		1^{st}			👤	9	+	○	○	+	▮▯▯▯		✓
Sandels [154]	2014	TUS SE		1^{st}			👤	9	+	−	∘	○	▮▯▯▯		✓
Wilke [155]	2013	TUS FR		semi			👤	20	○	○	○	○	▮▯▯▯		
Muratori [58]	2013	TUS US		1^{st}			👤	9	+	○	−	○	▮▯▯▯		
Muratori [156]	2013	TUS US		1^{st}			👤	3	○	○	○	+	▮▯▯▯		
Muratori [8]	2018	TUS US		1^{st}			👤	9	+	○	−	+	▮▯▯▯		
Johnson [157, 158]	2014	TUS US		1^{st}			👤	10	+	+	+	○	▮▯▯▯		
Aerts [159]	2014	TUS BE		semi			👤	3	○	○	○	○	▮▮▯▯		
Collin [160]	2014	TUS UK		1^{st}			👤	13	+	○	○	○	▮▯▯▯		✓
Fischer [161]	2015	TUS DE			■		👤	0	−	○	○	○	▯▯▯▯	✓	✓
Fischer [162]	2016	TUS DE			■		👤	0	−	−	+	○	▯▯▯▯	✓	✓
Fischer [163]	2019		MID	1^{st}			👤	4	○	○	○	−	▮▯▯▯		
"synPro" [161–163]		TUS DE	MID		■		👤	0	−	−	+	−	▯▯▯▯	✓	✓
Farzan [164]	2015	TUS US		1^{st}			👤	12	+	+	−	+	▮▯▯▯		✓
Nijhuis [165]	2016	TUS NL		high			👤	2	∘	○	∘	○	▮▮▮▯		✓
Bizzozero [166]	2016	TUS IT		1^{st}			👤	11	+	+	−	○	▮▯▯▯		✓
Gruosso [167]	2016	TUS IT		1^{st}			👤	11	+	+	−	+	▮▯▯▯		✓
Baetens [168]	2016	TUS BE		semi			👤	3	∘	∘	+	○	▮▮▯▯		
Flett [169]	2016	TUS UK		high			👥	3	○	○	○	○	▮▮▮▯	✓	
Flett [170]	2017	TUS UK		high			👥	3	∘	○	○	○	▮▮▮▯	✓	✓
Flett [171]	2021	TUS UK		high	■		👥	3	∘	∘	○	○	▮▮▮▯	✓	✓
Diao [172]	2017	TUS US		1^{st}			👤	9	+	+	+	○	▮▯▯▯		
Yamaguchi [173]	2017	TUS JP			■		👥	85	○	○	○	○	▮▯▯▯	✓	
Taniguchi [125]	2016	TUS JP			■		👥	85	+	+	+	○	▮▯▯▯	✓	✓
Bottaccioli [127]	2019	TUS IT		semi			👤	13	∘	+	○	○	▮▮▯▯		✓
Ramírez-M. [174]	2019	TUS UK		high			👤	8	○	○	○	○	▮▮▮▯		
Foteinaki [175]	2019	TUS DK			■		👤	10	−	○	○	○	▯▯▯▯		
Müller [176]	2020	TUS DE	MID	semi			👤	19	+	+	−	∘	▮▮▯▯		
Rueda [177]	2021	TUS CA		semi			👤	2	○	○	○	○	▮▮▯▯		
Kleinebrahm [57]	2021	TUS DE	MOP			■	👤	14	○	○	○	○	▮▮▮▮		
Jeong [178]	2021	TUS AU		1^{st}			👤	14	○	○	○	○	▮▯▯▯		
Koupaei [179]	2022	TUS US		1^{st}			👤	3	○	○	○	○	▮▯▯▯		
Chen [180]	2022	TUS US		semi			👤	7	+	+	○	○	▮▮▯▯		✓
Osman [181]	2023	TUS CA		semi			👤	13	+	+	○	○	▮▮▯▯		✓
Zhang [182]	2024	TUS UK		1^{st}			👤	2	+	○	○	○	▮▯▯▯		
Barsanti [183]	2024	TUS DE		semi			👤	13	+	○	○	○	▮▮▯▯		✓
Yu [184]	2024	TUS DE	MOP	semi			👤	17	+	+	∘	−	▮▮▯▯		
Wang [185]	2025	METER	LTDS	1^{st}			👤	9	+	○	○	+	▮▯▯▯		✓

−∘+: Linkage strength of activities and energy service demand (details in Figure 4). ○: Energy service demand not modeled.
👤: Occupants modeled individually. 👥: Household modeled as a unit (shared states). **"PDF"**: Probability density function.

Table 3
Comparison of the strengths and limitations of the individual modeling approaches.

Modeling approach	Strengths	Limitations
First-order Markov chain	+ Low computational complexity + Low data requirements* + Low implementation difficulty	- Low intrapersonal/temporal dependence
Semi-Markov chain	+ Realistic state durations and state change frequencies + Low computational complexity + Low data requirements* + Low implementation difficulty	- Temporal dependence is still limited because transitions remain conditioned only on the current state (Markov property).
Higher-order Markov chain	+ Can model longer time horizons + Improved (but still limited) temporal dependence	- Parameter count grows exponentially with order and number of states (curse of dimensionality) - Many states or long dependencies become infeasible (due to data requirements and computational complexity) - The relaxation (e.g., concrete past states or activities, variable order) is often based on strong assumptions or heuristics
PDF-based (Probability Density Function) approaches	+ Low computational complexity + Low data requirements* + Low implementation difficulty	- Temporal dependencies between activities (and time steps) are not directly captured - Require additional coupling assumptions such as post-processing of unrealistic schedules (e.g., overlapping activities)
Neural network-based approaches	+ Can capture long-range dependencies + Can learn cross-dependencies without subgroup splitting	- High data demand - Substantial training/tuning effort

* For estimating the model parameters given a moderately limited model structure (e.g., number of activities and distribution parameters). Requirements may increase correspondingly with additional model parameters needed for splitting into many subgroups or using many activities.

extend the model to four states, additionally distinguishing whether occupants are active ("not sleeping"). Appliance differentiation uses a probability density function conditioned on occupancy [147, 150]. Together, these studies [146, 147, 149, 150] comprise the CREST model or "richardsonpy". Several studies [46, 133, 148, 186, 187] adopted the CREST approach.

Other works [121, 153, 154] rely on the structure introduced by Widén and Wackelgård [152], which directly models nine activities using a Markov chain.

Apart from these multi-paper lines, two standalone contributions are noteworthy. Zhang et al. [182] model occupancy states and infer room-level presence by preprocessing time-use data with appliance-based distinctions. Fischer et al. [163] focus on location-based mobility modeling. Other models in Table 2 follow standard first-order Markov modeling [8, 58, 157, 158, 160, 164, 172, 178, 179, 185].

Semi-Markov chains. To better capture realistic activity sequences, semi-Markov models keep first-order transitions but sample state durations from activity-specific PDFs (Figure 5(b)). This matches empirical duration distributions. After each sampled duration ends, the next state is drawn by the standard Markov rule. Several models [159, 168, 176] use this structure implicitly without naming it. Standard semi-Markov chains without further specific deviations are applied in [127, 159, 168, 180, 181, 184] (see Table 2).

Other works extend scope while retaining the semi-Markov logic. Wilke et al. [155] assume Weibull-distributed durations and use a two-state profile directly from time-use data as a proxy for occupancy. Müller et al. [176] assign a physical location to each activity. Commuting is handled outside the chain with fixed durations inserted before and after work-related activity. Some activities allow multiple locations (e.g., eating), others are restricted to home (e.g., ironing). Rule-based constraints enforce consistency of location. Barsanti et al. [183] consider a variant that merges laundry and dishwashing into "other activities" resulting in an eleven-state model. These appliances are simulated with PDFs. Rueda et al. [177] estimate durations with a Cox regression that can also depend on time and external covariates via the hazard rate, capturing temporal and contextual effects.

Semi-Markov chains implement activity specific duration distributions and thereby control change frequency. Absent explicit duration modeling in a standard Markov chain,

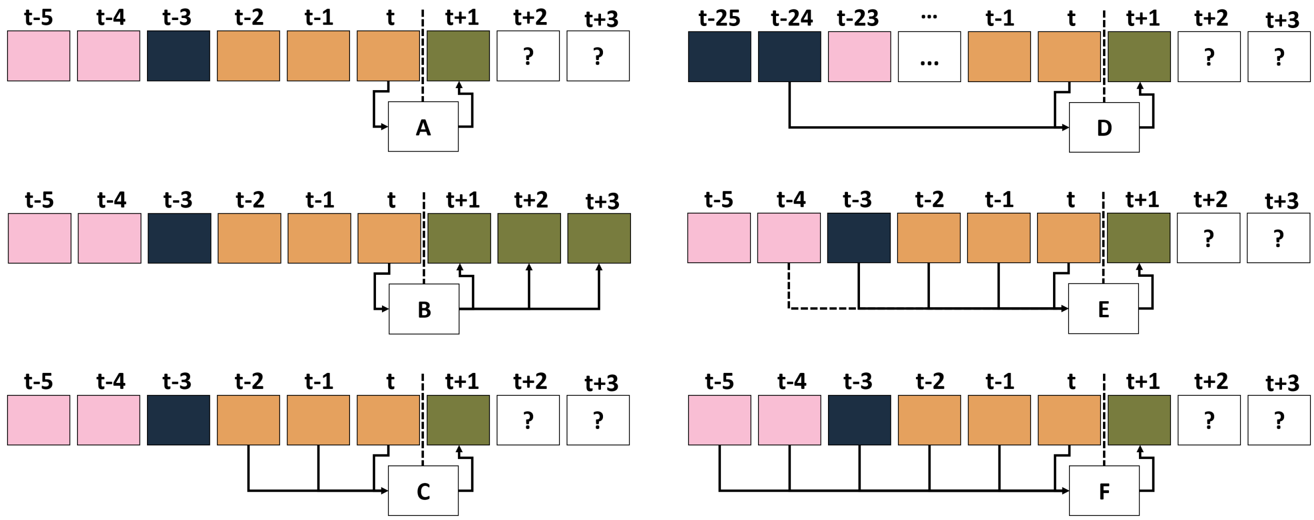


Figure 5: Different memory lengths of Markov chain approaches and neural network approaches. Colors represent different activity states. **A:** First-order Markov chain. **B:** Semi-Markov chain. **C:** High-order Markov chain used in Flett and Kelly [169–171]. **D:** High-order Markov chain used in Nijhuis et al. [165]. **E:** Variable-order Markov chain used in Ramírez-Mendiola et al. [174]. **F:** Transformer-based neural network used in Kleinebrahm et al. [57].

an instructive comparison is to assume a homogeneous chain (as in models that use constant transition probabilities within an hour). In that case, state durations follow a geometric distribution, which is often unrealistic for many common activities (a similar consideration was made by [127]).

High-order Markov chains. The standard first-order variant of a Markov chain depends on a single preceding state. Higher-order Markov chains extend this to multiple previous states, allowing deeper temporal dependence, but the number of transition parameters grows exponentially (n^{k+1} for order k and n states, including $n^k(n-1)$ free parameters).

Nijhuis et al. [165] add the occupancy status from exactly 24 hours earlier to capture diurnal effects (Figure 5(d)). Flett and Kelly [169, 170] let transition probabilities depend on elapsed duration, unlike semi-Markov models in which duration controls persistence rather than the next state (Figure 5(c)). Flett and Kelly [171] personalize daily rhythms from the population distribution by sampling each occupant's average wake time and shifting time-dependent transition probabilities within a wake window relative to the population mean. Ramírez-Mendiola et al. [174] use a variable-order Markov chain, selecting the memory length via iterative log-likelihood ratio tests, evaluating gains with Kullback–Leibler divergence, and stopping when gains are insignificant or at five past states (Figure 5(e)).

Probability density function (PDF) approaches. PDF-based approaches rely on stochastic sampling from empirical or fitted probability distributions to generate activity schedules. As such, they can be considered a class of Monte Carlo methods. PDF-based models present in Table 2 sample start times and durations independently for each activity, possibly allowing overlaps, do not condition on state history, and thus schedules are generated without Markovian dependency. Some studies [125, 161, 162, 173] calibrate using cumulative distribution functions to match daily counts per activity. Fischer et al. [161, 162] only implicitly model the underlying behavior by learning PDFs based on TUS to sample appliance starts rather than modeling activities. Foteinaki et al. [175] restrict schedules to a single activity at each time step, but treat each time step independently and therefore model activities without temporal dependencies. Yamaguchi and Shimoda [173] and Taniguchi et al. [125] first schedule routine behaviors such as sleeping, school/work, commuting, meals, and bathing for all household members using cumulative distribution functions anchored on wake-up times, with assumptions linking start times and durations. Remaining gaps are then filled probabilistically with non-routine activities, again one per person at a time. As previously described, Flett and Kelly [171] add a PDF component to capture individualized, consistent sleep, while the primary scheduler remains a Markov chain.

Neural network approaches. Neural networks provide an alternative modeling approach. In neural networks, many (often millions of) free parameters ("weights") are learned on a training set, checked for overfitting and tuned on a validation set, and evaluated on a held-out test set. In an autoregressive neural network, past states are used to predict the next activity with the highest probability using the learned weights. During training, prediction errors are used to adjust the weights.

Kleinebrahm et al. [57] linked the field of activity modeling with recent developments in language modeling using a transformer model (an attention-based sequence model, Figure 5(f)). Accordingly, the activity schedule modeling problem is treated as a domain-agnostic categorical time series that combines information from mobility patterns and in-home activities. Categorical time series (different activity states with time-of-day and weekday) are embedded in a continuous space, analogous to word embeddings in large language models. Similarly, sociodemographics can be handled via embeddings. When all input data are in a single space and embedded with a single model (parameters shared across all subgroups), the overall number of parameters remains manageable. Mobility-related activities are first modeled using an autoregressive neural network. In the second step, household activities are generated jointly based on past in-home activities and on the past and future mobility activities simulated in the previous step. In both steps, the model has access to the entire past simulation horizon.

3.3. Simulation object and states

The majority of studies presented in Table 2 use individual occupants as their simulation subject. Markov-based models split the input dataset into groups based on the occupants' sociodemographic variables, such as age and employment status, or on data-driven occupancy patterns (see Table **??** in the Appendix; an overview can be found in [183]). Separate group-differentiated Markov chains are parameterized and used to generate activity schedules, representative for each sociodemographic group. The trade-off between the number of sociodemographic groups and data required for constructing the models is discussed in [149, 169].

Another branch of studies (the CREST models) [146–151] first aggregates information from individual occupants from the input dataset, to obtain one sequence per household. Richardson et al. [146] define household states based on the number of occupants being "active and at home". Later versions introduce four occupancy states (active vs. passive; at home vs. absent), aggregating activity and presence so permutations with the same totals are identical [149, 150]. For example, a household with $n = 3$ occupants yields 4 Markov chain states with two occupancy states, or 20 states with four occupancy states (for $n = 6$: 7 and 84 states, respectively). Accounting for time-inhomogeneity, 144 transition matrices are needed for each household size, with matrix sizes from 4×4 (one occupant) to 84×84 (six occupants).

These studies train separate models for households of different sizes. The underlying idea is that, compared with occupant-specific Markov chain approaches, this better represents intrahousehold dependencies. However, the aggregation step from occupants to households reduces information and sample size, especially for large households, which can lead to under-parameterized models.

Flett and Kelly [169] argue for incorporating sociodemographic variables while simulating households. Two adults are merged into one unit, and children are modeled with a subsidiary Markov process conditioned on the parents' state, and other members are included but not modeled as interdependent [170]. In [125, 173], routine activities are modeled collectively at the household level. By using neural networks, Kleinebrahm et al. [57] achieve implicit sociodemographic differentiation without requiring separate models or reducing the number of states or the amount of training data.

Just as the number of states increases when households are the simulation object, finer granularity of activity states further increases the complexity of the model. Higher-order Markov models are typically limited to occupancy presence/active states because the number of parameters grows rapidly with more activity types. Ramírez-Mendiola et al. [174] model at most eight activity states.

3.4. Energy demand modeling

Appliances. Most models that go beyond basic activity scheduling and include energy service demands account for appliance usage. Multiple models derive appliance use by sampling probability density functions conditioned only on occupancy status (compare Table 6 in the Appendix). Nijhuis et al. [165] use a second Markov chain, which models appliance usage, linked to the occupancy states generated by the first Markov chain. Because there is no one-to-one activity link in these models, appliance differentiation is handled probabilistically. However, if multiple services are modeled, a single occupancy schedule across all demand modules provides a consistent behavioral basis that supports cross-service interlinkage.

In contrast, activity-linked demand models establish explicit connections between activities and appliances. Each activity state can be mapped to a specific appliance or to a set of possible appliances. The latter is often the case for cooking-related activities, where the appliance used may vary significantly. Table 6 in the Appendix summarizes the number of appliance-related states and whether activity-to-appliance assignment is deterministic or probabilistic. Some models also include an execution probability threshold, meaning an appliance is not guaranteed to be activated even if selected (probabilistic trigger for appliance start in Table 6 in the Appendix. To control the frequency of appliance starts, a calibration scalar or a cumulative distribution function may be applied, rather than treating each start as a single independent execution. A detailed review on that topic is provided by Yamaguchi et al. [69]. Households can be assigned appliance stocks (ownership, ratings/efficiencies) and a dwelling/building with electric and thermal characteristics.

When an appliance is activated, its load profile can be represented in different ways. Table 6 in the Appendix distinguishes these ways at a high level, although implementations may vary by appliance. First, a time-varying load profile may be assigned immediately or with a delay (e.g., a washing machine starting after a laundry activity, as in [127]). Second, an operating duration is sampled from an appliance-specific distribution and a constant load is applied over that period. This approach is suitable for a wide range of appliances and is particularly appropriate for those not directly tied to a modeled activity, such as background or cyclic loads (e.g., refrigerators, routers). Third, in cases where appliance use is directly linked to an activity in the schedule, the appliance runtime equals the activity's duration. A constant load is again assumed. As noted in Section 2.3, these approaches are not mutually exclusive and can be combined within a single model. For example, appliances like washing machines or dishwashers may follow detailed time-varying load patterns that exceed the duration of the triggering activity, reflecting full-cycle profiles with phases of different energy intensities (e.g., water heating, spinning). In contrast, simpler appliances may be modeled using constant loads over a fixed or sampled duration. Notably, a single device can exhibit both a constant baseline and activity peaks, for example, a refrigerator's base load plus compressor-driven spikes.

Hot water. Domestic hot water modeling involves two tasks, namely linking activity schedules to hot water draws and converting those draws to energy demand. The linkage mirrors appliance coupling. Models based solely on occupancy offer weak coupling, whereas most approaches link via the activity schedule and assign volumes using tapping profiles. Table C in the Appendix lists the included models with details on related activities and appliances. Models that fix or duration-scale volumes include Widén et al. [121], who link hot-water-related activities to appliances with fixed volumes for bathing and duration-scaled volumes for showering based on earlier specifications [112]. Osman et al. [181] apply a similar approach, choosing bathing appliances by duration and using fixed volumes otherwise. The proposed method by Widén et al. [112] is used in [154, 157, 158]. Sandels et al. [154] simulate hot water appliances with a separate Markov chain. Farzan et al. [164] map three activities to three appliances and scale demand with duration. Electric water heater's energy is modeled as a function of the activity duration in [125, 172]. User-type categorization also appears in [171, 181]. Some studies omit appliance-mapping details [125, 166].

Other models sample hot water volumes with probability distributions: conditional on activity [180]; conditional on occupancy [150, 168, 171]; or independent of the activity schedule [162]. Fischer et al. [162] operate in the same manner as for appliances by sampling start times, durations, and daily frequencies from distributions, then assigning the hot water activity and volume deterministically from the sampled duration. Frequency constraints are also applied in [176, 181].

Energy demand is then derived from volume. Many studies use simple conversions. Widén et al. [112] apply a linear relation; similar treatments appear in [125, 164, 166, 171, 172, 176, 181], although calculation details are often unspecified or not publicly documented. Baetens and Saelens [168] bypass appliance differentiation and sample demand directly from a distribution conditional on occupancy.

Fewer studies embed thermal system models. Sandels et al. [154] implement a boiler with heat losses. Fischer et al. [162] use DHWCalc by Jordan et al. [188] to generate tapping profiles and convert them via energy balance. Bottaccioli et al. [127] simulate an electric water heater using the model by R. Diao et al. [189]. Chen et al. [140] derive demand via ResStock [190]. McKenna et al. [150] compute demand with a thermal gas boiler model that also supplies space heating.

Heating. Heating-demand models vary in building detail, input drivers, and co-modeled effects; some include ventilation and cooling [58, 150, 162]. Many incorporate solar irradiance [150, 154, 162] and temperature-driven transmission losses. Recent work commonly uses occupancy profiles, enabling occupant-dependent modeling; internal heat gains from appliances should be included, and profiles kept consistent across modules.

By activity linkage, two types dominate: high-linkage models couple heating with metabolic heat and appliance gains, whereas low-linkage models treat heating as an independent load. An intermediate case is Nijhuis et al. [165], which applies occupancy-dependent setpoint temperatures but omits internal heat gains. Where applicable, on-site photovoltaic and micro combined heat and power systems, as well as storage systems (batteries and domestic hot water tanks), can be modeled as modular supply blocks driven by weather and simple controls. Net demand equals end-use demand minus on-site generation and storage flows, leaving the activity-linkage unchanged.

Mobility. Modeling mobility energy demand combines behavioral, technical, and spatial elements. Table D in the Appendix summarizes the models referenced below.

Activity-based electric vehicle demand uses some activity states in which the vehicle is used, so battery energy is consumed and the car is away from home, which precludes home charging. Location granularity spans one "away" state [153, 184], two states ("work/commuting" and "leisure/shopping") [8, 156, 164, 167], three out-of-home locations [163], and up to four locations [176]. Travel purposes, activity status, and locations are treated differently depending on the model. Wang et al. [185] define five trip purposes but do not describe how to translate them into full schedules.

Some models include mobility behavior without deriving electricity demand. Kleinebrahm et al. [57] define four mobility-related states including a general "outside" location and three explicit mobility activities (driving, co-driving, and other transport modes), avoiding consistency conflicts by hierarchical sampling of non-mobility activities in a subsequent step. Models without explicit household activities include Hilgert et al. [191], who simulate six trip purposes by using a hierarchical approach, and Roorda et al. [192], who sample frequency, start time, and duration for ten mobility activities, assign locations probabilistically, resolve conflicts with rules, and synchronize household members. Gruosso et al. [167] model driver interactions such as limited vehicle availability and fixed work shifts. Others assume a main driver [163, 164, 176] or otherwise unrestricted access.

The next step is to model vehicle energy consumption. Trip distances are often assumed to be proportional to activity duration (e.g., [153, 164, 167]), sometimes stratified by socio-demographics [164]. Several studies sample certain distances (e.g., commutes) a priori, assuming independence from activity duration (e.g., [8, 156, 163, 176]). Fischer et al. jointly sample distance and time to fit observed activity durations [163]. Yu et al. [184] sample driving distances probabilistically. Consumption is computed from average speed [153, 164, 176, 184, 185], differentiated by purpose [185], or by using acceleration profiles [167]. A two-dimensional Markov chain for velocity/acceleration parameterized by highway share and driving style is used in Muratori et al. [8, 156].

Charging depends on behavior for charging, charging power available or possible, and location. More public charging or charging at home reduces household demand [156, 163, 167, 185]. Most studies assume uncontrolled "charge-on-arrival"; alternatives include probabilistic timing [163, 164] and cost-optimized timing [164, 184]. Charging power is typically assumed to be Level 1/2 (Level 3 in [163]). Vehicle-specific charging limits appear in [167, 176].

Additional aspects vary across models. Not all studies specify whether "electric vehicles" are battery electric only. Plug-in hybrids appear in [8, 153], and Muratori et al. [156] also include hybrid electric and conventional internal combustion vehicles differentiated by exergetic efficiency. Modifiers include seasonality [153], thermal loads, and regenerative braking [167]. Many of these aspects are tailored to the respective study aims, yet remain interchangeable as needed.

4. Evaluation metrics of bottom-up residential energy demand models

After a brief introduction to the three validation dimensions (fidelity, diversity, generalization) in Section 4.1, Section 4.2 presents methods for validating generated activity schedules, and Section 4.3 presents methods for validating generated demand profiles.

In the following, we distinguish three **evaluation categories**: (i) **implementation verification** (checks that the model behaves as intended, often performed in-sample), (ii) **empirical validation** (quantitative agreement with held-out data), and (iii) **plausibility checks** (qualitative sanity checks, often visual). Verification and plausibility checks are useful diagnostics at both the activity and demand levels, but they are not a substitute for empirical validation.

4.1. Validation dimensions

Table 2 shows that multiple models for residential energy demand have been developed over nearly two decades (2008–2025). However, there is still no standard evaluation framework available to compare the performance of the different models, to enable improvements and track progress. Explicit treatment of benchmark datasets and validation frameworks remains limited (e.g., [193]). Because few datasets link time-use data with smart metering [77], broader and better-linked data would strengthen the activity–load transition (i.e., the mapping from household activities to electricity demand).

Simulated activity schedules or energy demand profiles can be regarded as synthetic data. Synthetic data generation is an active research area for data protection and for creating otherwise unavailable datasets [194], already applied to generate smart meter data directly [195, 196]. Real and synthetic data can be viewed as samples drawn from two distinct distributions, where a sample is a complete activity schedule. The goal is a synthetic distribution nearly indistinguishable from the real one. These distributions occupy support regions in a high-dimensional space. Alaa et al. [197] introduce three dimensions to evaluate synthetic data: Fidelity, Diversity, Generalization. Figure 6 illustrates a model's performance across the dimensions, using the example of activity schedule generation.

- **Fidelity** measures the realism of an individual synthetic sample. High fidelity means the generated sample is difficult to distinguish from comparable real samples. In Figure 6, ellipses mark support regions in a reduced-dimensional space spanned by nearby points. Two areas labeled A contain several synthetic red points, indicating high fidelity. In contrast, point D lies outside any support region of the real (blue) distribution.

- **Diversity** is the extent to which generated samples cover the variety present in the real data. In the example, area B is a support region, yet no synthetic points fall there, indicating low diversity. In contrast, the areas labeled A show reasonable diversity.

- **Generalization** measures how closely individual synthetic samples resemble real inputs. It is critical because excessive similarity may violate privacy, undermining a key advantage of synthetic data. This dimension must be evaluated, though it is hard to quantify or benchmark. Figure 6 illustrates this at point C, where two nearly identical points appear. The synthetic schedule is not authentic, signaling a potential privacy breach.

4.2. Validation of generated activity schedules

Despite many models, validation relies on a few metrics. Table 4 summarizes the employed methods and provides a coarse classification of validation dimensions based on the presented concept. Similar metrics are grouped even when names or scales differ. Definitions of individual metrics are given in [56, 80, 196], with [196] also proposing an initial classification of validation dimensions. Within the recent literature on activity schedule modeling, only state and duration probabilities are used by multiple authors. To support transparent benchmarking, a shared set of baseline metrics should be reported for comparability, and complemented by more specialized metrics where appropriate.

Implementation verification predominates across models. The most common metric compares daily time-dependent activity or occupancy probabilities. In Markov models, state probabilities converge by definition and by the law of large numbers, so this check mainly verifies implementation correctness. Several studies also investigate convergence

Table 4
Applied metrics at the activity level mapped to evaluation dimensions. **Implementation verification** is an evaluation category denoting in-sample diagnostics (whether a model behaves as intended). **Fidelity/diversity/generalization** are validation dimensions following the synthetic data evaluation perspective. A metric may contribute to different dimensions depending on the reference.

		Evaluation dimensions				
Metric family	**Metric name**	**Implementation verification**	**Fidelity**	**Diversity**	**Generalization**	**Studies employing the metric with respective error measure**
State probability matching	Occupancy probability	✓				**Visual/plot:** [181],[129],[127],[146],[132],[198],[179] **MAE:** [151],[129],[198],[169],[127] **MSE:** [151],[129],[127] **Percentage error:** [151]
	Activity probability	✓				**Visual/plot:** [174],[181],[184],[176],[180], [166],[175],[157],[155],[57],[173],[186],[199],[81],[127] **MAE:** [181],[155],[173],[69],[199],[127] **MSE:** [174],[181],[57],[199],[81],[173],[127] **Percentage error:** [174],[180],[127]
	Average occupancy variance			✓		[169],[171],[81]
	Convergence (speed) tests			✓		[171],[149],[174],[151],[157],[179]
Duration and transition statistics	Occupancy duration		✓			**Visual/plot:** [198], [169],[149] **MAE:** [169] **Percentage error:** [180],[149] **Earth movers distance (first-Wasserstein distance):** [169],[198]
	Activity duration		✓			**Visual/plot:** [180],[57],[174],[173] **MAE:** [174] **MSE:** [57],[174],[173] **Percentage error:** [174] **Correlation coefficient:** [179]
	Occupancy transition frequency		✓			**Visual/plot:** [186],[179],[180],[146],[149]
	Activity transition frequency		✓			**Visual/plot:** [176],[174],[69] **Mean:** [173] **MAE:** [174] **Spectral norm:** [174]
	Number of activities per day/week			✓		**Visual / plot:**[69],[180] **Visual / boxplot:** [57]
	(Peak) occupancy variance			✓		[77],[186]
Similarity between profiles	Levenshtein/ edit distance		✓			[159]
	Levenshtein distribution similarity			✓		[169]
	Accuracy		✓		✓	[81]
	F1-Score		✓			[81]
	Shannon's H entropy (synchronity index)			✓		[77],[69],[173]
	Occupants becoming active together			✓		[186],[169],[146]
	Sequence analysis methods (optimal matching)		✓			[77]
Similarity between days	Hamming distance		✓			[57]
	Autocorrelation		✓			[57]
	Mean/STD wake-up times			✓		[171]
Methodical aspects	Ten-fold cross validation	✓			✓	[155],[129]

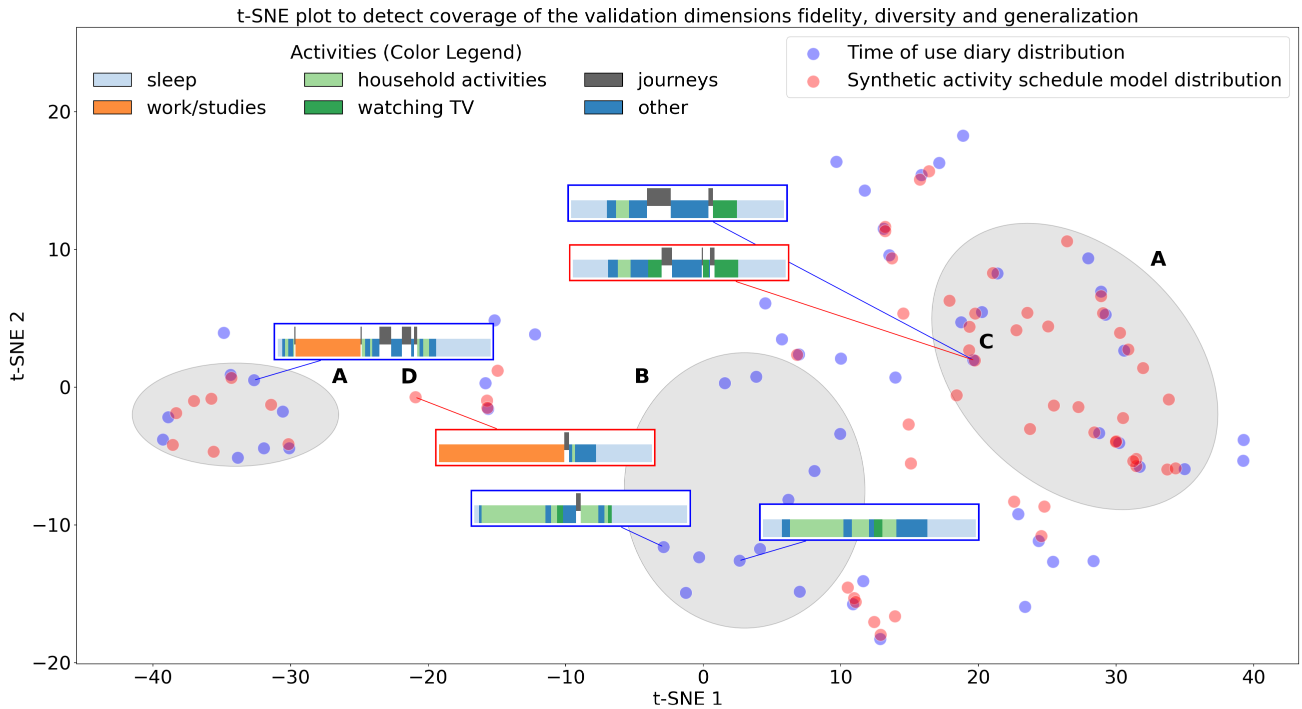


Figure 6: Visualization of the three validation dimensions in the context of activity schedules: Six activity states are taken from the Spanish Time Use Survey. Blue points represent a subset of the original data; red points are synthetic data generated by a model trained on a subset of the blue points (real data). All points are embedded into two dimensions using t-SNE. Closeness in this space reflects similarity based on the Levenshtein metric. The figure is intended to illustrate the validation dimensions, not to evaluate the model used.
A: Well-captured regions where diversity is ensured and high-fidelity synthetic data are generated.
B: Region not captured by the model. This area includes schedules with high household work and no studying or working activities, which are not reproduced by the model, indicating limited diversity. Two nearby points illustrate this.
C: A synthetic point nearly identical to a real one. While it shows high fidelity, it reflects low generalization and may pose a privacy risk.
D: A synthetic point with low fidelity, lying outside any support region of real data (no nearby blue points). The corresponding schedule includes more than twelve consecutive hours of work.

speed, which can hint at diversity but depends on additional factors [171]. In non-Markovian models, such as neural networks, state probability convergence is not guaranteed, so diversity and unbiased coverage require explicit checks. Average occupancy variance, introduced by Flett and Kelly [169, 171], departs from standard occupancy metrics and signals diversity. The choice of error measure, for example relative mean absolute error, relative mean squared error, or relative percentage error (similar to coefficient of variation, as in [151]), varies but does not change the validation type itself. Many studies still rely on visual comparisons instead of computed metrics, which hampers comparability (compare Table 4).

State durations, that is, activity lengths modeled appropriately, are also investigated across models. Evaluations include the distribution of state lengths, often assessed with plots. State duration evaluation is most relevant for first and higher order Markov chains and neural networks. Because semi-Markov models explicitly model state durations, the implied duration distribution is fixed by construction. An important measure is occupancy transition frequency (also called cumulative occupancy variation [63]). Related counts include occupants becoming active, unoccupied episodes, and switch-on events. These metrics can reveal excessive oscillations, for example overuse of fixed length appliances (e.g., washing machines). The distribution of activities per day or week is another indicator of variability, and can be visualized with boxplots [57]. Finally, peak occupancy variance captures the proportion of transitions between consecutive states in generated profiles. Profile similarity may be computed for individual profiles or for sets (e.g., real and synthetic) using a minimum interset distance, which serves as both a fidelity measure and an overfitting indicator. Applying the same measures to subsets supports diversity assessment. Levenshtein distance is robust to small temporal shifts. Other metrics are largely similar and are rarely used in practice. Repetitiveness across multiple days requires metrics that capture cross day dependence. Kleinebrahm et al. [57] evaluate repetitive behavior with Hamming distance and autocorrelation. Flett and Kelly [171] analyze diversity in continuous occupant profiles, which initially collapsed toward the mean, and show that assigning specific wake times captures dependencies across consecutive days in the generated data.

Additional validations in individual studies are typically tailored to model-specific design, limiting transferability (e.g. [155, 173, 174]). The corresponding metrics should not be undervalued merely because they examine a narrow or model-specific aspect. However, comparative studies remain scarce due to the limited availability of open data and open-source models, and the lack of standardized metrics. Rueda et al. [177] compare state duration performance across methods. Flett and Kelly [169] benchmark occupancy probability against alternative models. Yamaguchi et al. [69] report insufficient entropy in several published models. However, none of these studies work with open datasets and therefore do not provide a benchmark for future model developments.

4.3. Validation of generated demand profiles

Meaningful validation requires metered observations. Accordingly, we include only models validated against metered data. For grouping we do not distinguish mean from total or standard deviation from variance within the respective metric. Combined activity and consumption datasets provide the strongest basis.

One problem is the reliance on in-sample validation. A similar issue occurs at the activity level when features of activity schedules are compared to the databases from which they were derived. Furthermore, metered data are often used to calibrate end-use parameters and to fit an additive residual term for unmodeled loads omitted by the initial model. This practice reduces the value of subsequent validation, because calibration can mask model errors. Muratori [8] illustrates this: one dataset is used for calibration and for estimating lighting demand via regression on residuals, while a second dataset is held out for out of sample validation.

Combined datasets such as METER or multiple smart meter sources are often unavailable, so validation defaults to highly aggregated profiles such as monthly or annual averages (for the models investigated, this is the case, for example, in [125, 127, 131, 148, 160, 161, 163, 165, 166, 168, 170, 171, 175, 176, 180, 185]).

Appliance-level checks can be performed by aggregating each appliance's modeled demand across load profiles [160, 171, 176]. Hour-of-day load distributions can likewise be evaluated [161]. Typical metrics include means and standard deviations [58, 164, 165, 168], bias [127], percentiles or boxplots [80]. Some studies use hypothesis tests for distributional similarity [164] or regression analyses with scatter plots [58]. Several also report the index of agreement [127].

Typical load metrics provide additional comparison indicators. Common quantities include the load level and load factor ([152, 163]), which describe the ratio of average power to peak power. The power factor [160] expresses the ratio of active to reactive demand. The load duration curve ([80, 161]) summarizes the load distribution as a sorted curve or a probability density [165]. The simultaneity (coincidence) factor [148, 150, 152] and simultaneous peak power [176] compare peaks across households. Correlation metrics include pairwise correlation and autocorrelation [127, 168]. Variability measures include the normalization factor [57, 112] and the coefficient of variation [170], both describing deviations from the mean. Of particular interest, the Piecewise Aggregate Approximation (PAA) edit distance [170, 171] compares segmented time series, capturing neighborhood structure by aggregating values and reducing sensitivity to individual points. Because demand values are continuous, Euclidean-based edit distances are feasible, unlike at the activity level.

Only a few models validate domestic hot water, heating, and mobility demand. Domestic hot water is validated against metered data [150, 162], against the DHWCalc model [162], and is evaluated with load duration curves [162]. Heating validation uses electricity or gas data [150, 181], and load duration curves [162], and comparisons with CREST [151]. Some work covers multiple building types [184]. For mobility, evaluations use presence data [163], location profiles [176], or combined electricity loads from multiple services; which are assessed with load duration curves [163] or aggregated demand comparisons [184].

5. Discussion and future research needs

This discussion highlights three priorities as outcomes of comparing the state-of-the-art **(RQ1)** with requirements, best practices, and future research needs **(RQ2)**, and with evaluation criteria **(RQ3)**: the need for better activity models in Section 5.1, requirements for datasets and validation in Section 5.2, and consistent linkage of activities to energy service demands in Section 5.3. It concludes with the limitations of this review in Section 5.4.

5.1. Need for better activity models

Better activity models are needed to capture intrapersonal (temporal) and intrahousehold dependencies. A high-quality household representation should meet the requirements for mobility, thermal comfort, hot water, and other energy demands.

Intrapersonal dependencies are modeled only to a limited extent in most approaches. PDF-based models do not capture intrapersonal dependencies because they ignore the temporal order between activity states. In Markov chain-based models, intrapersonal dependencies are present but limited. Temporal dependencies are determined mainly by the Markov order. The numerous developments of higher-order variants reflect the need to extend temporal dependence beyond the one-step Markov property, but the gains remain limited. For future work, the ceiling of higher-order approaches is constrained by the exponential increase in parameters and data requirements arising from the discrete treatment of the state space. By subgrouping, datasets are completely decoupled. However, human behavior is not expected to be completely distinct across sociodemographic subgroups, which implies a loss of information. Neural-network approaches that operate in a continuous space and are not limited by the Markov property are therefore promising for achieving significantly higher intrapersonal stability. Furthermore, integrating more metadata, such as sociodemographics, preferably in a data-driven manner, can improve the model, rather than reducing data availability through submodel partitioning.

Currently, most models ignore intrahousehold dependencies. Models often simulate individuals and then aggregate behavior, thereby neglecting interactions among household members. Although improvements in modeling accuracy have been observed when accounting for household connections and moving beyond individual profile modeling (in McKenna et al. [149] and Flett and Kelly [169–171]), research in this area is widely overlooked.

A key reason why intrahousehold modeling remains underdeveloped is that it is constrained by data availability, computational burden, and conceptual complexity. First, the number of independent training sequences decreases when households (rather than individuals) are the simulation object. Second, moving from individual to household modeling shifts the learning target from marginal (single occupant) behavior to a joint distribution for multiple occupants, which is inherently more complex due to intrahousehold dependencies. In particular, modeling household members jointly leads to combinatorial growth in the number of possible joint configurations (e.g., combinations of occupants' presence/active states or activities at a given time). This typically increases the number of parameters required, making it difficult to jointly represent population heterogeneity (hierarchical structure via sociodemographic differentiation), high state-space resolution (many activity states), intrapersonal temporal dependencies (long memory/autocorrelation), and intrahousehold dependencies (cross-correlations/joint schedule generation). The resulting trade-off is illustrated for selected Markov-based approaches in Figure 7. Some approaches bypass this trade-off by introducing strong structural assumptions or rule-based coordination mechanisms. However, these assumptions are often hard to justify empirically and may introduce systematic bias, so they should be kept to a minimum. Third, intrahousehold dependencies reflect coordination patterns such as joint activities and parallel or conflicting activities. These patterns do not need to be represented via explicit, interpretable rules. Ideally, they are learned implicitly from data containing activity schedules for all household members. In practice, many existing approaches still rely on hand-crafted rules and assumptions that are difficult to validate empirically.

As a result, models typically prioritize only a subset of these objectives (e.g., household-level aggregation with few states, or detailed activities without joint coupling), highlighting an inherent trade-off rather than a single missing implementation detail. Accordingly, approaches that consider household dependencies are limited to small sets of activity states (in the CREST models [146, 147, 149, 150]), specific family constellations (in Flett and Kelly [169–171]), assumption-heavy dependency structures among household members (in Yamaguchi et al. [173]), or incompatibility constraints between activity schedules (in the synPro models [161–163]). These approaches are more assumption-driven than data-driven, although time-use surveys typically

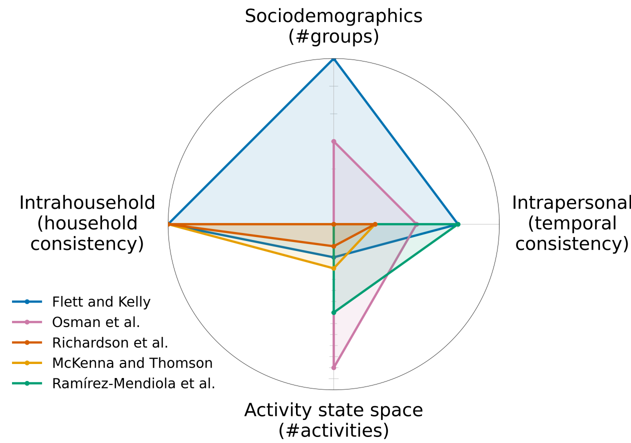


Figure 7: Schematic complexity of Markov model design trade-offs. Radar profiles compare Markov model specifications across four modeling dimensions for exemplary models (Flett and Kelly [169], Osman et al. [181], Richardson et al. [146], McKenna and Thomson [149], Ramírez-Mendiola et al. [200]).

provide direct co-use information or allow inference via household affiliation. Overall, intrahousehold dependencies are rarely modeled, despite their increasing importance, for instance, for joint mobility behavior.

In a data-driven approach, multiple occupant activity schedules should be modeled jointly as a multivariate time series, avoiding rule-based assumptions about how occupants influence each other, in particular, who the activity-determining occupants are or which activities are routine, because such assumptions risk introducing algorithmic bias.

Dependencies beyond a single day are rarely modeled, as such information is not directly available in time-use surveys. Nijhuis et al. [165] condition on the occupancy state exactly 24 hours earlier, which is likely insufficient. Flett and Kelly [171] link days via sleep patterns, which is more plausible, though wake-time variation is rule-based and constrained by a three-state occupancy model. Kleinebrahm et al. [57] tackle cross-day stability via mobility behavior.

Rule-based assumptions should be avoided, as mentioned in intrahousehold dependencies but also regarding intrapersonal dependencies. Whenever possible, one should prefer more data-driven learning in order to prevent assumption bias and confirmation bias. This also applies to linking: where an explicit activity-to-demand mapping exists, adding an additional probabilistic trigger for execution introduces unnecessary randomness and may weaken the connection to the behavioral basis. Probabilistic triggering remains useful when mappings are ambiguous (e.g., aggregated activity states) or when calibrating execution rates. In cases where data are not available, such as beyond single-day dependency, one should limit assumptions to the minimum necessary for combining datasets.

Parallel activities by the same occupant are common but often omitted. Models often treat model-generated overlaps as parallel activities rather than secondary activities contained directly in the survey. Linking main and secondary activities with smart-meter data has been explored [200].

Interhousehold dependencies deserve future study, especially for seasonal peak days [110]. Long-term smart meter series can capture cross-day effects. Shared environmental drivers, notably weather (e.g., [110, 199, 201]), can induce correlated demand across dwellings [150], affecting heating and lighting [148] and electric vehicle demand [202], and thus behavior. But this also underscores the need for a better data foundation.

In summary, the majority of present works rely on Markov chains and PDF-based models that are not designed to capture highly time-dependent activity schedules, a limitation that is hard to overcome. Consequently, intrapersonal dependencies are rarely captured. Intrahousehold dependencies are either largely neglected, since models typically simulate occupants independently, or addressed through assumptions that limit generalizability. Activity schedules therefore lack the consistency needed as inputs to related energy service demands. Neural networks demonstrate the potential to overcome these issues, such as by incorporating higher intrapersonal dependencies in a data-driven manner without relying on assumptions.

5.2. Requirements for datasets and validation

Datasets with longer observation periods are needed, because typical time-use surveys span only one or a few days, limiting both the analysis and validation of cross-day dependencies. To analyze dependencies over days, Nijhuis et al. [165] and Flett and Kelly [171] rely on an older version of a Dutch dataset, which captures seven consecutive days of household behavior. Beyond integrating mobility behavior, Kleinebrahm et al. [57] use the mobility dataset to achieve longer temporal consistency that German time-use survey data cannot provide. The Swiss time-use survey is promising because it features a longer observation period of 28 days [91]. Empirical validation can only assess time scales that are present in the available reference data. When longer horizons are constructed by combining datasets, the resulting cross-day structure cannot be directly validated without corresponding multi-day observations and should therefore be treated explicitly as an assumption.

However, combining multiple datasets will remain necessary in the future, as outlined in Chapter 2.2. Furthermore, this should be used even more, in particular to transfer datasets from countries other than the target country, as most works currently do (compare Table 2). Many surveys are already harmonized by design, and country can be integrated as a factor similar to sociodemographics, so a multinational framework should be considered in the future. Based on real time-use data, investigations regarding spatial analyses, from intra-national urban–rural differences to cross-country comparisons (e.g., [51, 138, 199, 203]), country-specific appliance use (e.g., [204–206]) and how to deal with long-term behavioral trends and the impacts of disruptive events such as COVID-19 (e.g., [54, 123, 207–210]) are already present.

Comparable metrics are required, ideally applied at the individual schedule level to preserve high fidelity to intrapersonal dependencies. Visual plots are useful for checking plausibility, but they do not allow for cross-model comparisons. As outlined in Section 4, most models rely on in-sample checks. In contrast, out-of-sample validation using a different dataset is often infeasible due to contextual differences. Moreover, in-sample checks mostly preserve state probabilities and serve as implementation checks rather than conceptual validation. Therefore, they should be named as such and are not a substitute for empirical validation. Because aggregation can hide timing errors, peaks, and correlations, validation should, whenever possible, be conducted at the most disaggregated level available. Fidelity, diversity, and generalization should be measured with feasible metrics, leveraging concepts from synthetic data research. For policy-relevant applications such as flexibility assessments and peak-demand projections, evaluation must go beyond individual-level statistics. In particular, approaches that simulate occupants independently cannot be evaluated for intrahousehold synchronization and joint activity patterns, although these dependencies strongly affect coincident peaks and downstream flexibility estimates. Therefore, benchmarking should include metrics at both the individual and household levels.

To make models easier to adjust and further develop, to track progress, and to enable their use in tools without long data-acquisition processes, more open work is needed: minimal benchmark datasets, transferable validation frameworks [193], and modular implementations to swap technology modules and reflect country specifics. Because few datasets link time-use data with smart metering [77], broader data would strengthen the activity–load transition. Community efforts highlight the need for accessible, interoperable datasets; synthetic data offer privacy-preserving avenues for energy research [211].

5.3. Consistent linkage of activities to energy service demands

Energy service demands are only partially represented in the reviewed models, as summarized in Table 2. Only a small number of studies address all four demand-service categories, but none provides a consistent representation of occupant behavior across services. Mobility, in particular, is significantly underrepresented despite its growing contribution to household electricity demand. The importance of including mobility is highlighted by Ramírez-Mendiola et al. [212], who investigate different commuting types and show that potential electric-vehicle charging can markedly raise evening household peak demand. This gap may bias system planning and flexibility assessments if mobility-driven peaks and load shifting options are omitted.

The link between activity schedules and energy demand is weak in many models, even though it is critical for cross-service consistency, i.e., capturing inter-service correlations and maintaining temporal stability within each demand module. Most models use simple occupants' presence rather than activities, widening the mapping, increasing reliance on probability distributions, and reducing closeness to the actual activity. Furthermore, a more granular set of activity states is generally beneficial, as it provides more information for the transformation process than an aggregated state that includes multiple, potentially diverse, energy-related activities. Activity-based models still show weak linkages. Few capture multiple, tightly linked services, and none capture high-resolution space heating and mobility together, despite their large loads and flexibility potential in the future. In particular, weak, stochastic coupling may underestimate coincident peaks across services.

Assigning appropriate appliance demand to specific activities remains challenging for future models. Appliance sharing mainly arises from joint, activity-dependent use. When such joint activities are modeled, shared demand can be allocated explicitly. Yet most models capture only random coincidence, treating this as the entirety of appliance sharing.

Per-activity energy intensities are frequently simplified. Ramírez-Mendiola et al. [200] analyze the combined METER dataset [100, 101] for selected activities and identify daytime discrepancies between reported and metered use, including delays in cooking appliance operation relative to reported time and underreported TV usage. Electrical demand also varies according to meal type [213]. This underscores the need for higher fidelity activity-to-load mappings and highlights the value of combined datasets like METER.

In summary, current models rarely integrate all energy service demands consistently. Components should be driven by activity schedules that are tightly linked across services to avoid additional assumptions. Although methods could support this, no reviewed model attains strong linkage across all demands.

Overall, recent reviews and models underweight activity schedule quality, cross-service coverage, and the evaluation of synthetic generation, while overlooking recent advances. Addressing these points is crucial for improving activity-based load modeling and preparing models for future challenges.

5.4. Limitations

This review rarely covers modeling of building typologies. While the modularity of activity-based bottom-up models is a strength, applying the reviewed approaches to specific building typologies or retrofit pathways requires additional, case-specific modeling assumptions (e.g., envelope and HVAC characteristics, control strategies) that are not standardized across studies.

The reviewed modeling literature is concentrated in high-income jurisdictions, reflecting where modeling efforts and applied case studies have been most active. At the same time, time-use surveys exist across all continents, though with uneven coverage and varying survey designs.

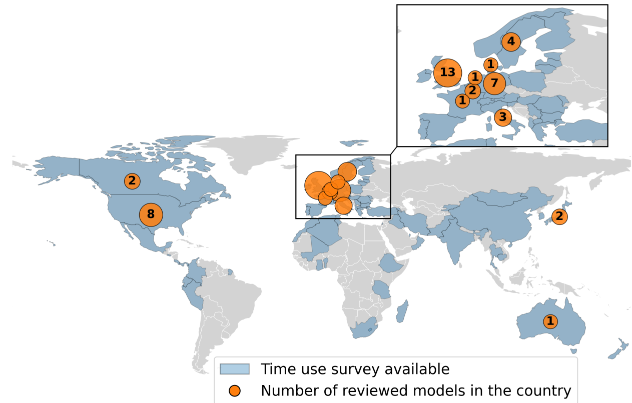


Figure 8: Global coverage of time-use surveys and reviewed models. Time-use survey coverage is based on the compilation by Charmes [89]. Switzerland was added manually [91]. The coverage should be understood as a broad indication and is not exhaustive.

Differences in survey design, variable definitions, and contextual conditions can lead to survey-specific biases and constrain transferability across countries and population groups. Nevertheless, time-use surveys are available in multiple countries where currently no models are published (compare Figure 8), and should be part of future research. Also, the bottom-up and modular character of these models can support transfer to regions with sparser data, for example by using data from more comparable countries.

High activity resolution (as available in time-use surveys) enables more specific activity-to-demand mappings (e.g., TV watching mapped to TV use), which supports interpretable analysis of which activities benefit or are penalized under dynamic tariffs and which activity-linked loads could plausibly be shifted. For example, today the activity "laundry" may be mapped directly to appliance starts. In future, bottom-up models could extend this by integrating assumptions about deferrable execution (e.g., delayed start or smart control). In contrast, when device starts are conditioned only on coarse occupancy states (e.g., "at home and active"), the behavioral basis is less specific, limiting attribution and reducing the ability to assess targeted behavioral or technology interventions. Nevertheless, for coarse objectives such as aggregate annual demand or average daily load shapes at low temporal resolution, simpler occupancy-based approaches can be sufficient. Even when not strictly necessary, higher-resolution activity modeling is unlikely to be detrimental if the added complexity remains manageable. Detailed activity modeling provides clear added value when analyses depend on cross-service correlations and coincident peaks, technology-specific flexibility potentials, or distribution-level constraints, where timing and the explainability of peaks matter.

6. Conclusion

Residential energetic load modeling is needed to understand electricity demand and flexibility, especially in light of future changes, as the electrification of the mobility and heating sectors increases household electricity demand. By simulating household behavior, activity-based bottom-up models are suitable for understanding how energy demand arises. These models have the potential to generate high-temporal-resolution activity data and to provide a consistent basis for all energy service demands, adequately capturing coincident peaks. Modeling behavioral activity data is needed due to a lack of open data and the need to combine heterogeneous datasets. Our review identifies a large number of models and addresses three research questions.

Existing models show several significant **shortcomings** **(RQ1)**. First, Markov chains (39/45) and probability density function-based models (5/45) predominate. Both approaches are structurally limited in accounting for long-range temporal dependencies, which reduces temporal consistency in generated activity schedules and thus cannot provide a consistent basis for energy demand modeling. While neural networks are state-of-the-art in many data domains, they are scarcely used in the field of activity-based modeling. Yet the available evidence suggests they can better learn long-range dependencies. Second, in holistic, activity-based household demand models, mobility and electric vehicle charging are still underrepresented, and their activity-modeling requirements are seldom treated explicitly. In particular, interactions between household members are widely neglected, as many models still simulate occupants independently. Third, the concept of consistent sector coupling has not yet been realized, as no model exists that captures all energy demands, including appliances, domestic hot water, space heating, and mobility, at a highly interlinked level. Across the reviewed models, our highest linkage category is, in principle, reachable for each demand type. However, no single model implements this level of linkage consistently across services within one framework, which limits the ability to represent simultaneous peaks. One example is concurrent space heating demand and home vehicle charging. Modelers should be more aware of the future challenges in modeling energy demand in residential buildings.

To adequately address the modeling needs of a future sector-coupled energy system, the following **requirements** arise **(RQ2)**. A core requirement is that all energy service demands should be derived from a consistent behavioral basis to capture coincident peaks. Models should also be able to simulate long-range temporal consistency to support planning applications such as capacity expansion and investment analysis, where day-to-day variability and autocorrelation affect demand peaks and flexibility availability. Moreover, mobility modeling should ensure consistent mobility patterns (e.g., transportation mode consistency for round trips and similar commuting times and distances over days). This also requires accounting for intrahousehold constraints and interactions, for example shared vehicle availability and joint trips. From a policy and planning perspective, integrating electric vehicle charging into a model with consistent, cross-service household demand representation improves peak demand projections by capturing coincident peaks (e.g., heating and charging) and supports grid-reinforcement planning. It also enables credible assessment of smart charging, vehicle-to-grid, and time-of-use tariffs as flexibility measures to mitigate congestion and reduce system costs.

Finally, **evaluation** practices remain limited **(RQ3)**. The literature lacks open benchmarking datasets and comparable metrics that make scientific progress over time visible. Domain-agnostic approaches from synthetic-data research offer potential for future development, not only for validation but also for modeling.

Overall, progress in activity-based bottom-up residential demand modeling will require stronger cross-service consistency, improved mobility integration, and reproducible benchmarking to inform planning and policy more reliably under emerging energy system challenges.

CRediT authorship contribution statement

Jonathan Vogl: Conceptualization, Methodology, Writing – original draft, Visualization, Investigation. **Max Kleinebrahm:** Conceptualization, Methodology, Writing – original draft, Supervision, Investigation. **Moritz Raab:** Writing – review & editing. **Russell McKenna:** Writing – review & editing. **Wolf Fichtner:** Writing – review & editing, Funding acquisition, Supervision.

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.

Acknowledgments

This work was supported by the project AsimutE (Autoconsommation et Stockage Intelligents pour une Meilleure Utilisation de l'Énergie) from the European Territorial Cooperation program Interreg.

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 clarity and readability of the manuscript. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

References

[1] C. Camarasa, The energy efficiency policy package: key catalyst for building decarbonisation and climate action, https://www.iea.org/commentaries/the-energy-efficiency-policy-package-key-catalyst-for-building-decarbonisation-and-climate-action (2023).

[2] R. van Heerden, O. Y. Edelenbosch, V. Daioglou, T. Le Gallic, L. B. Baptista, A. Di Bella, F. P. Colelli, J. Emmerling, P. Fragkos, R. Hasse, J. Hoppe, P. Kishimoto, F. Leblanc, J. Lefèvre, G. Luderer, G. Marangoni, A. Mastrucci, H. Pettifor, R. Pietzcker, P. Rochedo,

B. van Ruijven, R. Schaeffer, C. Wilson, S. Yeh, E. Zisarou, D. van Vuuren, Demand-side strategies enable rapid and deep cuts in buildings and transport emissions to 2050, Nature Energy 10 (3) (2025) 380–394. doi:10.1038/s41560-025-01703-1.

[3] International Energy Agency (IEA), The future of heat pumps, https://www.iea.org/reports/the-future-of-heat-pumps (2022).

[4] International Energy Agency (IEA), Net zero by 2050: A roadmap for the global energy sector, https://www.iea.org/reports/net-zero-by-2050 (2021).

[5] L. Lanz, B. Noll, T. S. Schmidt, B. Steffen, Comparing the levelized cost of electric vehicle charging options in Europe, Nature communications 13 (1) (2022) 5277. doi:10.1038/s41467-022-32835-7.

[6] International Energy Agency, Electric vehicle charging – global ev outlook 2025, Global EV Outlook 2025 chapter page, licence: CC BY 4.0; accessed 7 Oct 2025 (May 2025).
URL https://www.iea.org/reports/global-ev-outlook-2025/electric-vehicle-charging

[7] S. Luh, R. Kannan, R. McKenna, T. J. Schmidt, T. Kober, How, where, and when to charge electric vehicles – net-zero energy system implications and policy recommendations, Environmental Research Communications 5 (9) (2023) 095004, publisher: IOP Publishing. doi:10.1088/2515-7620/acf363.
URL https://doi.org/10.1088/2515-7620/acf363

[8] M. Muratori, Impact of uncoordinated plug-in electric vehicle charging on residential power demand, Nature Energy 3 (3) (2018) 193–201. doi:10.1038/s41560-017-0074-z.

[9] E. Zeyen, V. Hagenmeyer, T. Brown, Mitigating heat demand peaks in buildings in a highly renewable European energy system, Energy 231 (2021) 120784. doi:10.1016/j.energy.2021.120784.

[10] D. Connolly, Heat Roadmap Europe: Quantitative comparison between the electricity, heating, and cooling sectors for different European countries, Energy 139 (2017) 580–593. doi:10.1016/j.energy.2017.07.037.

[11] J. Lotze, M. Moser, G. Savvidis, D. Keles, V. Hagenmeyer, The complementary role of energy system and power grid models: An analysis of the European energy transformation from a holistic perspective, Energy Conversion and Management 315 (2024) 118761. doi:10.1016/j.enconman.2024.118761.

[12] T. Boßmann, I. Staffell, The shape of future electricity demand: Exploring load curves in 2050s Germany and Britain, Energy 90 (2015) 1317–1333. doi:10.1016/j.energy.2015.06.082.

[13] L. Kotzur, P. Markewitz, M. Robinius, G. Cardoso, P. Stenzel, M. Heleno, D. Stolten, Bottom-up energy supply optimization of a national building stock, Energy and Buildings 209 (2020) 109667. doi:10.1016/j.enbuild.2019.109667.

[14] I. Staffell, S. Pfenninger, The increasing impact of weather on electricity supply and demand, Energy 145 (2018) 65–78. doi:10.1016/j.energy.2017.12.051.

[15] T. Knittel, C. Lowry, M. McPherson, P. Wild, A. Rowe, Electrifying end-use demands: A rise in capacity and flexibility requirements, Energy 320 (2025) 135373. doi:10.1016/j.energy.2025.135373.

[16] L. Liu, G. He, M. Wu, G. Liu, H. Zhang, Y. Chen, J. Shen, S. Li, Climate change impacts on planned supply–demand match in global wind and solar energy systems, Nature Energy 8 (8) (2023) 870–880. doi:10.1038/s41560-023-01304-w.

[17] M. Victoria, N. Haegel, I. M. Peters, R. Sinton, A. Jäger-Waldau, C. del Cañizo, C. Breyer, M. Stocks, A. Blakers, I. Kaizuka, K. Komoto, A. Smets, Solar photovoltaics is ready to power a sustainable future, Joule 5 (5) (2021) 1041–1056. doi:10.1016/j.joule.2021.03.005.

[18] R. Way, M. C. Ives, P. Mealy, J. D. Farmer, Empirically grounded technology forecasts and the energy transition, Joule 6 (9) (2022) 2057–2082. doi:10.1016/j.joule.2022.08.009.

[19] F. J. M. M. Nijsse, J.-F. Mercure, N. Ameli, F. Larosa, S. Kothari, J. Rickman, P. Vercoulen, H. Pollitt, The momentum of the solar energy transition, Nature Communications 14 (1) (2023) 6542. doi:10.1038/s41467-023-41971-7.

[20] M. R. M. Cruz, D. Z. Fitiwi, S. F. Santos, J. P. S. Catalão, A comprehensive survey of flexibility options for supporting the low-carbon energy future, Renewable and Sustainable Energy Reviews 97 (2018) 338–353. doi:10.1016/j.rser.2018.08.028.

[21] I. Staffell, S. Pfenninger, N. Johnson, A global model of hourly space heating and cooling demand at multiple spatial scales, Nature Energy 8 (12) (2023) 1328–1344. doi:10.1038/s41560-023-01341-5.

[22] M. Muratori, P. Jadun, B. Bush, D. Bielen, L. Vimmerstedt, J. Gonder, C. Gearhart, D. Arent, Future integrated mobility-energy systems: A modeling perspective, Renewable and Sustainable Energy Reviews 119 (2020) 109541. doi:10.1016/j.rser.2019.109541.

[23] T. Brown, D. Schlachtberger, A. Kies, S. Schramm, M. Greiner, Synergies of sector coupling and transmission reinforcement in a cost-optimised, highly renewable European energy system, Energy 160 (2018) 720–739. doi:10.1016/j.energy.2018.06.222.

[24] H. Li, Z. Wang, T. Hong, M. A. Piette, Energy flexibility of residential buildings: A systematic review of characterization and quantification methods and applications, Advances in Applied Energy 3 (2021) 100054. doi:10.1016/j.adapen.2021.100054.

[25] L. Brodnicke, F. Kachirayil, P. Gabrielli, G. Sansavini, R. McKenna, Transforming decentralized energy systems: Flexible EV charging and its impact across urbanization degrees, Applied Energy 384 (2025) 125303. doi:10.1016/j.apenergy.2025.125303.

[26] R. V. Jones, A. Fuertes, K. J. Lomas, The socio-economic, dwelling and appliance related factors affecting electricity consumption in domestic buildings, Renewable and Sustainable Energy Reviews 43 (2015) 901–917. doi:10.1016/j.rser.2014.11.084.

[27] J. Chen, X. Wang, K. Steemers, A statistical analysis of a residential energy consumption survey study in Hangzhou, China, Energy and Buildings 66 (2013) 193–202. doi:10.1016/j.enbuild.2013.07.045.

[28] P. van den Brom, A. Meijer, H. Visscher, Performance gaps in energy consumption: household groups and building characteristics, Building Research and Information 46 (1) (2018) 54–70. doi:10.1080/09613218.2017.1312897.

[29] A. Kavousian, R. Rajagopal, M. Fischer, Determinants of residential electricity consumption: Using smart meter data to examine the effect of climate, building characteristics, appliance stock, and occupants' behavior, Energy 55 (2013) 184–194. doi:10.1016/j.energy.2013.03.086.

[30] S. Wei, R. Jones, P. de Wilde, Driving factors for occupant-controlled space heating in residential buildings, Energy and Buildings 70 (2014) 36–44. doi:10.1016/j.enbuild.2013.11.001.

[31] A. Rinaldi, M. Schweiker, F. Iannone, On uses of energy in buildings: Extracting influencing factors of occupant behaviour by means of a questionnaire survey, Energy and Buildings 168 (2018) 298–308. doi:10.1016/j.enbuild.2018.03.045.

[32] A. Bertrand, A. Mastrucci, N. Schüler, R. Aggoune, F. Maréchal, Characterisation of domestic hot water end-uses for integrated urban thermal energy assessment and optimisation, Applied Energy 186 (2017) 152–166. doi:10.1016/j.apenergy.2016.02.107.

[33] M. Anvari, E. Proedrou, B. Schäfer, C. Beck, H. Kantz, M. Timme, Data-driven load profiles and the dynamics of residential electricity consumption, Nature Communications 13 (1) (2022) 4593. doi:10.1038/s41467-022-31942-9.

[34] M. Kleinebrahm, Future residential energy system design, Ph.D. thesis, Karlsruher Institut für Technologie (KIT), 37.12.01; LK 01 (2024). doi:10.5445/IR/1000170239.

[35] M. Armstrong, M. C. Swinton, H. Ribberink, I. Beausoleil-Morrison, J. Millette, Synthetically derived profiles for representing occupant-driven electric loads in Canadian Housing, Journal of Building Performance Simulation 2 (1) (2009) 15–30. doi:10.1080/19401490802706653.

[36] M. Aydinalp, V. Ismet Ugursal, A. S. Fung, Modeling of the appliance, lighting, and space-cooling energy consumptions in the residential sector using neural networks, Applied Energy 71 (2) (2002) 87–110. doi:10.1016/S0306-2619(01)00049-6.

[37] M. Aydinalp, V. Ismet Ugursal, A. S. Fung, Modeling of the space and domestic hot-water heating energy-consumption in the residential sector using neural networks, Applied Energy 79 (2) (2004) 159–178. doi:10.1016/j.apenergy.2003.12.006.

[38] A. Capasso, W. Grattieri, R. Lamedica, A. Prudenzi, A bottom-up approach to residential load modeling, IEEE Transactions on Power Systems 9 (2) (1994) 957–964. doi:10.1109/59.317650.

[39] F. Causone, S. Carlucci, M. Ferrando, A. Marchenko, S. Erba, A data-driven procedure to model occupancy and occupant-related electric load profiles in residential buildings for energy simulation, Energy and Buildings 202 (2019) 109342. doi:10.1016/j.enbuild.2019.109342.

[40] F. Charbonnier, T. Morstyn, M. McCulloch, Home electricity data generator (HEDGE): An open-access tool for the generation of electric vehicle, residential demand, and PV generation profiles, MethodsX 12 (2024) 102618. doi:10.1016/j.mex.2024.102618.

[41] R. Claeys, R. Cleenwerck, J. Knockaert, J. Desmet, Stochastic generation of residential load profiles with realistic variability based on wavelet-decomposed smart meter data, Applied Energy 350 (2023) 121750. doi:10.1016/j.apenergy.2023.121750.

[42] L. G. Swan, V. I. Ugursal, Modeling of end-use energy consumption in the residential sector: A review of modeling techniques, Renewable and Sustainable Energy Reviews 13 (8) (2009) 1819–1835. doi:10.1016/j.rser.2008.09.033.

[43] K. Gram-Hanssen, Efficient technologies or user behaviour, which is the more important when reducing households' energy consumption?, Energy Efficiency 6 (3) (2013) 447–457. doi:10.1007/s12053-012-9184-4.

[44] K. Steemers, G. Y. Yun, Household energy consumption: a study of the role of occupants, Building Research & Information 37 (5-6) (2009) 625–637. doi:10.1080/09613210903186661.

[45] R. C. Sonderegger, Movers and stayers: The resident's contribution to variation across houses in energy consumption for space heating, Energy and Buildings 1 (3) (1978) 313–324. doi:10.1016/0378-7788(78)90011-7.

[46] G. Buttitta, W. J. N. Turner, O. Neu, D. P. Finn, Development of occupancy-integrated archetypes: Use of data mining clustering techniques to embed occupant behaviour profiles in archetypes, Energy and Buildings 198 (2019) 84–99. doi:10.1016/j.enbuild.2019.05.056.

[47] V. Martinaitis, E. K. Zavadskas, V. Motuzienė, T. Vilutienė, Importance of occupancy information when simulating energy demand of energy efficient house: A case study, Energy and Buildings 101 (2015) 64–75. doi:10.1016/j.enbuild.2015.04.031.

[48] T. S. Blight, D. A. Coley, Sensitivity analysis of the effect of occupant behaviour on the energy consumption of passive house dwellings, Energy and Buildings 66 (2013) 183–192. doi:10.1016/j.enbuild.2013.06.030.

[49] C. Hiller, Influence of residents on energy use in 57 Swedish houses measured during four winter days, Energy and Buildings 54 (2012) 376–385. doi:10.1016/j.enbuild.2012.06.030.

[50] M. Bonte, F. Thellier, B. Lartigue, Impact of occupant's actions on energy building performance and thermal sensation, Energy and Buildings 76 (2014) 219–227. doi:10.1016/j.enbuild.2014.02.068.

[51] D. Sood, I. Alhindawi, U. Ali, J. A. McGrath, M. A. Byrne, D. Finn, J. O'Donnell, Simulation-based evaluation of occupancy on energy consumption of multi-scale residential building archetypes, Journal of Building Engineering 75 (2023) 106872. doi:10.1016/j.jobe.2023.106872.

[52] S. Akbari, F. Haghighat, Occupancy and occupant activity drivers of energy consumption in residential buildings, Energy and Buildings 250 (2021) 111303. doi:10.1016/j.enbuild.2021.111303.

[53] E. Proedrou, A Comprehensive Review of Residential Electricity Load Profile Models, IEEE Access 9 (2021) 12114–12133. doi:10.1109/ACCESS.2021.3050074.

[54] A. Sekar, E. Williams, R. Chen, Changes in Time Use and Their Effect on Energy Consumption in the United States, Joule 2 (3) (2018) 521–536. doi:10.1016/j.joule.2018.01.003.

[55] Y. Shimoda, Y. Yamaguchi, Y. Iwafune, K. Hidaka, A. Meier, Y. Yagita, H. Kawamoto, S. Nishikiori, Energy demand science for a decarbonized society in the context of the residential sector, Renewable and Sustainable Energy Reviews 132 (2020) 110051. doi:10.1016/j.rser.2020.110051.

[56] X. Kang, J. An, D. Yan, A systematic review of building electricity use profile models, Energy and Buildings 281 (2023) 112753. doi:10.1016/j.enbuild.2022.112753.

[57] M. Kleinebrahm, J. Torriti, R. McKenna, A. Ardone, W. Fichtner, Using neural networks to model long-term dependencies in occupancy behavior, Energy and Buildings 240 (2021) 110879. doi:10.1016/j.enbuild.2021.110879.

[58] M. Muratori, M. C. Roberts, R. Sioshansi, V. Marano, G. Rizzoni, A highly resolved modeling technique to simulate residential power demand, Applied Energy 107 (2013) 465–473. doi:10.1016/j.apenergy.2013.02.057.

[59] T. Yunusov, J. Torriti, Distributional effects of Time of Use tariffs based on electricity demand and time use, Energy Policy 156 (2021) 112412. doi:10.1016/j.enpol.2021.112412.

[60] J. Torriti, T. Yunusov, It's only a matter of time: Flexibility, activities and time of use tariffs in the United Kingdom, Energy Research & Social Science 69 (2020) 101697. doi:10.1016/j.erss.2020.101697.

[61] X. Xu, C.-f. Chen, Energy efficiency and energy justice for U.S. low-income households: An analysis of multifaceted challenges and potential, Energy Policy 128 (2019) 763–774. doi:10.1016/j.enpol.2019.01.020.

[62] A. Grandjean, J. Adnot, G. Binet, A review and an analysis of the residential electric load curve models, Renewable and Sustainable Energy Reviews 16 (9) (2012) 6539–6565. doi:10.1016/j.rser.2012.08.013.

[63] J. Torriti, A review of time use models of residential electricity demand, Renewable and Sustainable Energy Reviews 37 (2014) 265–272. doi:10.1016/j.rser.2014.05.034.

[64] D. Yan, W. O'Brien, T. Hong, X. Feng, H. Burak Gunay, F. Tahmasebi, A. Mahdavi, Occupant behavior modeling for building performance simulation: Current state and future challenges, Energy and Buildings 107 (2015) 264–278. doi:10.1016/j.enbuild.2015.08.032.

[65] I. Gaetani, P.-J. Hoes, J. L. Hensen, Occupant behavior in building energy simulation: Towards a fit-for-purpose modeling strategy, Energy and Buildings 121 (2016) 188–204. doi:10.1016/j.enbuild.2016.03.038.

[66] F. Stazi, F. Naspi, M. D'Orazio, A literature review on driving factors and contextual events influencing occupants' behaviours in buildings, Building and Environment 118 (2017) 40–66. doi:10.1016/j.buildenv.2017.03.021.

[67] E. Delzendeh, S. Wu, A. Lee, Y. Zhou, The impact of occupants' behaviours on building energy analysis: A research review, Renewable and Sustainable Energy Reviews 80 (2017) 1061–1071. doi:10.1016/j.rser.2017.05.264.

[68] E. Fuentes, L. Arce, J. Salom, A review of domestic hot water consumption profiles for application in systems and buildings energy performance analysis, Renewable and Sustainable Energy Reviews 81 (2018) 1530–1547. doi:10.1016/j.rser.2017.05.229.

[69] Y. Yamaguchi, S. Yilmaz, N. Prakash, S. K. Firth, Y. Shimoda, A cross analysis of existing methods for modelling household appliance use, Journal of Building Performance Simulation 12 (2) (2018) 160–179. doi:10.1080/19401493.2018.1497087.

[70] T. Hong, Y. Chen, Z. Belafi, S. D'Oca, Occupant behavior models: A critical review of implementation and representation approaches in building performance simulation programs, Building Simulation 11 (1) (2018) 1–14. doi:10.1007/s12273-017-0396-6.

[71] Y. Zhang, X. Bai, F. P. Mills, J. C. V. Pezzey, Rethinking the role of occupant behavior in building energy performance: A review, Energy and Buildings 172 (2018) 279–294. doi:10.1016/j.enbuild.2018.05.017.

[72] B. F. Balvedi, E. Ghisi, R. Lamberts, A review of occupant behaviour in residential buildings, Energy and Buildings 174 (2018) 495–505.

doi:10.1016/j.enbuild.2018.06.049.

[73] G. Happle, J. A. Fonseca, A. Schlueter, A review on occupant behavior in urban building energy models, Energy and Buildings 174 (2018) 276–292. doi:10.1016/j.enbuild.2018.06.030.

[74] B. Dong, D. Yan, Z. Li, Y. Jin, X. Feng, H. Fontenot, Modeling occupancy and behavior for better building design and operation—A critical review, Building Simulation 11 (5) (2018) 899–921. doi:10.1007/s12273-018-0452-x.

[75] J. Li, Z. J. Yu, F. Haghighat, G. Zhang, Development and improvement of occupant behavior models towards realistic building performance simulation: A review, Sustainable Cities and Society 50 (2019) 101685. doi:10.1016/j.scs.2019.101685.

[76] S. Carlucci, M. De Simone, S. K. Firth, M. B. Kjærgaard, R. Markovic, M. S. Rahaman, M. K. Annaqeeb, S. Biandrate, A. Das, J. W. Dziedzic, G. Fajilla, M. Favero, M. Ferrando, J. Hahn, M. Han, Y. Peng, F. Salim, A. Schlüter, C. van Treeck, Modeling occupant behavior in buildings, Building and Environment 174 (2020) 106768. doi:10.1016/j.buildenv.2020.106768.

[77] J. Torriti, Temporal aggregation: Time use methodologies applied to residential electricity demand, Utilities Policy 64 (2020) 101039. doi:10.1016/j.jup.2020.101039.

[78] N. Rezvany, T. Hillel, M. Bierlaire, Integrated models of transport and energy demand: A literature review and framework, in: Proceedings of the 21st Swiss Transport Research Conference (STRC 2021), Monte Verità, Ascona, Switzerland, 2021, pp. 1–36.
URL https://transp-or.epfl.ch/documents/proceedings/RezHilBie_STRC2021.pdf

[79] S. Chen, G. Zhang, X. Xia, Y. Chen, S. Setunge, L. Shi, The impacts of occupant behavior on building energy consumption: A review, Sustainable Energy Technologies and Assessments 45 (2021) 101212. doi:10.1016/j.seta.2021.101212.

[80] M. Osman, M. Ouf, A comprehensive review of time use surveys in modelling occupant presence and behavior: Data, methods, and applications, Building and Environment 196 (2021) 107785. doi:10.1016/j.buildenv.2021.107785.

[81] Y. Li, Y. Yamaguchi, Y. Shimoda, Impact of the pre-simulation process of occupant behaviour modelling for residential energy demand simulations, Journal of Building Performance Simulation 15 (3) (2022) 287–306. doi:10.1080/19401493.2021.2022759.

[82] S. Dabirian, K. Panchabikesan, U. Eicker, Occupant-centric urban building energy modeling: Approaches, inputs, and data sources - A review, Energy and Buildings 257 (2022) 111809. doi:10.1016/j.enbuild.2021.111809.

[83] A. Kewo, A Rigorous Standalone Literature Review of Residential Electricity Load Profiles, Energies 16 (10) (2023) 4072–4072. doi:10.3390/en16104072.

[84] S. Vosoughkhosravi, A. Jafari, Y. Zhu, Application of American time use survey (ATUS) in modelling energy-related occupant-building interactions: A comprehensive review, Energy and Buildings 294 (2023) 113245. doi:10.1016/j.enbuild.2023.113245.

[85] O. Ahmed, N. Sezer, M. Ouf, L. L. Wang, I. G. Hassan, State-of-the-art review of occupant behavior modeling and implementation in building performance simulation, Renewable and Sustainable Energy Reviews 185 (2023) 113558. doi:10.1016/j.rser.2023.113558.

[86] A. Mylonas, A. Tsangrassoulis, J. Pascual, Modelling occupant behaviour in residential buildings: A systematic literature review, Building and Environment 265 (2024) 111959. doi:10.1016/j.buildenv.2024.111959.

[87] A. Banfi, M. Ferrando, P. Li, X. Shi, F. Causone, Integrating Occupant Behaviour into Urban-Building Energy Modelling: A Review of Current Practices and Challenges, Energies 17 (17) (2024) 4400. doi:10.3390/en17174400.

[88] H. Frazis, J. Stewart, How to think about time-use data: What inferences can we make about long- and short-run time use from time diaries?, Annals of Economics and Statistics 105-106 (2012) 231–245. doi:10.2307/23646463.

[89] J. Charmes, Time use across the world: Findings of a world compilation of time use surveys, Background paper, United Nations Development Programme, Human Development Report Office, New York, background paper for the 2015 Human Development Report; updated Feb. 2016 (2015).
URL https://hdr.undp.org/system/files/documents/charmeshdr2015final.pdf

[90] A. Roeters, J. D. Vlasblom, A week at a glance (2018).
URL https://digitaal.scp.nl/timeuse1/a-week-at-a-glance/

[91] C. Winkler, A. Meister, K. W. Axhausen, The TimeUse+ data set: 4 weeks of time use and expenditure data based on GPS tracks, Transportationdoi:10.1007/s11116-024-10517-1.

[92] K. Fisher, J. Gershuny, A. H. Gauthier, Multinational time use study (MTUS), 1961-2019, accessed 24 Sep 2025 (2019).
URL https://www.timeuse.org/mtus

[93] Harmonised european time use surveys (hetus), Eurostat webpage, accessed 24 Sep 2025 (2019).
URL https://ec.europa.eu/eurostat/web/time-use-surveys

[94] I. (INE), Encuesta de empleo del tiempo (eet): 2002–2003 y 2009–2010 [time use survey (eet): 2002–2003 and 2009–2010], iNE microdata catalogue webpage (2010).
URL https://datos.gob.es/es/catalogo/e00055401-encuesta-de-empleo-del-tiempo-2009-2010

[95] U.S. Bureau of Labor Statistics, American time use survey user's guide: Understanding the ATUS 2003 to 2020, accessed 24 Sep 2025 (2021).
URL https://www.bls.gov/tus/atususersguide.pdf

[96] R. Follmer, Mobilität in deutschland – mid kurzbericht, Kurzbericht FE-Nr. VB600001, infas Institut für angewandte Sozialwissenschaft GmbH; Deutsches Zentrum für Luft- und Raumfahrt (DLR), Institut für Verkehrsforschung; IVT Research GmbH; infas 360 GmbH, Bonn; Berlin, version 1.2 (May 2025).
URL http://www.mobilitaet-in-deutschland.de

[97] Transport for London, Travel in london 2024: The travel behaviour of london residents based on the london travel demand survey — 2023/24 update, Tech. rep., Transport for London, London, © Transport for London 2024 (Dec. 2024).
URL https://tfl.gov.uk/corporate/publications-and-reports/travel-in-london-reports-past-years

[98] S. Bricka, T. Reuscher, P. Schroeder, M. Fisher, J. Beard, X. L. Sun, Summary of travel trends: 2022 national household travel survey, Tech. Rep. FHWA-HPL-24-009, United States. Federal Highway Administration. Office of Policy and Governmental Affairs, Washington, DC, trends in travel behavior, 1969–2022 (Jan. 2024).
URL https://rosap.ntl.bts.gov/view/dot/73764

[99] L. Ecke, B. Chlond, M. Magdolen, P. Vortisch, Deutsches Mobilitätspanel (MOP) – wissenschaftliche begleitung und auswertungen. bericht 2019/2020: Alltagsmobilität und Fahrleistung, Tech. rep., Karlsruher Institut für Technologie (KIT), Karlsruhe, forschungsbericht; veröffentlicht in KITopen am 01.02.2021 (Oct. 2020). doi:10.5445/IR/1000126557.

[100] P. Grünewald, Meterdata: Documentation of the database and collection methods, https://github.com/PhilGrunewald/MeterData, gitHub repository (2019).

[101] P. Grünewald, M. Diakonova, Meter: Uk household electricity and activity survey, 2016–2019: Secure access, https://datacatalogue.ukdataservice.ac.uk/studies/study/8475, dataset (2019). doi:10.5255/UKDA-SN-8475-1.

[102] J. Torriti, Understanding the timing of energy demand through time use data: Time of the day dependence of social practices, Energy Research & Social Science 25 (2017) 37–47. doi:10.1016/j.erss.2016.12.004.

[103] A. Satre-Meloy, M. Diakonova, P. Grünewald, Daily life and demand: an analysis of intra-day variations in residential electricity consumption with time-use data, Energy Efficiency 13 (3) (2020) 433–458. doi:10.1007/s12053-019-09791-1.

[104] J. Pawlak, A. Faghih Imani, A. Sivakumar, How do household activities drive electricity demand? Applying activity-based modelling in the context of the United Kingdom, Energy Research & Social Science 82 (2021) 102318. doi:10.1016/j.erss.2021.102318.

[105] A. de Almeida, P. Fonseca, R. Bandeirinha, T. Fernandes, R. Araújo, U. Nunes, M. Dupret, J. P. Zimmermann, B. Schlomann, E. Gruber, et al., Residential monitoring to decrease energy use and carbon emissions in europe, Publishable report (remodece, intelligent energy europe programme), Institute of Systems and Robotics (ISR), University of Coimbra, Coimbra, Portugal (Nov. 2008).
URL https://remodece.isr.uc.pt/downloads/REMODECE_PublishableReport_Nov2008_FINAL.pdf

[106] ENERTECH, Review of all existing european monitoring campaigns in households, Tech. Rep. Work Package 2, Document 1.1 (D2), REMODECE Project (Intelligent Energy Europe), Coimbra, accessed 24 Sep 2025 (Jul. 2006).
URL https://remodece.isr.uc.pt/downloads/REMODECE_Review_monitoring%20campaign_D2.pdf

[107] W. Jung, Z. Wang, T. Hong, F. Jazizadeh, Smart thermostat data-driven U.S. residential occupancy schedules and development of a U.S. residential occupancy schedule simulator, Building and Environment 243 (2023) 110628. doi:10.1016/j.buildenv.2023.110628.

[108] R. Melfi, B. Rosenblum, B. Nordman, K. Christensen, Measuring building occupancy using existing network infrastructure, in: 2011 International Green Computing Conference and Workshops, 2011, pp. 1–8. doi:10.1109/IGCC.2011.6008560.

[109] V. M. Barthelmes, R. Li, R. K. Andersen, W. Bahnfleth, S. P. Corgnati, C. Rode, Profiling occupant behaviour in Danish dwellings using time use survey data, Energy and Buildings 177 (2018) 329–340. doi:10.1016/j.enbuild.2018.07.044.

[110] O. Olawale, B. Gilbert, J. Reyna, Aggregate Residential Demand Flexibility Behavior: A Novel Assessment Framework (May 2022). doi:10.2139/ssrn.4103335.

[111] J.-H. Yoo, K. H. Kim, Development of methodology for estimating electricity use in residential sectors using national statistics survey data from South Korea, Energy and Buildings 75 (2014) 402–409. doi:10.1016/j.enbuild.2014.02.033.

[112] J. Widén, M. Lundh, I. Vassileva, E. Dahlquist, K. Ellegård, E. Wäckelgård, Constructing load profiles for household electricity and hot water from time-use data—Modelling approach and validation, Energy and Buildings 41 (7) (2009) 753–768. doi:10.1016/j.enbuild.2009.02.013.

[113] O. Neu, B. Sherlock, S. Oxizidis, D. Flynn, D. Finn, Developing building archetypes for electrical load shifting assessment: Analysis of Irish residential stock, in: Proceedings of the CIBSE ASHRAE Technical Symposium 2014: Moving to a New World of Building Systems Performance, Dublin, Ireland, 2014, pp. 1–19.
URL http://hdl.handle.net/10197/8136

[114] A. Satre-Meloy, M. Diakonova, P. Grünewald, Cluster analysis and prediction of residential peak demand profiles using occupant activity data, Applied Energy 260 (2020) 114246. doi:10.1016/j.apenergy.2019.114246.

[115] T. Okada, Y. Shoda, Y. Yamaguchi, Y. Shimoda, Data Preparation to Address Heterogeneity in Time Use Data Based Activity Modelling, in: Proceedings of the 16th IBPSA Conference (Building Simulation 2019), Rome, Italy, 2019, pp. 2356–2363. doi:10.26868/25222708.2019.211095.
URL https://publications.ibpsa.org/conference/paper/?id=bs2019_211095

[116] Y.-S. Chiou, Deriving u.s. household energy consumption profiles from american time use survey data – a bootstrap approach, in: Proceedings of Building Simulation 2009: 11th International IBPSA Conference, Glasgow, Scotland, 2009, pp. 151–158.
URL https://publications.ibpsa.org/proceedings/bs/2009/papers/bs2009_0151_158.pdf

[117] Y.-S. Chiou, A time use survey derived integrative human-physical household system energy performance model, in: Proceedings of PLEA 2009: 26th Conference on Passive and Low Energy Architecture, Quebec City, Canada, 2009, pp. 51–57.
URL https://web.faaad.ulaval.ca/plea2009/Papers/1.CHALLENGE/1.1%20Occupants/ORAL/1-1-08-PLEA2009Quebec.pdf

[118] Y.-S. Chiou, K. M. Carley, C. I. Davidson, M. P. Johnson, A high spatial resolution residential energy model based on American Time Use Survey data and the bootstrap sampling method, Energy and Buildings 43 (12) (2011) 3528–3538. doi:10.1016/j.enbuild.2011.09.020.

[119] M. Kleinebrahm, J. M. Weinand, E. Naber, R. McKenna, A. Ardone, W. Fichtner, Two million European single-family homes could abandon the grid by 2050, Joule 7 (11) (2023) 2485–2510. doi:10.1016/j.joule.2023.09.012.

[120] R. Gerike, T. Gehlert, F. Leisch, Time use in travel surveys and time use surveys – Two sides of the same coin?, Transportation Research Part A: Policy and Practice 76 (2015) 4–24. doi:10.1016/j.tra.2015.03.030.

[121] J. Widén, A. Molin, K. Ellegård, Models of domestic occupancy, activities and energy use based on time-use data: deterministic and stochastic approaches with application to various building-related simulations, Journal of Building Performance Simulation 5 (1) (2012) 27–44. doi:10.1080/19401493.2010.532569.

[122] S. Wolf, D. Calì, M. J. Alonso, R. Li, R. K. Andersen, J. Krogstie, H. Madsen, Room-level occupancy simulation model for private households, Journal of Physics: Conference Series 1343 (1) (2019) 012126. doi:10.1088/1742-6596/1343/1/012126.

[123] X. Zhou, Y. Lu, S. Hu, Z. Yang, D. Yan, New perspectives on temporal changes in occupancy characteristics of residential buildings, Journal of Building Engineering 64 (2023) 105590. doi:10.1016/j.jobe.2022.105590.

[124] M. Adolph, R. Streblow, D. Müller, Occupancy Profiles for Single Rooms in Residential Buildings, in: J. Mathur, V. Garg (Eds.), Proceedings of Building Simulation 2015: 14th Conference of IBPSA, Hyderabad, India, 2015, pp. 1434–1440. doi:10.26868/25222708.2015.2383.

[125] A. Taniguchi, T. Inoue, M. Otsuki, Y. Yamaguchi, Y. Shimoda, A. Takami, K. Hanaoka, Estimation of the contribution of the residential sector to summer peak demand reduction in Japan using an energy end-use simulation model, Energy and Buildings 112 (2016) 80–92. doi:10.1016/j.enbuild.2015.11.064.

[126] D. Sood, S. Wolf, D. Calì, R. Korsholm Andersen, R. Li, H. Madsen, J. O'Donnell, Room-level domestic occupancy simulation model using time use survey data, Journal of Building Performance Simulation (2025) 1–15Advance online publication. doi:10.1080/19401493.2025.2465508.

[127] L. Bottaccioli, S. Di Cataldo, A. Acquaviva, E. Patti, Realistic Multi-Scale Modeling of Household Electricity Behaviors, IEEE Access 7 (2019) 2467–2489. doi:10.1109/ACCESS.2018.2886201.

[128] X. Feng, D. Yan, T. Hong, Simulation of occupancy in buildings, Energy and Buildings 87 (2015) 348–359. doi:10.1016/j.enbuild.2014.11.067.

[129] C. Zhang, Z. Luo, Y. Rezgui, T. Zhao, Enhancing building energy consumption prediction introducing novel occupant behavior models with sparrow search optimization and attention mechanisms: A case study for forty-five buildings in a university community, Energy 294 (2024) 130896. doi:10.1016/j.energy.2024.130896.

[130] D. Mitra, N. Steinmetz, Y. Chu, K. S. Cetin, Typical occupancy profiles and behaviors in residential buildings in the United States, Energy and Buildings 210 (2020) 109713. doi:10.1016/j.enbuild.2019.109713.

[131] I. Richardson, M. Thomson, D. Infield, A. Delahunty, Domestic lighting: A high-resolution energy demand model, Energy and Buildings 41 (7) (2009) 781–789. doi:10.1016/j.enbuild.2009.02.010.

[132] J. Widén, A. M. Nilsson, E. Wäckelgård, A combined Markov-chain and bottom-up approach to modelling of domestic lighting demand, Energy and Buildings 41 (10) (2009) 1001–1012. doi:10.1016/j.enbuild.2009.05.002.

[133] E. J. Palacios-Garcia, A. Chen, I. Santiago, F. J. Bellido-Outeiriño, J. M. Flores-Arias, A. Moreno-Munoz, Stochastic model for lighting's electricity consumption in the residential sector. Impact of energy saving actions, Energy and Buildings 89 (2015) 245–259.

doi:10.1016/j.enbuild.2014.12.028.

[134] S. D'Oca, V. Fabi, S. Corgnati, R. Andersen, Effect of thermostat and window opening occupant behavior models on energy use in homes, Journal of Building Performance Simulation 7. doi:10.1007/s12273-014-0191-6.

[135] V. Fabi, R. V. Andersen, S. P. Corgnati, B. W. Olesen, A methodology for modelling energy-related human behaviour: Application to window opening behaviour in residential buildings, Building Simulation 6 (4) (2013) 415–427. doi:10.1007/s12273-013-0119-6.

[136] R. Andersen, V. Fabi, J. Toftum, S. P. Corgnati, B. W. Olesen, Window opening behaviour modelled from measurements in Danish dwellings, Building and Environment 69 (2013) 101–113. doi:10.1016/j.buildenv.2013.07.005.

[137] F. Haldi, D. Calì, R. K. Andersen, M. Wesseling, D. Müller, Modelling diversity in building occupant behaviour: a novel statistical approach, Journal of Building Performance Simulation 10 (5-6) (2017) 527–544. doi:10.1080/19401493.2016.1269245.

[138] P. Pachanapan, P. Trairat, S. Kanprachar, Synthetic Domestic Electricity Demand in Thailand using A Modified High Resolution Modelling Tool by CREST, ECTI Transactions on Electrical Engineering, Electronics, and Communications 19 (2) (2021) 145–154. doi:10.37936/ecti-eec.2021192.234341.

[139] Y. Chen, X. Liang, T. Hong, X. Luo, Simulation and visualization of energy-related occupant behavior in office buildings, Building Simulation 10 (6) (2017) 785–798. doi:10.1007/s12273-017-0355-2.

[140] Y. Chen, T. Hong, X. Luo, An agent-based stochastic Occupancy Simulator, Building Simulation 11 (1) (2018) 37–49. doi:10.1007/s12273-017-0379-7.

[141] S. Gilani, W. O'Brien, H. B. Gunay, Simulating occupants' impact on building energy performance at different spatial scales, Building and Environment 132 (2018) 327–337. doi:10.1016/j.buildenv.2018.01.040.

[142] P. D. Andersen, A. Iversen, H. Madsen, C. Rode, Dynamic modeling of presence of occupants using inhomogeneous Markov chains, Energy and Buildings 69 (2014) 213–223. doi:10.1016/j.enbuild.2013.10.001.

[143] J. Page, D. Robinson, N. Morel, J. L. Scartezzini, A generalised stochastic model for the simulation of occupant presence, Energy and Buildings 40 (2) (2008) 83–98. doi:10.1016/j.enbuild.2007.01.018.

[144] C. Wang, D. Yan, Y. Jiang, A novel approach for building occupancy simulation, Building Simulation 4 (2) (2011) 149–167. doi:10.1007/s12273-011-0044-5.

[145] R. Markovic, E. Azar, M. K. Annaqeeb, J. Frisch, C. v. Treeck, Day-ahead prediction of plug-in loads using a long short-term memory neural network, Energy and Buildings 234 (2021) 110667. doi:10.1016/j.enbuild.2020.110667.

[146] I. Richardson, M. Thomson, D. Infield, A high-resolution domestic building occupancy model for energy demand simulations, Energy and Buildings 40 (8) (2008) 1560–1566. doi:10.1016/j.enbuild.2008.02.006.

[147] I. Richardson, M. Thomson, D. Infield, C. Clifford, Domestic electricity use: A high-resolution energy demand model, Energy and Buildings 42 (10) (2010) 1878–1887. doi:10.1016/j.enbuild.2010.05.023.

[148] N. Good, L. Zhang, A. Navarro-Espinosa, P. Mancarella, High resolution modelling of multi-energy domestic demand profiles, Applied Energy 137 (2015) 193–210. doi:10.1016/j.apenergy.2014.10.028.

[149] E. McKenna, M. Krawczynski, M. Thomson, Four-state domestic building occupancy model for energy demand simulations, Energy and Buildings 96 (2015) 30–39. doi:10.1016/j.enbuild.2015.03.013.

[150] E. McKenna, M. Thomson, High-resolution stochastic integrated thermal–electrical domestic demand model, Applied Energy 165 (2016) 445–461. doi:10.1016/j.apenergy.2015.12.089.

[151] G. Buttitta, D. P. Finn, A high-temporal resolution residential building occupancy model to generate high-temporal resolution heating load profiles of occupancy-integrated archetypes, Energy and Buildings 206 (2020) 109577. doi:10.1016/j.enbuild.2019.109577.

[152] J. Widén, E. Wäckelgård, A high-resolution stochastic model of domestic activity patterns and electricity demand, Applied Energy 87 (6) (2010) 1880–1892. doi:10.1016/j.apenergy.2009.11.006.

[153] P. Grahn, J. Munkhammar, J. Widén, K. Alvehag, L. Söder, PHEV Home-Charging Model Based on Residential Activity Patterns, IEEE Transactions on Power Systems 28 (3) (2013) 2507–2515. doi:10.1109/TPWRS.2012.2230193.

[154] C. Sandels, J. Widén, L. Nordström, Forecasting household consumer electricity load profiles with a combined physical and behavioral approach, Applied Energy 131 (2014) 267–278. doi:10.1016/j.apenergy.2014.06.048.

[155] U. Wilke, F. Haldi, J.-L. Scartezzini, D. Robinson, A bottom-up stochastic model to predict building occupants' time-dependent activities, Building and Environment 60 (2013) 254–264. doi:10.1016/j.buildenv.2012.10.021.

[156] M. Muratori, M. J. Moran, E. Serra, G. Rizzoni, Highly-resolved modeling of personal transportation energy consumption in the United States, Energy 58 (2013) 168–177. doi:10.1016/j.energy.2013.02.055.

[157] B. J. Johnson, M. R. Starke, O. A. Abdelaziz, R. K. Jackson, L. M. Tolbert, A method for modeling household occupant behavior to simulate residential energy consumption, in: ISGT 2014, 2014, pp. 1–5. doi:10.1109/ISGT.2014.6816483.

[158] B. J. Johnson, M. R. Starke, O. A. Abdelaziz, R. K. Jackson, L. M. Tolbert, A MATLAB based occupant driven dynamic model for predicting residential power demand, in: 2014 IEEE PES T&D Conference and Exposition, Chicago, IL, USA, 2014, pp. 1–5. doi:10.1109/TDC.2014.6863381.

[159] D. Aerts, J. Minnen, I. Glorieux, I. Wouters, F. Descamps, A method for the identification and modelling of realistic domestic occupancy sequences for building energy demand simulations and peer comparison, Building and Environment 75 (2014) 67–78. doi:10.1016/j.buildenv.2014.01.021.

[160] A. J. Collin, G. Tsagarakis, A. E. Kiprakis, S. McLaughlin, Development of Low-Voltage Load Models for the Residential Load Sector, IEEE Transactions on Power Systems 29 (5) (2014) 2180–2188. doi:10.1109/TPWRS.2014.2301949.

[161] D. Fischer, A. Härtl, B. Wille-Haussmann, Model for electric load profiles with high time resolution for German households, Energy and Buildings 92 (2015) 170–179. doi:10.1016/j.enbuild.2015.01.058.

[162] D. Fischer, T. Wolf, J. Scherer, B. Wille-Haussmann, A stochastic bottom-up model for space heating and domestic hot water load profiles for German households, Energy and Buildings 124 (2016) 120–128. doi:10.1016/j.enbuild.2016.04.069.

[163] D. Fischer, A. Harbrecht, A. Surmann, R. McKenna, Electric vehicles' impacts on residential electric local profiles–A stochastic modelling approach considering socio-economic, behavioural and spatial factors, Applied Energy 233 (2019) 644–658. doi:10.1016/j.apenergy.2018.10.010.

[164] F. Farzan, M. A. Jafari, J. Gong, F. Farzan, A. Stryker, A multi-scale adaptive model of residential energy demand, Applied Energy 150 (2015) 258–273. doi:10.1016/j.apenergy.2015.04.008.

[165] M. Nijhuis, M. Gibescu, J. F. G. Cobben, Bottom-up Markov Chain Monte Carlo approach for scenario based residential load modelling with publicly available data, Energy and Buildings 112 (2016) 121–129. doi:10.1016/j.enbuild.2015.12.004.

[166] F. Bizzozero, G. Gruosso, N. Vezzini, A time-of-use-based residential electricity demand model for smart grid applications, in: 2016 IEEE 16th International Conference on Environment and Electrical Engineering (EEEIC), 2016, pp. 1–6. doi:10.1109/EEEIC.2016.7555400.

[167] G. Gruosso, Analysis of impact of electrical vehicle charging on low voltage power grid, in: 2016 International Conference on Electrical Systems for Aircraft, Railway, Ship Propulsion and Road Vehicles & International Transportation Electrification Conference (ESARS-ITEC), 2016, pp. 1–6. doi:10.1109/ESARS-ITEC.2016.7841365.

[168] R. Baetens, D. Saelens, Modelling uncertainty in district energy simulations by stochastic residential occupant behaviour, Journal of Building Performance Simulationdoi:10.1080/19401493.2015.1070203.

[169] G. Flett, N. Kelly, An occupant-differentiated, higher-order Markov Chain method for prediction of domestic occupancy, Energy and Buildings 125 (2016) 219–230. doi:10.1016/j.enbuild.2016.05.015.

[170] G. Flett, N. Kelly, A disaggregated, probabilistic, high resolution method for assessment of domestic occupancy and electrical demand, Energy and Buildings 140 (2017) 171–187. doi:10.1016/j.enbuild.2017.01.069.

[171] G. Flett, N. Kelly, Modelling of individual domestic occupancy and energy demand behaviours using existing datasets and probabilistic modelling methods, Energy and Buildings 252 (2021) 111373. doi:10.1016/j.enbuild.2021.111373.

[172] L. Diao, Y. Sun, Z. Chen, J. Chen, Modeling energy consumption in residential buildings: A bottom-up analysis based on occupant behavior pattern clustering and stochastic simulation, Energy and Buildings 147 (2017) 47–66. doi:10.1016/j.enbuild.2017.04.072.

[173] Y. Yamaguchi, Y. Shimoda, A stochastic model to predict occupants' activities at home for community-/urban-scale energy demand modelling, Journal of Building Performance Simulation 10 (5-6) (2017) 565–581. doi:10.1080/19401493.2017.1336255.

[174] J. L. Ramírez-Mendiola, P. Grünewald, N. Eyre, Residential activity pattern modelling through stochastic chains of variable memory length, Applied Energy 237 (2019) 417–430. doi:10.1016/j.apenergy.2019.01.019.

[175] K. Foteinaki, R. Li, C. Rode, R. K. Andersen, Modelling household electricity load profiles based on Danish time-use survey data, Energy and Buildings 202 (2019) 109355. doi:10.1016/j.enbuild.2019.109355.

[176] M. Müller, F. Biedenbach, J. Reinhard, Development of an Integrated Simulation Model for Load and Mobility Profiles of Private Households, Energies 13 (15) (2020) 3843. doi:10.3390/en13153843.

[177] L. Rueda, S. Sansregret, B. Le Lostec, K. Agbossou, N. Henao, S. Kelouwani, A Probabilistic Model to Predict Household Occupancy Profiles for Home Energy Management Applications, IEEE Access 9 (2021) 38187–38201. doi:10.1109/ACCESS.2021.3063502.

[178] B. Jeong, J. Kim, R. de Dear, Creating household occupancy and energy behavioural profiles using national time use survey data, Energy and Buildings 252 (2021) 111440. doi:10.1016/j.enbuild.2021.111440.

[179] D. M. Koupaei, K. S. Cetin, U. Passe, Stochastic residential occupancy schedules based on the American Time-Use Survey, Science and Technology for the Built Environmentdoi:10.1080/23744731.2022.2087536.

[180] J. Chen, R. Adhikari, E. Wilson, J. Robertson, A. Fontanini, B. Polly, O. Olawale, Stochastic simulation of occupant-driven energy use in a bottom-up residential building stock model, Applied Energy 325 (2022) 119890. doi:10.1016/j.apenergy.2022.119890.

[181] M. Osman, M. Ouf, E. Azar, B. Dong, Stochastic bottom-up load profile generator for Canadian households' electricity demand, Building and Environment 241 (2023) 110490. doi:10.1016/j.buildenv.2023.110490.

[182] R. Zhang, T. Zhou, H. Ye, J. Darkwa, Introducing a novel method for simulating stochastic movement and occupancy in residential spaces using time-use survey data, Energy and Buildings 304 (2024) 113854. doi:10.1016/j.enbuild.2023.113854.

[183] M. Barsanti, S. Yilmaz, C. R. Binder, Informing targeted Demand-Side Management: Leveraging appliance usage patterns to model residential energy demand heterogeneity, Energy and Buildings 321 (2024) 114639. doi:10.1016/j.enbuild.2024.114639.

[184] S. Yu, P. Mascherbauer, T. Haupt, H. Rickmann, M. Kochanski, K. Skorna, L. Kranzl, Modeling Households' Behavior, Energy System Operation, and Interaction in the Energy Community (Apr. 2024). doi:10.2139/ssrn.4807715.

[185] H. Wang, F. Guo, A. Sivakumar, Analysing the impact of electric vehicle charging on households: An interrelated load profile generation approach, Energy and Buildings 335 (2025) 115558. doi:10.1016/j.enbuild.2025.115558.

[186] M. A. López-Rodríguez, I. Santiago, D. Trillo-Montero, J. Torriti, A. Moreno-Munoz, Analysis and modeling of active occupancy of the residential sector in Spain: An indicator of residential electricity consumption, Energy Policy 62 (2013) 742–751. doi:10.1016/j.enpol.2013.07.095.

[187] A. Bampoulas, F. Pallonetto, E. Mangina, D. P. Finn, A Bayesian deep-learning framework for assessing the energy flexibility of residential buildings with multicomponent energy systems, Applied Energy 348 (2023) 121576. doi:10.1016/j.apenergy.2023.121576.

[188] U. Jordan, K. Vajen, Realistic domestic hot-water profiles in different time scales, Technical report, Universität Marburg, FB Physik, FG Solar; IEA SHC Task 26, Marburg, Germany, version 2.0 (May 2001).
URL https://sel.me.wisc.edu/trnsys/trnlib/iea-shc-task26/iea-shc-task26-load-profiles-description-jordan.pdf

[189] R. Diao, S. Lu, M. Elizondo, E. Mayhorn, Z. Yu, N. Samaan, Electric water heater modeling and control strategies for demand response, in: 2012 IEEE Power and Energy Society General Meeting, San Diego, CA, 2012, pp. 1–8. doi:10.1109/PESGM.2012.6345632.

[190] E. J. Wilson, ResStock – targeting energy and cost savings for U.S. homes, Fact Sheet NREL/FS-5500-68653, National Renewable Energy Laboratory (NREL), Golden, CO (Sep. 2017).
URL https://www.osti.gov/biblio/1398250

[191] T. Hilgert, M. Heilig, M. Kagerbauer, P. Vortisch, Modeling Week Activity Schedules for Travel Demand Models, Transportation Research Record 2666 (1) (2017) 69–77. doi:10.3141/2666-08.

[192] M. J. Roorda, E. J. Miller, K. M. N. Habib, Validation of TASHA: A 24-h activity scheduling microsimulation model, Transportation Research Part A: Policy and Practice 42 (2) (2008) 360–375.
URL https://ideas.repec.org//a/eee/transa/v42y2008i2p360-375.html

[193] D. Neuroth, N. Pflugradt, J. M. Weinand, C. Büsing, D. Stolten, ETHOS.ActivityAssure—An open-source validation framework for synthetic European activity profiles, Energy and Buildings 326 (2025) 115036. doi:10.1016/j.enbuild.2024.115036.

[194] Z. Qian, B.-C. Cebere, M. van der Schaar, Synthcity: facilitating innovative use cases of synthetic data in different data modalities (Jan. 2023). doi:10.48550/arXiv.2301.07573.

[195] S. Chai, G. Chadney, Faraday: Synthetic smart meter generator for the smart grid (2024). doi:10.48550/arXiv.2404.04314.

[196] M. Turowski, B. Heidrich, L. Weingärtner, L. Springer, K. Phipps, B. Schäfer, R. Mikut, V. Hagenmeyer, Generating synthetic energy time series: A review, Renewable and Sustainable Energy Reviews 206 (2024) 114842. doi:10.1016/j.rser.2024.114842.

[197] A. Alaa, B. V. Breugel, E. S. Saveliev, M. van der Schaar, How Faithful is your Synthetic Data? Sample-level Metrics for Evaluating and Auditing Generative Models, in: Proceedings of the 39th International Conference on Machine Learning, 2022, pp. 290–306. doi:10.48550/arXiv.2102.08921.

[198] L. Rueda, K. Agbossou, A. Cardenas, N. Henao, S. Kelouwani, A comprehensive review of approaches to building occupancy detection, Building and Environment 180 (2020) 106966. doi:10.1016/j.buildenv.2020.106966.

[199] Y. Li, Y. Yamaguchi, J. Torriti, Y. Shimoda, Modeling of occupant behavior considering spatial variation: Geostatistical analysis and application based on American time use survey data, Energy and Buildings 281 (2023) 112754. doi:10.1016/j.enbuild.2022.112754.

[200] J. L. Ramírez-Mendiola, P. Grünewald, N. Eyre, Linking intraday variations in residential electricity demand loads to consumers' activities: What's missing?, Energy and Buildings 161 (2018) 63–71. doi:10.1016/j.enbuild.2017.12.012.

[201] I. Bromley-Dulfano, X. Zhu, B. Mather, Behavioral and Population Data-Driven Distribution System Load Modeling, in: 2022 IEEE 49th Photovoltaics Specialists Conference (PVSC), Philadelphia,

PA, USA, 2022, pp. 0907–0912. doi:10.1109/PVSC48317.2022.9938823.

[202] Y. Al-Wreikat, C. Serrano, J. R. Sodré, Effects of ambient temperature and trip characteristics on the energy consumption of an electric vehicle, Energy 238 (2022) 122028. doi:10.1016/j.energy.2021.122028.

[203] J. Min, Z. Hausfather, Q. F. Lin, A High-Resolution Statistical Model of Residential Energy End Use Characteristics for the United States, Journal of Industrial Ecology 14 (5) (2010) 791–807. doi:10.1111/j.1530-9290.2010.00279.x.

[204] R. Stamminger, A. Schmitz, Load profiles and flexibility in operation of washing machines and dishwashers in Europe, International Journal of Consumer Studies 41 (2) (2017) 178–187. doi:10.1111/ijcs.12325.

[205] Y. Yamaguchi, C.-f. Chen, Y. Shimoda, Y. Yagita, Y. Iwafune, H. Ishii, Y. Hayashi, An integrated approach of estimating demand response flexibility of domestic laundry appliances based on household heterogeneity and activities, Energy Policy 142 (2020) 111467. doi:10.1016/j.enpol.2020.111467.

[206] A. Sekar, E. Williams, R. Chen, Heterogeneity in time and energy use of watching television, Energy Policy 93 (2016) 50–58. doi:10.1016/j.enpol.2016.02.035.

[207] B. Anderson, J. Torriti, Explaining shifts in UK electricity demand using time use data from 1974 to 2014, Energy Policy 123 (2018) 544–557. doi:10.1016/j.enpol.2018.09.025.

[208] B. Anderson, Laundry, energy and time: Insights from 20 years of time-use diary data in the United Kingdom, Energy Research & Social Science 22 (2016) 125–136. doi:10.1016/j.erss.2016.09.004.

[209] M. Jalas, J. K. Juntunen, Energy intensive lifestyles: Time use, the activity patterns of consumers, and related energy demands in Finland, Ecological Economics 113 (2015) 51–59. doi:10.1016/j.ecolecon.2015.02.016.

[210] D. Mitra, Y. Chu, K. Cetin, COVID-19 impacts on residential occupancy schedules and activities in U.S. Homes in 2020 using ATUS, Applied Energy 324 (2022) 119765. doi:10.1016/j.apenergy.2022.119765.

[211] LF Energy, Opensynth – synthetic data for energy modeling, accessed 24 Sep 2025 (2024).
URL https://lfenergy.org/projects/opensynth/

[212] J. L. Ramirez-Mendiola, G. Mattioli, J. Anable, J. Torriti, I'm coming home (to charge): The relation between commuting practices and peak energy demand in the United Kingdom, Energy Research & Social Science 88 (2022) 102502. doi:10.1016/j.erss.2022.102502.

[213] P. Grünewald, M. Diakonova, The electricity footprint of household activities – implications for demand models, Energy and Buildings 174 (2018) 635–641. doi:10.1016/j.enbuild.2018.06.034.

Appendix

A. Details of subgroup differentiation of reviewed models

Table 5: Categories used to subgroup occupants in the reviewed models, with the number of distinguishing characteristics for each subgroup in brackets. Not all combinatorially possible options are investigated. Data-driven indicates clustering by similar activity patterns (outputs), as opposed to a priori subgroup differentiation.

Model	(Partially) data-driven clustering	Number of sub-groups	Age	Income	Gender	Household type (composition)	Household role (individual)	Number of household members	Employment status	Day type
Aerts et al. [159]	✓	7								
Baetens and Saelens [168]	✓							✓	✓(4)	✓(3)
Barsanti et al. [183]		21				✓(5)		✓(4)	✓(4)	✓
Bizzozero et al. [166]			✓(2)				✓(3)		✓(5)	
Bottaccioli et al. [127]		12			✓(2)		✓(1)		✓(5)	✓(2)
Buttitta and Finn [151]	✓	6								✓(2)
Chen et al. [180]	✓	4								✓(2)
Collin et al. [160]		14						✓	✓(2)	
Diao et al. [172]	✓	10								✓(2)
Farzan et al. [164]			✓(6)		✓(2)				✓(2)	✓(2)
Fischer et al. [161]		7						✓(4)	✓(3)	
Flett and Kelly [169]			✓(3)		✓(2)	✓(3)			✓(3)	✓(3)
Foteinaki et al. [175]										✓(2)
Good et al. [148]								✓(6)		✓(2)
Jeong et al. [178]						✓		✓(3)		✓(2)
Johnson et al. [157]		5	✓(2)		✓(2)				✓(2)	
Kleinebrahm et al. [57]			✓(7)						✓(6)	✓(7)
Koupaei et al. [179]								✓(5)		✓(3)
McKenna et al. [149]								✓(6)		✓(2)
Müller et al. [176]		21	✓(2)		✓(2)	✓(6)		✓(5)	✓(10)	✓(4)
Muratori et al. [58]		5	✓(3)						✓(2)	✓(2)
Nijhuis et al. [165]			✓					✓		✓
Osman et al. [181]	✓	6/9	✓		✓(2)	✓		✓		✓(2)
Richardson et al. [146]								✓(6)		✓(2)
Rueda et al. [177]			✓	✓	✓(2)	✓	✓	✓	✓	✓
Wilke et al. [155]		37			✓(2)	✓(4)			✓(6)	✓(7)
Yamaguchi et al. [173]		59	✓(4)		✓(2)	✓(2)	✓(4)		✓(2)	
Yu et al. [184]		8							✓(5)	✓(2)
Zhang et al. [182]		6	✓(3)							✓(2)

B. Details of appliance modeling of reviewed models

Table 6: Modeling of appliance demand in activity-based load profile models

Model	Linkage between activity schedule and appliance usage			Appliance selection			Trigger of appliance start			Duration of electricity demand per appliance		
	Activities not interlinked	Linked via occupancy	Linked via activities	Appliance-related states	Deterministic (one-to-one)	Probabilistic (one-to-many)	Deterministic	Probabilistic	Calibration scalar or cumulative distribution	Fix load pattern	Probabilistic duration	Duration as in activity schedule
Widén and Wäckelgård [152]			✓	6	–	✓	✓	–	–	✓	(✓)	✓
Widén et al. [121]			✓	6	–	✓	✓	–	–	✓	(✓)	✓
Grahn et al. [153]			✓	6	–	✓	✓	–	–	✓	(✓)	✓
Sandels et al. [154]			✓	6	–	✓	✓	–	–	✓	(✓)	✓
Muratori et al. [58]			✓	5	✓	–	✓	–	–	–	–	✓
Muratori [8]			✓	5	✓	–	✓	–	–	–	–	✓
Johnson et al. [157],[158]			✓	?	✓	–	✓	–	–	✓	–	✓
Collin et al. [160]			✓	10	✓	–	–	✓	–	✓	–	✓
Farzan et al. [164]			✓	6	✓	–	✓	–	–	–	–	✓
Bizzozero et al. [166]			✓	7	✓	–	✓	–	–	(✓)	–	✓
Gruosso et al. [167]			✓	7	✓	–	✓	–	–	(✓)	–	✓
Diao et al. [189]			✓	6	✓	–	✓	–	–	–	–	✓
Taniguchi et al. [125]			✓	13+	–	✓	✓	–	–	(✓)	–	(✓)
Müller et al. [176]			✓	10	–	✓	✓	–	–	✓	–	✓
Chen et al. [180]			✓	4	–	✓	✓	–	–	✓	–	✓
Osman et al. [181]			✓	4	–	✓	✓	–	–	✓	(✓)	✓
Zhang et al. [182]			✓	(4)	(✓)	–	✓	–	–	–	–	✓
Barsanti et al. [183]			✓	?	✓	✓	–	✓	✓	✓	–	–
Yu et al. [184]			✓	11	–	✓	–	✓	–	✓	–	–
Wang et al. [185]			✓	11	✓	–	–	✓	–	✓	–	(✓)
Richardson et al. [147]		✓		Has to be probabilistic, as no detailed information provided at activity level			–	✓	✓	✓	–	✓
Good et al. [148]		✓					–	✓	✓	✓	–	✓
McKenna and Thomson [150]		✓					–	✓	✓	✓	–	✓
Nijhuis et al. [165]		✓					–	✓	–	–	✓	–
Baetens and Saelens [168]		✓					–	✓	✓	–	✓	–
Flett and Kelly [170]		✓					–	✓	✓	(✓)	(✓)	(✓)
Flett and Kelly [171]		✓					–	✓	✓	(✓)	(✓)	(✓)
Bottaccioli et al. [127]		✓					–	✓	✓	✓	(✓)	–
Fischer et al. [161]	✓						–	✓	✓	✓	(✓)	–
Fischer et al. [162]	✓						–	✓	✓	✓	(✓)	–
Foteinaki et al. [175]	✓						✓	–	–	–	✓	–

C. Details of hot water modeling of reviewed models

Table 7: Modeling of hot water demand including activity-based load profile models

Model	Linkage activity schedule and hot water demand				Hot water demand			Energy demand		Comment
	Independent	Occupancy	DHW-related activities	Hot water appliances	Deterministic	Probabilistic	Not specified	Proportional to hot water use	Hot water system model	
Sandels et al. [154]	✓			4	✓			✓	✓	Separate Markov chain; based on Widén et al. [112]
Fischer et al. [162]	✓			3		✓			✓	
McKenna and Thomson [150]		✓		3		✓			✓	Combined with heating
Baetens and Saelens [168]		✓		0		✓			✓	
Flett and Kelly [171]		✓		2		✓		(✓)		Energy demand not specified; different behavior groups
Widén et al. [121]			✓(4)	25	✓			✓		Based on Widén et al. [112]
Johnson et al.[158]			✓(3)	4	✓				✓	Based on Widén et al. [112]
Farzan et al. [164]			✓(3)	3	✓			✓		Only gas demand
Bizzozero et al. [166], Gruosso et al. [167]			✓(?)	?			✓	(✓)		Energy demand not specified
L. Diao [172]			✓(3)	-	✓			✓		Only electric demand of water heaters
Taniguchi et al. [125]			✓(?)	?			✓	✓		Only electric demand of water heaters;
Bottacioli et al. [127]			✓(2)	2		✓			✓	As R. Diao et al. [189]
Müller et al. [176]			✓(4)	4		✓		(✓)		Daily frequency restrictions energy demand not specified
Chen et al. [180]			✓(4)	5		✓			✓	
Osman et al. [181]			✓(4)	4	✓			✓		Duration-based mapping; daily frequency restrictions; austere & wasteful volumes

D. Details of mobility modeling of reviewed models

Table 8: Modeling of mobility behavior and demand in activity-based approaches

Model	Activities				Demand		Charging		
	At-home activities	Mobility-related states	Locations (apart home)	Multiple drivers	Distances	Speed /Velocity	Charging points	Charging Behavior	Power level (L1,L2,L3)
⊕ Grahn et al. [153]	✓	1		–	Duration dependent	Average	1	Direct	L1, L2
⊕ Muratori et al. [156]	–	2		–	Partly constant	Two-Dimensional Markov Chain	1/2	Direct	L1, L2
⊕ Muratori [8]	✓	2		–	Partly constant	Two-Dimensional Markov Chain	1	Direct	L1, L2
⊕ Gruosso et al. [167]	✓	2		(✓)	Duration dependent	Acceleration, Urban /Rural	2	Direct	Maximum by car type
⊕ Farzan et al. [164]	✓	2		–	Duration dependent	Average	1	Optimized or random	L1
⊕ Yu et al. [184]	✓	8	1	–	Probabilistic	Average	1	Optimized	not specified
⊕ Wang et al. [185]	✓	5		–	Duration dependent	Trip averages	1+	Direct	L1 or lower
⊙ Müller et al. [176]	✓	8	4	–	Partly constant	Average	1	Direct	Maximum by car type
⊖ Fischer et al. [163]	–	7	3	–	Partly constant	Different (probabilistic)	1/2	Different (probabilistic)	L1, L2, L3
○ Roorda et al. [192]	–	10	3+	✓	No demand modeled (only mobility activities)				
○ Kleinebrahm et al. [57]	✓	4	1	(✓)					
○ Hilgert et al. [191]	–	6		–					

E. Details of time-use survey data sources

Table 9: Main activity data sources of reviewed models. Participant numbers are taken directly from the papers. One reason for the difference in participant numbers is that filtered subsets are sometimes used.

Country	Abbreviation	Used in paper (first author)	Participants: Households	Participants: Persons
Australia	TUS AU	Jeong [178]	3 626	6 902
Belgium	TUS BE 05	Aerts [159], Baetens [168]	3 455	6 400
Canada	TUS CA 15-16	Rueda [177], Osman [181]	?	17 390
Denmark	TUS DK 08/09	Foteinaki [175]	4 679	9 640
France	TUS FR 98/99	Wilke [155]	7 949	15 441
Germany	HETUS DE	Fischer [161]	5 200	14 000
		Fischer [162]	7 200	32 000
	TUS DE 12/13	Müller [176]	5 000	11 000
		Barsanti [183]	4 021	10 364
		Yu [184]	5 040	12 000
	TUS DE 01/02	Kleinebrahm [57]	5 443	11 921
	MID 08/09	Fischer [163]	20 000	40 000 (70 000 trips)
	MID 17	Müller [176]	5 000	11 000
	MOP 01-17	Kleinebrahm [57]	900–1 900	1 500–3 100
	MOP	Müller [176], Yu [184]	?	?
Italy	TUS IT 08/09	Bizzozero [166], Gruosso [167]	?	?
	TUS IT 13	Bottaccioli [127]	27 000	60 000
Japan	TUS JP 06	Yamaguchi [173], Taniguchi [125]	7 681	18 291
Netherlands	TUS NL	Nijhuis [165]	?	2 042
	TUS NL 05	Flett [171] (only validation)	?	?
Sweden	TUS SE 96	Widen [152], Grahn [153]	169	431
		Widen [121], Sandels [154]	179	463
	TUS SE 07	Widen [121, 152] (only validation)	5	13
United Kingdom	TUS UK 00	Richardson [146, 147], Collin [160], Good [148], McKenna [149, 150]	?	?
		Flett [169–171]	?	20 000
	TUS UK 05	Flett [169] (only validation)	?	5 000
	UK HES	Wang [185]	250	?
	TUS UK 14/15	Ramírez-Mendiola [174]	?	15 000
		Buttitta [151]	4 733	10 208
		Zhang [182]	4 238	10 208
	METER	Wang [185]	14	?
	LTDS	Wang [185]	14	?
United States	TUS US	Farzan [164]	?	?
	TUS US 03–09	Muratori [8, 58]	?	?
		Muratori [156]	?	13 000
	TUS US 03–11	Johnson [157, 158]	?	124 517
	TUS US 09	Diao [172]	?	13 133
	TUS US 13–17	Chen [180]	?	55 000
	TUS US 19	Koupaei [179]	?	?

Working Paper Series in Production and Energy

recent issues

Impressum

Karlsruher Institut für Technologie

Institut für Industriebetriebslehre und Industrielle Produktion (IIP)
Deutsch-Französisches Institut für Umweltforschung (DFIU)

Hertzstr. 16
D-76187 Karlsruhe

KIT – Universität des Landes Baden-Württemberg und
nationales Forschungszentrum in der Helmholtz-Gemeinschaft

Working Paper Series in Production and Energy
No. 76, March 2026 (revised version, first version in September 2025)

ISSN 2196-7296