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

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Abstract

Electrified heating and mobility, the uptake of air conditioning and distributed energy resources are reshaping residential electricity demand and will require substantial investment. Yet the dependencies that drive present and future residential demand across sociodemographic characteristics, occupant activities, energy service demands, local technologies, and interactions with the overarching energy system remain poorly understood. Activity-based, bottom-up models make these dependencies explicit, better informing flexible operation and investment in low-carbon technologies.

We review 45 activity-based residential models and assess coverage of appliances, domestic hot water, space heating and cooling, and mobility (electric vehicle charging), which are rarely considered jointly in one integrated model. We identify methodological gaps for consistently modeling behavior: 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 in isolation rather than entire households, thereby overlooking interdependencies among occupants. Second, predominant use of Markov models or independent univariate sampling limits temporal consistency. Based on these findings, future studies should combine complementary behavioral datasets with sophisticated models (e.g., deep neural networks) capable of capturing complex dependencies to generate high-quality synthetic behavioral data as a basis for future bottom-up residential energy demand modeling. Further progress requires open datasets and reproducible validation frameworks to benchmark and compare activity-based models and to ensure consistent progress in the field. Currently, there is no model available in the literature that derives energy demand for thermal comfort, hot water, mobility, and other services consistently from one fundamental representation of household behavior.

Highlights

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- Reviews activity-based, bottom-up models for residential energy-demand profiles.
- Covers all energy service demands: appliances, hot water, thermal comfort, mobility.
- Examines activity schedule generation: 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

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ABSTRACT

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We review 45 activity-based residential models and assess coverage of appliances, domestic hot water, space heating and cooling, and mobility (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 in isolation rather than entire households, thereby overlooking interdependencies among occupants. Second, predominant use of Markov models or independent univariate sampling limits temporal consistency. Based on these findings, future studies should combine complementary behavioral datasets with sophisticated models (e.g., deep neural networks) capable of capturing complex dependencies to generate high-quality synthetic behavioral data as a basis for future bottom-up residential energy demand modeling. Further progress requires open datasets and reproducible validation frameworks to benchmark and compare activity-based models and to ensure consistent progress in the field. Currently, there is no model available in the literature that derives energy demand for thermal comfort, hot water, mobility, and other services consistently from one fundamental representation of household behavior.

1. Introduction

The residential sector is pivotal to decarbonizing the energy system. In 2023, the residential sector accounted for 26% of the EU's final energy consumption, of which 63% was used for space heating and 15% for water heating [1]. Despite electricity comprising 26% of the residential sector's energy mix, only 7% of that electricity serves space heating and 18% serves water heating [1]. With the introduction of heat pumps alongside the decarbonisation of electricity supply, future energy demand for space heating and water heating will be supplied by electricity, marking a substantial shift given these services' high share of residential consumption and today's low level of electrification.

Electrified mobility will also further increase household electricity demand. Currently, electric vehicle charging is not explicitly counted within residential sector statistics [1]. In 2022, for example, transport comprised 31% of the EU's final energy use, with road vehicles responsible for 74% of that total and 91% of their fuel supplied by gasoline and diesel [2]. Cars and vans alone consumed 74% of road transport energy (own calculations based on [2]). As electric vehicle uptake grows, around 75% of all charging sessions are expected to occur at home [3], adding a substantial new load to residential grids [4].

Together, the electrification of heating and mobility will transform both the magnitude and the temporal profile of residential electricity demand (see Figure 1). Ahead of the 2035 zero-emission-only car registration mandate in the EU [5], electric vehicles have already grown from a 2% market share in 2018 to 23% in 2023 [6]. Simultaneously, the share of ambient heat from heat pumps in space and water heating rose from 1.7% in 2017 to about 5% in 2022 in EU households [7].

In Europe, the increased uptake of heat pumps and electric vehicles will not only contribute to an expected doubling of overall electricity demand by mid-century ($\approx$ 2050) [8–10], but will also amplify daily and seasonal peaks and steepen ramp rates, stressing networks and driving costly upgrades [11–14]. Flexibility is needed to prevent grid congestion and costly expansions [14], 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. Simultaneously, households are becoming prosumers, installing more photovoltaics and batteries as costs fall [10, 12, 17, 18]. In parallel, the renewable share of the energy system will rise [18–20]. Consequently, the system will become more weather-dependent [13, 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 or managed electric vehicle charging, behind-the-meter batteries, and thermal storage with heat pumps, enabling households to adapt demand to variable supply [23–25].

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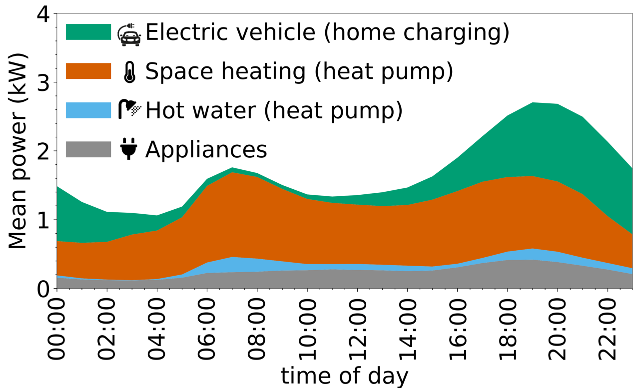

Figure 1: Average daily electricity demand of a median household in 2045, divided by energy service. Values are means across winter days. See [15] for data and methodology.

Despite the residential sector's importance, the drivers of household energy demand are currently largely unknown [26]. A fundamental understanding of the underlying factors that shape residential demand dynamics is lacking, as reflected in the numerous models and publications attempting to explain the temporal composition of residential demand (see Table 2). 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. More detailed submetering data come with additional costs and are not yet widely available [27].

In order 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 that more detailed information in hand, for example, distribution system operators can implement targeted grid expansions proactively, avoiding the grid congestion and voltage-band violations that occur when critical peaks go unaddressed like with uncontrolled charging [28]. Furthermore, energy utilities can provide targeted dynamic tariffs to enhance that flexibility without leading to unfair distributional effects [29–31].

Such granular understanding of residential energy demand can be achieved through bottom-up models that reconstruct household load profiles from appliance-level usage [27, 32]. Based on household behavior, including each occupant's activity schedule, bottom-up models provide a common basis for emerging energy demands [43, 60]. Residential energy demand models enable the study, understanding and forecasting of dependencies between socio-demographic household determinants, technical and environmental parameters, occupant behavior and associated energy demands [27, 48, 61, 62]. Compared to data-driven approaches [26], which implicitly represent underlying dependencies by learning patterns between and within demand profiles, bottom-up approaches provide explicit dependencies, high interpretability and easy-to-tweak relationships, e.g. in response to behavioral changes [61] or technological innovations as well as to support system design [54].

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 [27]	2009		✓	✓	
Grandjean et al. [32]	2012	✓	✓	✓	
Torriti [33]	2014				
Yan et al. [34]	2015			✓	
Gaetani et al.[35]	2016	✓	✓	✓	
Stazi et al. [36]	2017			✓	
Delzendeh et al. [37]	2017		✓	✓	
Fuentes et al. [38]	2018		✓		
Yamaguchi et al. [39]	2018	✓			
Hong et al. [40]	2018			✓	
Zhang et al. [41]	2018			✓	
Balvedi et al. [42]	2018			✓	
Happle et al. [43]	2018	✓	✓	✓	
Dong et al. [44]	2018	✓		✓	
Li et al. [45]	2019	✓	✓	✓	
Carlucci et al. [46]	2020			✓	
Torriti [47]	2020	✓			
Proedrou et al. [48]	2021	✓			
Rezvany et al. [49]	2021	✓			✓
Chen et al. [50]	2021		✓	✓	
Osman and Ouf [51]	2021	✓	✓	✓	
Li et al. [52]	2022				
Dabirian et al. [53]	2022	✓	✓	✓	
Kang et al. [54]	2023	✓	✓		
Kewo et al. [55]	2023	✓			
Vosoughkhosravi et al. [56]	2023	✓	✓	✓	
Ahmed et al. [57]	2023		✓	✓	
Mylonas et al. [58]	2024	✓	✓	✓	
Banfi et al. [59]	2024	✓	✓	✓	
Present work	**2025**	✓	✓	✓	✓

As can be seen in Table 1, no existing review study has consistently addressed all four household energy service demand categories, with mobility-related demand for electric vehicles particularly underrepresented. Existing reviews that cover multiple demand categories typically treat them in isolation rather than examining interconnections. Therefore, 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 energy

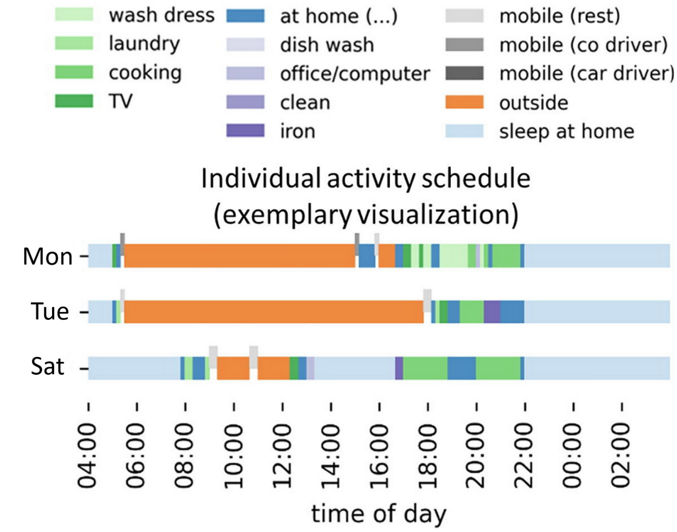

Figure 2: Example of an activity schedule constructed from a synthetic time-use survey sample (image based on [63]). The activity schedule specifies the start time, duration, and type of activities for an occupant at each point in time during the day.

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

(RQ1) Are current residential activity-based energy demand models capable of consistently modeling energy demand for energy service demands 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?

(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 describes the general structure of an activity-based, bottom-up load profile model, outlines the data sources, and explains the necessity for synthetic activity schedules. 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. Bottom-up residential energy demand modeling

Prior work shows a dependence of demand for energy services on occupant behavior [64–67]. Specifically, variations in daily activity schedules can produce highly different energy demands [68–73], whereas homes with similar occupancy patterns tend to experience coincident peak loads [74]. Sociodemographic factors not only shape occupants' routines and energy consumption but also influence appliance ownership and building characteristics [75–84]. For water heating, Bertrand et al. [85] found that over 80% of hot water consumption in urban areas results from showering. For space heating, individual thermal preferences and perceived comfort can differ substantially even within the same sociodemographic group [81, 86]. 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 capture the diversity of household configurations and behavioral impacts [26].

These shortcomings can be addressed with bottom-up, activity-based models. An example of an activity schedule is illustrated in Figure 2. Based on the behavior of household occupants as foundational component, activity-based demand 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.

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 8 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 [51, 87]. Only a few surveys offer longer observation periods [87–89]. Time-use surveys contain sociodemographic information about the occupants as well as data on household affiliation. Multiple versions exist for different years or countries, many of which are included in the Multinational Time Use Study (MTUS) [90] or the Harmonised European Time Use Survey (HETUS) [91]. Although most TUS datasets are subject to data protection, a few are openly accessible [92, 93].

Beyond time-use surveys, national mobility surveys provide representative travel-behavior data. These surveys are conducted repeatedly over multiple years, see Table 8 in the appendix. One-day travel diaries are collected by Germany's Mobilität in Deutschland (MiD) in repeated cross-sections [94], London's Travel Demand Survey (LTDS) [95], and the U.S. National Household Travel Survey (NHTS) [96]. The Deutsches Mobilitätspanel (MOP) provides seven-day panel data [97]. Overall, several partly harmonized, country-representative datasets provide a solid basis for activity-based energy-demand models; purely smart-meter-driven approaches are ill-suited to this methodology [26, 98–104].

Multiple alternative data sources may provide additional value but are mostly not representative, limiting their generalizability. Charging-only data (e.g., wallbox measurements)

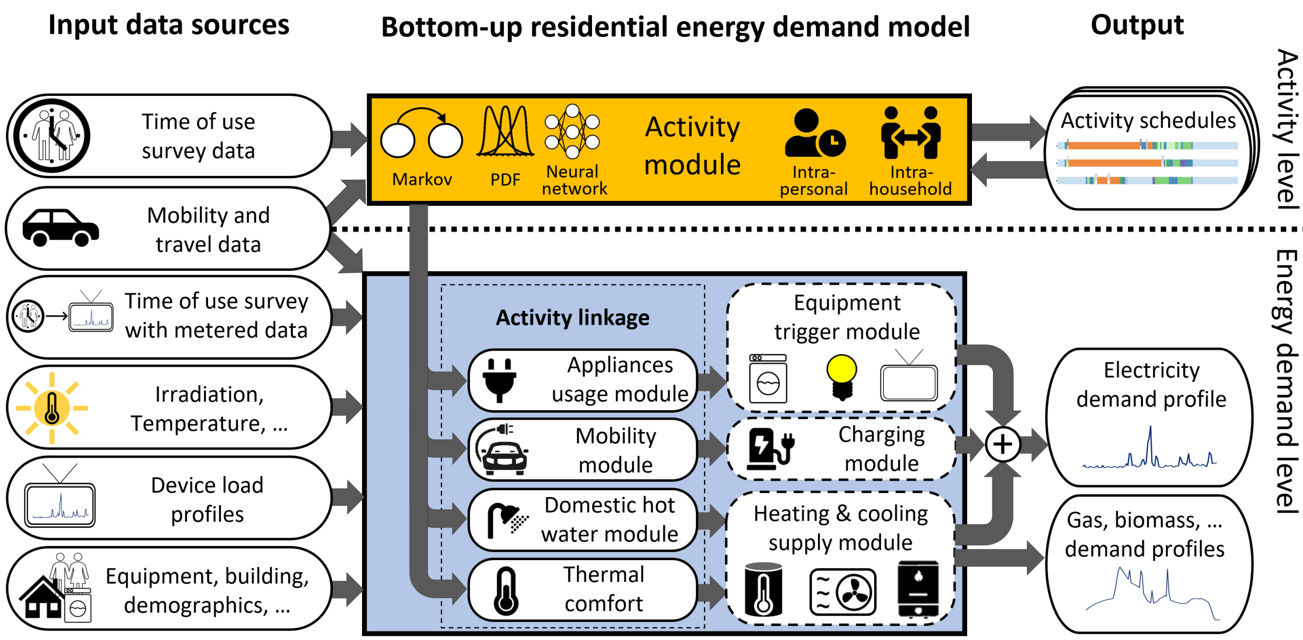

Figure 3: Components and information flow in bottom-up activity-based load profile modeling.

lack behavioral context unless paired with activity information. The METER dataset, 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 use [105–107]. Data on load profiles for individual appliances (e.g., [108, 109]) can help link modeled appliances to their corresponding electrical loads. Sensor-based measurements, e.g., CO_2 concentration, window-opening states, thermostat datasets [110], or Wi-Fi usage [111], typically rely on small, purpose-specific samples. Comprehensive reviews on occupancy detection are available (see [112–115]). Case studies that rely solely on these types of data are not considered further in this work.

2.2. On the need for activity modeling

There is a need for modeling activity data. 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 activities, 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. Consequently, models that use data directly [68, 116–119] or derive activity schedules [73, 120–125] 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 [12, 126]. Based on our review, we identified that these two aspects are the primary motivations for simulation in current activity models: to address privacy constraints and to extend profile length.

Synthesizing activity data by modeling can tackle these shortcomings by deriving statistical properties such as the

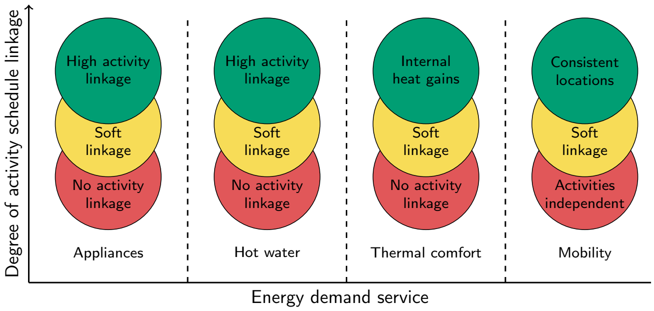

Figure 4: Categories of linkage between an activity schedule and the different energy demand services.

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, enabling fully shareable bottom-up models and supporting long simulation horizons with effectively unlimited synthetic samples.

Additionally, we believe the use of models instead of direct data can be motivated by further reasons. No dataset includes both activity and mobility data (3) [127] 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 the time-use 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. The degree of linkage can vary across demand modules, but stronger coupling yields closer alignment with the activity schedule, and tighter coupling also enhances consistency across energy-service demands (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 5 in the appendix). Lighting use follows occupant-presence rather than specific activities, though room-differentiated occupancy schedules can refine lighting-demand estimates. [76, 125, 128–136]. 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 5 in the appendix). In multi-occupant households, appliances may be used simultaneously across multiple activity schedules, leading to **appliance sharing** 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.

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 [3], 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 7 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 can represent charging strategies (direct, delayed, smart charging) and vehicle-to-grid (V2G) interactions.

3. Review of activity-based energy demand models

This section provides a review of activity-based energy demand models. Different modeling approaches and their defining characteristics are discussed. Further, models are categorized by modeled energy demand services, accounting for appliances, hot water, heating, and mobility, are captured by the models and to what extent they are linked to activity schedules. The structure of this section is guided by the characteristics of the reviewed models, as 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). 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 [137–139] or on window-opening within building performance simulation [140–143], pure country transfers without substantive methodological changes [144], and non-residential contexts such as offices or schools [145–151]. 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.

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 8. "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.

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. [152], who introduce a two-state occupancy model (present vs. absent) for multiple occupants. McKenna et al. [155, 156] extend the model to four states, additionally distinguishing whether occupants are active ("not sleeping"). Appliance differentiation uses a probability density function conditioned on occupancy [153, 156]. Together, these studies comprise the CREST model or "richardsonpy" [152, 153, 155, 156]. The CREST approach is adopted by multiple works [68, 139, 154, 191, 192].

A second stream centers on the structure introduced by Widén and Wackelgård [158], which directly models nine activities using a Markov chain [128, 158–160].

Zhang et al. [187] model occupancy states and infer room-level presence by preprocessing time-use data with appliance-based distinctions. Fischer et al. [169] focus on location-based mobility modeling. Other models in Table 2 follow standard first-order Markov modeling [4, 28, 163, 164, 166, 170, 178, 183, 184, 187, 190].

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 use this structure implicitly without naming it [165, 174, 182]. Standard

Table 2
Reviewed activity models for simulated residential energy demand of energy services, grouped by research lines.

Model (first author)	Year	Activity model: Data source (see Table 8) – time use	Data source – mobility	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 [152]	2008	TUS UK		1^{st}			👥	2	○	○	○	○	▱▱▱▱	✓	✓
Richardson [153]	2010	TUS UK		1^{st}			👥	2	∘	○	○	○	▱▱▱▱	✓	✓
Good [154]	2015	TUS UK		1^{st}			👥	2	∘	∘	+	○	▱▱▱▱	✓	✓
McKenna [155]	2015	TUS UK		1^{st}			👥	4	○	○	○	○	▱▱▱▱	✓	
McKenna [156]	2016	TUS UK		1^{st}			👥	4	∘	∘	+	○	▱▱▱▱	✓	✓
Buttitta [157]	2020	TUS UK		1^{st}			👤	3	○	○	∘	○	▰▱▱▱		
Widén [158]	2010	TUS SE		1^{st}			👤	9	+	○	○	○	▰▱▱▱		✓
Widén [128]	2012	TUS SE		1^{st}			👤	9	+	+	+	○	▰▱▱▱		✓
Grahn [159]	2013	TUS SE		1^{st}			👤	9	+	○	○	+	▰▱▱▱		✓
Sandels [160]	2014	TUS SE		1^{st}			👤	9	+	−	∘	○	▰▱▱▱		✓
Wilke [161]	2013	TUS FR		semi			👤	20	○	○	○	○	▰▱▱▱		
Muratori [28]	2013	TUS US		1^{st}			👤	9	+	○	−	○	▰▱▱▱		
Muratori [162]	2013	TUS US		1^{st}			👤	3	○	○	○	+	▰▱▱▱		
Muratori [4]	2018	TUS US		1^{st}			👤	9	+	○	−	+	▰▱▱▱		
Johnson [163, 164]	2014	TUS US		1^{st}			👤	10	+	+	+	○	▰▱▱▱		
Aerts [165]	2014	TUS BE		semi			👤	3	○	○	○	○	▰▰▱▱		
Collin [166]	2014	TUS UK		1^{st}			👤	13	+	○	○	○	▰▱▱▱		✓
Fischer [167]	2015	TUS DE			■		👤	0	−	○	○	○	▱▱▱▱	✓	✓
Fischer [168]	2016	TUS DE			■		👤	0	−	−	+	○	▱▱▱▱	✓	✓
Fischer [169]	2019		MID	1^{st}			👤	4	○	○	○	−	▰▱▱▱		
"synPro" [167–169]		TUS DE	MID		■		👤	0	−	−	+	−	▱▱▱▱	✓	✓
Farzan [170]	2015	TUS US		1^{st}			👤	12	+	+	−	+	▰▱▱▱		✓
Nijhuis [171]	2016	TUS NL		high			👤	2	∘	○	∘	○	▰▰▰▱		✓
Bizzozero [172]	2016	TUS IT		1^{st}			👤	11	+	+	−	○	▰▱▱▱		✓
Gruosso [173]	2016	TUS IT		1^{st}			👤	11	+	+	−	+	▰▱▱▱		✓
Baetens [174]	2016	TUS BE		semi			👤	3	∘	∘	+	○	▰▰▱▱		
Flett [175]	2016	TUS UK		high			👥	3	○	○	○	○	▰▰▰▱	✓	
Flett [176]	2017	TUS UK		high			👥	3	∘	○	○	○	▰▰▰▱	✓	✓
Flett [177]	2021	TUS UK		high	■		👥	3	∘	∘	○	○	▰▰▰▱	✓	✓
Diao [178]	2017	TUS US		1^{st}			👤	9	+	+	+	○	▰▱▱▱		
Yamaguchi [179]	2017	TUS JP			■		👥	85	○	○	○	○	▰▱▱▱	✓	
Taniguchi [132]	2016	TUS JP			■		👥	85	+	+	+	○	▰▱▱▱	✓	✓
Bottaccioli [134]	2019	TUS IT		semi			👤	13	∘	+	○	○	▰▰▱▱		✓
Ramírez-M. [180]	2019	TUS UK		high			👤	8	○	○	○	○	▰▰▰▱		
Foteinaki [181]	2019	TUS DK			■		👤	10	−	○	○	○	▱▱▱▱		
Müller [182]	2020	TUS DE	MID	semi			👤	19	+	+	−	∘	▰▰▱▱		
Rueda [82]	2021	TUS CA		semi			👤	2	○	○	○	○	▰▰▱▱		
Kleinebrahm [63]	2021	TUS DE	MOP			■	👤	14	○	○	○	○	▰▰▰▰		
Jeong [183]	2021	TUS AU		1^{st}			👤	14	○	○	○	○	▰▱▱▱		
Koupaei [184]	2022	TUS US		1^{st}			👤	3	○	○	○	○	▰▱▱▱		
Chen [185]	2022	TUS US		semi			👤	7	+	+	○	○	▰▰▱▱		✓
Osman [186]	2023	TUS CA		semi			👤	13	+	+	○	○	▰▰▱▱		✓
Zhang [187]	2024	TUS UK		1^{st}			👤	2	+	○	○	○	▰▱▱▱		
Barsanti [188]	2024	TUS DE		semi			👤	13	+	○	○	○	▰▰▱▱		✓
Yu [189]	2024	TUS DE	MOP	semi			👤	17	+	+	∘	−	▰▰▱▱		
Wang [190]	2025	METER	LTDS	1^{st}			👤	9	+	○	○	+	▰▱▱▱		✓

− ∘ +: Degree of activity linkage of the energy service demand, details in Figure 4. ○: Energy service demand not modeled.
👤 or 👥: Occupants modeled individually or activities of a household modeled as one. **"PDF"**: Probability density function.

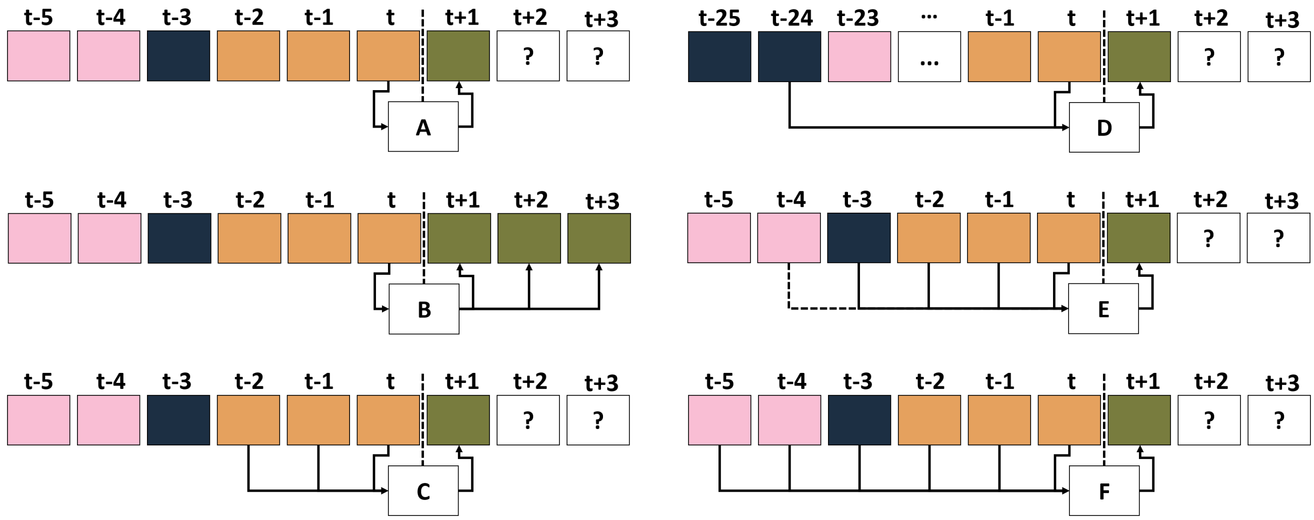

Figure 5: Different memory lengths of Markov chain approaches and neural network approaches. Colors represent different activity states. **A:** First-order Markov chain. **B:** Semi-Markov chain. **C:** High-order Markov chain used in Flett and Kelly [175–177]. **D:** High-order Markov chain used in Nijhuis et al. [171]. **E:** Variable-order Markov chain used in Ramírez-Mendiola et al. [180]. **F:** Transformer-based neural network used in Kleinebrahm et al. [63].

semi-Markov chains without further specific deviations are applied in [134, 165, 174, 185, 186, 189].

Other works extend scope while retaining the semi-Markov logic. Wilke et al. [161] assume Weibull-distributed durations and use a two-state profile directly from time-use data as a proxy for occupancy. Müller et al. [182] 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. [188] 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. [82] 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, 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 [134]).

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. [171] add the occupancy status from exactly 24 hours earlier to capture diurnal effects (Figure 5(d)). Flett and Kelly [175, 176] 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 [177] 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. [180] 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 calibrate using cumulative distribution functions to match daily counts per activity [132, 167, 168, 179]. Fischer et al. [167, 168] only implicitly model the underlying behavior by learning PDFs based on TUS to sample appliance starts rather than modeling activities. Foteinaki et al. [181] 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 [179] and Taniguchi et al. [132] 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 [177] 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. [63] 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 4 in the appendix; an overview can be found in [188]). 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 [155, 175].

Another branch of studies [152–157] first aggregates information from individual occupants from the input dataset, to obtain one sequence per household. Richardson et al. [152] 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 [155, 156]. 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 [175] 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 [176]. In [132, 179], routine activities are modeled collectively at the household level. By using neural networks, Kleinebrahm et al. [63] achieve implicit sociodemographic differentiation without separate models, without reducing the number of states or 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. [180] 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 [153, 154, 156, 174, 176, 177, 187]. Nijhuis et al. [171] 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, using the same occupancy schedule for all energy service demands if modeled provides a consistent behavioral basis.

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 5 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 [134, 153, 154, 156, 166–168, 171, 174, 176, 177, 188–190]. 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. [39].

When an appliance is activated, its load profile can be represented in different ways. Table 5 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 [134]). 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.

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 6 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. [128], who link hot-water-related activities to appliances with fixed volumes for bathing and duration-scaled volumes for showering based on earlier specifications [119]. Osman et al. [186] apply a similar approach, choosing bathing appliances by duration and using fixed volumes otherwise. The proposed method by Widén et al. [119] is used in [160, 163, 164]. Sandels et al. [160] simulate hot water appliances with a separate Markov chain. Farzan et al. [170] 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 [132, 178]. User-type categorization also appears in [177, 186]. Some studies omit appliance-mapping details [132, 172].

Other models sample hot water volumes with probability distributions: conditional on activity [185]; conditional on occupancy [156, 174, 177]; or independent of the activity schedule [168]. Fischer et al. [168] 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 [182, 186].

Energy demand is then derived from volume. Many studies use simple conversions. Widén et al. [119] apply a linear relation; similar treatments appear in [132, 170, 172, 177, 178, 182, 186], although calculation details are often unspecified or not publicly documented. Baetens and Saelens [174] bypass appliance differentiation and sample demand directly from a distribution conditional on occupancy.

Fewer studies embed thermal system models. Sandels et al. [160] implement a boiler with heat losses. Fischer et al. [168] use DHWCalc by Jordan et al. [193] to generate tapping profiles and convert them via energy balance. Bottaccioli et al. [134] simulate an electric water heater using the model by R. Diao et al. [194]. Chen et al. [146] derive demand via ResStock [195]. McKenna et al. [156] 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 [28, 156, 168]. Many incorporate solar irradiance [156, 160, 168] and temperature-driven transmission losses. Recent work commonly uses occupancy profiles, enabling occupant-dependent modeling; internal 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. [171], which applies occupancy-depending setpoint temperatures but omits internal gains.

Mobility. Modeling mobility energy demand combines behavioral, technical, and spatial elements. Table 7 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 [159, 189], two states ("work/commuting" and "leisure/shopping") [4, 162, 170, 173], three out-of-home locations [169], and up to four locations [182]. Travel purposes, activity status, and locations are treated differently depending on the model. Wang et al. [190] 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. [63] 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. [196], who simulate six trip purposes by using a hierarchical approach, and Roorda et al. [197], 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. [173] model driver interactions such as limited vehicle availability and fixed work shifts. Others assume a main driver [169, 170, 182] or otherwise unrestricted access.

The next step is to model vehicle energy consumption. Trip distances are often assumed to be proportional to activity duration [159, 170, 173], sometimes stratified by socio-demographics [170]. Several studies sample certain distances (e.g., commutes) a priori, assuming independence from activity duration [4, 162, 169, 182]. Fischer et al. jointly sample distance and time to fit observed activity durations [169]. Yu et al. [189] sample driving distances probabilistically. Consumption is computed from average speed [159, 170, 182, 189, 190], differentiated by purpose [190], or by using acceleration profiles [173]. A two-dimensional Markov chain for velocity/acceleration parameterized by highway share and driving style is used in Muratori et al. [4, 162].

Charging depends on behavior for charging, charging power available or possible, and location. More public charging or charging at home reduces household demand [162, 169, 173, 190]. Most studies assume uncontrolled "charge-on-arrival"; alternatives include probabilistic timing [169, 170] and cost-optimized timing [170, 189]. Charging power is typically assumed to be Level 1/2 (Level 3 in [169]). Vehicle-specific charging limits appear in [173, 182].

Additional aspects vary across models. Not all studies specify whether "electric vehicles" are battery electric only. Plug-in hybrids appear in [4, 159], and Muratori et al. [162] also include hybrid electric and conventional internal combustion vehicles differentiated by exergetic efficiency. Modifiers include seasonality [159], thermal loads, and regenerative braking [173]. Many elements can be tailored to study aims.

4. Evaluation of bottom-up residential energy demand models

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., [198]). Because few datasets link time-use data with smart metering [47], 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 synthetic data. Synthetic data generation is an active research area for data protection and for creating otherwise unavailable datasets [199], already applied to generate smart meter data directly [200, 201]. 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. [202] 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.

4.1. Validation of generated activity schedules

Despite many models, validation relies on a few metrics. Table 3 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 [51, 54, 201], with [201] 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.

Empirical 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 speed, which can hint at diversity but depends on additional factors [177]. 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 [175, 177], 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 [157]), varies but does not change the validation type itself.

Table 3
Commonly applied metrics at the activity level and their respective dimensions of validation.

Validation Category	Metric name	Dimensions of validation: Check model implementation	Fidelity	Diversity	Generalization	Studies employing the metric with respective error measure
Empirical model verification	Occupancy probability	✓				**Visual/plot:** [186],[136],[134],[152],[138],[114],[184] **MAE:** [157],[136],[114],[175],[134] **MSE:** [157],[136],[134] **Percentage error:** [157]
	Activity probability	✓				**Visual/plot:** [180],[186],[189],[182],[185], [172],[181],[163],[161],[63],[179],[191],[203],[52],[134] **MAE:** [186],[161],[179],[39],[203],[134] **MSE:** [180],[186],[63],[203],[52],[179],[134] **Percentage error:** [180],[185],[134]
	Average occupancy variance			✓		[175],[177],[52]
	Convergence (speed) tests			✓		[177],[155],[180],[157],[163],[184]
Duration evaluations	Occupancy duration		✓			**Visual/plot:** [114], [175],[155] **MAE:** [175] **Percentage error:** [185],[155] **Earth movers distance (first-Wasserstein distance):** [175],[114]
	Activity duration		✓			**Visual/plot:** [185],[63],[180],[179] **MAE:** [180] **MSE:** [63],[180],[179] **Percentage error:** [180] **Correlation coefficient:** [184]
	Occupancy transition frequency		✓			**Visual/plot:** [191],[184],[185],[152],[155]
	Activity transition frequency		✓			**Visual/plot:** [182],[180],[39] **Mean:** [179] **MAE:** [180] **Spectral norm:** [180]
	Number of activities per day/week			✓		**Visual / plot:**[39],[185] **Visual / boxplot:** [63]
	(Peak) occupancy variance			✓		[47],[191]
Similarity between profiles	Levenshtein/ edit distance		✓			[165]
	Levenshtein distribution similarity			✓		[175]
	Accuracy		✓		✓	[52]
	F1-Score		✓			[52]
	Shannon's H entropy (synchronity index)			✓		[47],[39],[179]
	Occupants becoming active together			✓		[191],[175],[152]
	Sequence analysis methods (optimal matching)		✓			[47]
Similarity between days	Hamming distance		✓			[63]
	Autocorrelation		✓			[63]
	Mean/STD wake-up times			✓		[177]
Methodical aspects	Ten-fold cross validation	✓			✓	[161],[136]

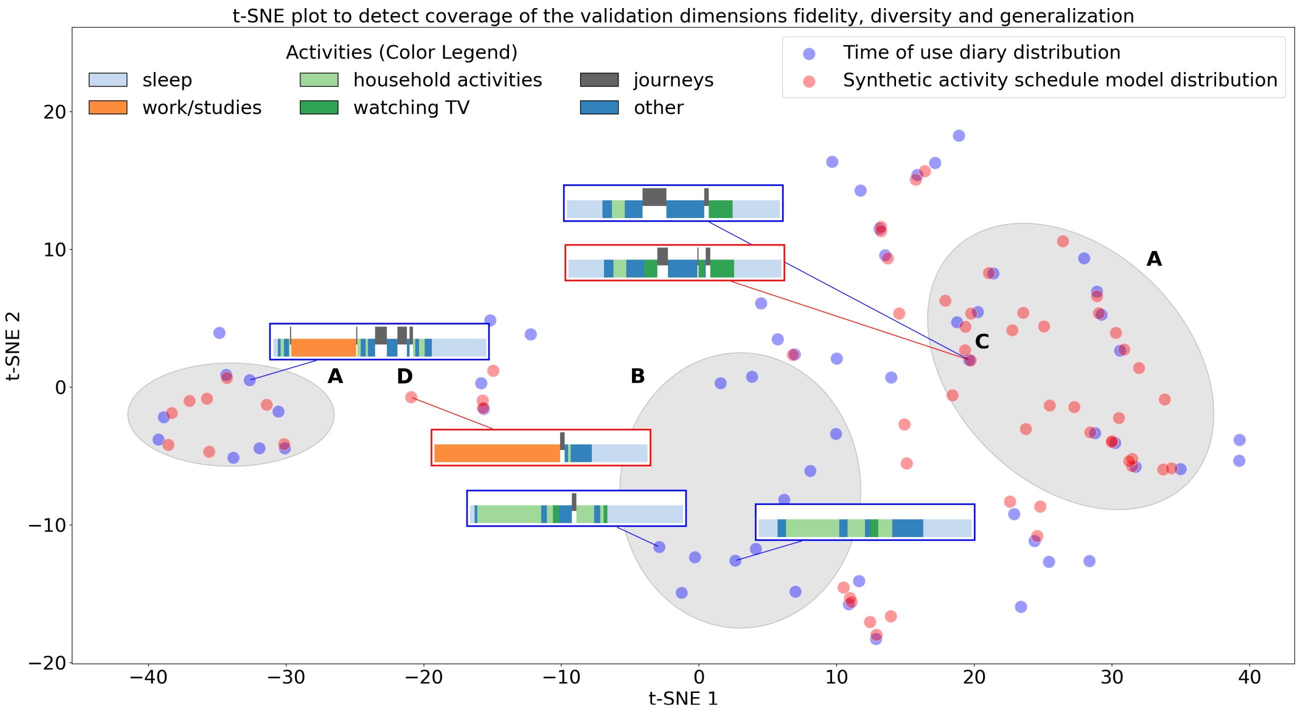

Figure 6: Visualization of the three validation dimensions in the context of activity schedules: Six activity states are taken from the Spanish Time Use Survey. Blue points represent a subset of the original data; red points are synthetic data generated by a model trained on a subset of the blue points (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.

Many studies still rely on visual comparisons instead of computed metrics, which hampers comparability (compare Table 3).

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 [33]). 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 [63]. 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 inter set 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. [63] evaluate repetitive behavior with Hamming distance and autocorrelation. Flett and Kelly [177] 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 [161, 179, 180]. Comparative studies remain scarce due to limited model and data availability and the lack of standardized metrics. Rueda et al. [82] compare state duration performance across methods. Flett and Kelly [175] benchmark occupancy probability against alternative models. Yamaguchi et al. [39] 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.

4.2. 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 [4] 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 ([132, 134, 137, 154, 166, 167, 169, 171, 172, 174, 176, 177, 181, 182, 185, 190]).

Appliance-level checks can be performed by aggregating each appliance's modeled demand across load profiles [166, 177, 182]. Hour-of-day load distributions can likewise be evaluated [167]. Typical metrics include means and standard deviations [28, 170, 171, 174], bias [134], percentiles or boxplots [51]. Some studies use hypothesis tests for distributional similarity [170] or regression analyses with scatter plots [28]. Several also report the index of agreement [134].

Typical load metrics provide additional comparison indicators. Common quantities include the load level and load factor ([158, 169]), which describe the ratio of average power to peak power; the power factor [166], which expresses the ratio of active to reactive demand; and the load duration curve ([51, 167]), which summarizes the load distribution as a sorted curve or a probability density [171]. The simultaneity (coincidence) factor [154, 156, 158] and simultaneous peak power [182] compare peaks across households. Correlation metrics include pairwise correlation and autocorrelation [134, 174]. Variability measures include the normalization factor [63, 119] and the coefficient of variation [176], both describing deviations from the mean. Of particular interest, the Piecewise Aggregate Approximation (PAA) edit distance [176, 177] 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 [156, 168], against the DHWCalc model [168], and is evaluated with load duration curves [168]. Heating validation uses electricity or gas data [156, 186], and load duration curves [168], and comparisons with CREST [157]. Some work covers multiple building types [189]. For mobility, evaluations use presence data [169], location profiles [182], or combined electricity loads from multiple services; which are assessed with load duration curves [169] or aggregated demand comparisons [189].

5. Discussion and future research needs

This discussion highlights three priorities: the need for better activity models, requirements for datasets and validation, and consistent linkage of activities to energy service demands.

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 between household members. Comparing the CREST model, which is a state transition model based on counts of active or sleeping occupants, with a version that aggregates individually sampled occupants, McKenna et al. [155] find lower state probability accuracy for the latter, suggesting that even weak dependencies matter. Likewise, Flett and Kelly's combined approach better matches time-use data, but it targets families with dependent children and implicitly assumes strong parent-child dependency [175–177]. Only synPro [167–169] and Yamaguchi et al. [179] model activities beyond occupants' presence and incorporate intrahousehold dependencies. In synPro, profiles are generated individually and incompatible combinations are rejected, yet the selection rule is insufficiently described and the effective coupling strength remains unclear. Yamaguchi et al. [179] assume routine household behaviors and interactions, for example, enforced shared meals, and select routines accordingly. This approach is less data-driven, although time-use surveys typically 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. [171] condition on the occupancy state exactly 24 hours earlier, which is likely insufficient. Flett and Kelly [177] 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. [63] 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. 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 [204].

Interhousehold dependencies deserve future study, especially for seasonal peak days [117]. Long-term smart meter series can capture cross-day effects. Shared environmental drivers, notably weather [117, 203, 205], couple dwellings [156], affecting heating and lighting [154] and electric vehicle demand [206], and thus behavior. But this also underscores the need for a better data foundation.

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. To analyze dependencies over days, Nijhuis et al. [171] and Flett and Kelly [177] rely on an older version of a Dutch dataset, which captures seven consecutive days of household behavior. Beyond integrating mobility behavior, Kleinebrahm et al. [63] 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 [89].

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 [73, 144, 203, 207], country-specific appliance use [208–210] and how to deal with long-term behavioral trends and the impacts of disruptive events such as COVID-19 [61, 130, 211–214] are already present.

Comparable metrics are required, ideally applied at the individual schedule level to preserve high fidelity to intrapersonal dependencies. As outlined in Section 4, most models rely on in-sample checks, and only a few label them explicitly. 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. Because aggregation loses information, it should be postponed to later stages (e.g., the load-profile level when only aggregate demand is needed). Fidelity, diversity, and generalization should be measured with feasible metrics, leveraging concepts from synthetic data research.

To make models easier to adjust and further develop, to track progress, and to enable use in tools without long data-acquisition processes, more open work is needed: minimal benchmark datasets, transferable validation frameworks [198], and modular implementations to swap technology modules and reflect country specifics. Because few datasets link time-use data with smart metering [47], 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 [215].

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. Mobility, in particular, is consistently underrepresented despite its growing contribution to household electricity demand. The importance of including mobility is highlighted by Ramírez-Mendiola et al. [216], 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 capturing inter-service correlations and maintaining the temporal stability of individual energy-service demands. 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.

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. [204] analyze the combined METER dataset 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. This underscores the need for higher fidelity activity-to-load mappings and highlights the value of combined datasets like METER.

Current models rarely integrate all energy service demands consistently. Components should be driven by activity schedules that are tightly linked across services. 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.

6. Conclusion

Residential energetic load modeling is needed to understand demand and flexibility, especially in light of future changes as the electrification of the mobility and heating sectors shifts demand to households. By simulating household behavior, activity-based bottom-up models are suitable for understanding how energy demand arises. These models can generate high-temporal-resolution activity data and 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 shows that a large number of models exist. Currently, Markov chains and PDF-based models predominate. However, they struggle to account for long-range temporal dependencies, resulting in low-fidelity activity schedules, and thus cannot provide a consistent basis for energy demand modeling and further investigations such as capacity expansion and investment planning. Neural networks are rarely studied but can overcome this shortcoming. Interactions between household members are widely neglected, as models tend to simulate individual occupants independently. This aspect is particularly important for mobility activities conducted jointly or separately, especially when car availability is limited. However, the review revealed that mobility modeling is underrepresented and barely covered in recent reviews, including its requirements for activity-based modeling. 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. Modelers should be more aware of the future challenges in modeling energy demand in residential buildings.

Validation methods are currently limited. 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.

CRediT authorship contribution statement

Jonathan Vogl: Conceptualization, Methodology, Writing – original draft, Visualization, Investigation. **Max Kleine-brahm:** 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.

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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.

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Appendix

A. Details of subgroup differentiation of reviewed models

Table 4: 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. [165]	✓	7								
Baetens and Saelens [174]	✓							✓	✓(4)	✓(3)
Barsanti et al. [188]		21				✓(5)		✓(4)	✓(4)	✓
Bizzozero et al. [172]			✓(2)				✓(3)		✓(5)	
Bottaccioli et al. [134]		12			✓(2)		✓(1)		✓(5)	✓(2)
Buttitta and Finn [157]	✓	6								✓(2)
Chen et al. [185]	✓	4								✓(2)
Collin et al. [166]		14						✓	✓(2)	
Diao et al. [178]	✓	10								✓(2)
Farzan et al. [170]			✓(6)		✓(2)				✓(2)	✓(2)
Fischer et al. [167]		7						✓(4)	✓(3)	
Flett and Kelly [175]			✓(3)		✓(2)	✓(3)			✓(3)	✓(3)
Foteinaki et al. [181]										✓(2)
Good et al. [154]								✓(6)		✓(2)
Jeong et al. [183]						✓		✓(3)		✓(2)
Johnson et al. [163]		5	✓(2)		✓(2)				✓(2)	
Kleinebrahm et al. [63]			✓(7)						✓(6)	✓(7)
Koupaei et al. [184]								✓(5)		✓(3)
McKenna et al. [155]								✓(6)		✓(2)
Müller et al. [182]		21	✓(2)		✓(2)	✓(6)		✓(5)	✓(10)	✓(4)
Muratori et al. [28]		5	✓(3)						✓(2)	✓(2)
Nijhuis et al. [171]			✓					✓		✓
Osman et al. [186]	✓	6/9	✓		✓(2)	✓		✓		✓(2)
Richardson et al. [152]								✓(6)		✓(2)
Rueda et al. [82]			✓	✓	✓(2)	✓	✓	✓	✓	✓
Wilke et al. [161]		37			✓(2)	✓(4)			✓(6)	✓(7)
Yamaguchi et al. [179]		59	✓(4)		✓(2)	✓(2)	✓(4)		✓(2)	
Yu et al. [189]		8							✓(5)	✓(2)
Zhang et al. [187]		6	✓(3)							✓(2)

B. Details of appliance modeling of reviewed models

Table 5: 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 [158]			✓	6	–	✓	✓	–	–	✓	(✓)	✓
Widén et al, [128]			✓	6	–	✓	✓	–	–	✓	(✓)	✓
Grahn et al. [159]			✓	6	–	✓	✓	–	–	✓	(✓)	✓
Sandels et al. [160]			✓	6	–	✓	✓	–	–	✓	(✓)	✓
Muratori et al. [28]			✓	5	✓	–	✓	–	–	–	–	✓
Muratori [4]			✓	5	✓	–	✓	–	–	–	–	✓
Johnson et al. [163],[164]			✓	?	✓	–	✓	–	–	✓	–	✓
Collin et al. [166]			✓	10	✓	–	–	✓	–	✓	–	✓
Farzan et al. [217]			✓	6	✓	–	✓	–	–	–	–	✓
Bizzozero et al. [172]			✓	7	✓	–	✓	–	–	(✓)	–	✓
Gruosso et al. [173]			✓	7	✓	–	✓	–	–	(✓)	–	✓
Diao et al. [194]			✓	6	✓	–	✓	–	–	–	–	✓
Taniguchi et al. [132]			✓	13+	–	✓	✓	–	–	(✓)	–	(✓)
Müller et al. [182]			✓	10	–	✓	✓	–	–	✓	–	✓
Chen et al. [185]			✓	4	–	✓	✓	–	–	✓	–	✓
Osman et al. [186]			✓	4	–	✓	✓	–	–	✓	(✓)	✓
Zhang et al. [187]			✓	(4)	(✓)	–	✓	–	–	–	–	✓
Barsanti et al. [188]			✓	?	✓	✓	–	✓	✓	✓	–	–
Yu et al. [189]			✓	11	–	✓	–	✓	–	✓	–	–
Wang et al. [190]			✓	11	✓	–	–	✓	–	✓	–	(✓)
Richardson et al. [153]		✓		Has to be probabilistic, as no detailed information provided at activity level			–	✓	✓	✓	–	✓
Good et al. [154]		✓					–	✓	✓	✓	–	✓
McKenna and Thomson [156]		✓					–	✓	✓	✓	–	✓
Nijhuis et al. [171]		✓					–	✓	–	–	✓	–
Baetens and Saelens [174]		✓					–	✓	✓	–	✓	–
Flett and Kelly [176]		✓					–	✓	✓	(✓)	(✓)	(✓)
Flett and Kelly [177]		✓					–	✓	✓	(✓)	(✓)	(✓)
Bottaccioli et al. [134]		✓					–	✓	✓	✓	(✓)	–
Fischer et al. [167]	✓						–	✓	✓	✓	(✓)	–
Fischer et al. [168]	✓						–	✓	✓	✓	(✓)	–
Foteinaki et al. [181]	✓						✓	–	–	–	✓	–

C. Details of hot water modeling of reviewed models

Table 6: 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. [160]	✓			4	✓			✓	✓	Separate Markov chain; based on Widén et al. [119]
Fischer et al. [168]	✓			3		✓			✓	
McKenna and Thomson [156]		✓		3		✓			✓	Combined with heating
Baetens and Saelens [174]		✓		0		✓			✓	
Flett and Kelly [177]		✓		2		✓		(✓)		Energy demand not specified; different behavior groups
Widén et al. [128]			✓(4)	25	✓			✓		Based on Widén et al. [119]
Johnson et al.[164]			✓(3)	4	✓				✓	Based on Widén et al. [119]
Farzan et al. [170]			✓(3)	3	✓			✓		Only gas demand
Bizzozero et al. [172], Gruosso et al. [173]			✓(?)	?			✓	(✓)		Energy demand not specified
L. Diao [178]			✓(3)	-	✓			✓		Only electric demand of water heaters
Taniguchi et al. [132]			✓(?)	?			✓	✓		Only electric demand of water heaters;
Bottacioli et al. [134]			✓(2)	2		✓			✓	As R. Diao et al. [194]
Müller et al. [182]			✓(4)	4		✓		(✓)		Daily frequency restrictions energy demand not specified
Chen et al. [185]			✓(4)	5		✓			✓	
Osman et al. [186]			✓(4)	4	✓			✓		Duration-based mapping; daily frequency restrictions; austere & wasteful volumes

D. Details of mobility modeling of reviewed models

Table 7: 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. [159]	✓	1		–	Duration dependent	Average	1	Direct	L1, L2
+ Muratori et al. [162]	–	2		–	Partly constant	Two-Dimensional Markov Chain	1/2	Direct	L1, L2
+ Muratori [4]	✓	2		–	Partly constant	Two-Dimensional Markov Chain	1	Direct	L1, L2
+ Gruosso et al. [173]	✓	2		(✓)	Duration dependent	Acceleration, Urban / Rural	2	Direct	Maximum by car type
+ Farzan et al. [170]	✓	2		–	Duration dependent	Average	1	Optimized or random	L1
+ Yu et al. [189]	✓	8	1	–	Probabilistic	Average	1	Optimized	not specified
+ Wang et al. [190]	✓	5		–	Duration dependent	Trip averages	1+	Direct	L1 or lower
∘ Müller et al. [182]	✓	8	4	–	Partly constant	Average	1	Direct	Maximum by car type
− Fischer et al. [169]	–	7	3	–	Partly constant	Different (probabilistic)	1/2	Different (probabilistic)	L1, L2, L3
○ Roorda et al. [197]	–	10	3+	✓	No demand modeled (only mobility activities)				
○ Kleinebrahm et al. [63]	✓	4	1	(✓)					
○ Hilgert et al. [196]	–	6		–					

E. Details of time-use survey data sources

Table 8: 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 [183]	3 626	6 902
Belgium	TUS BE 05	Aerts [165], Baetens [174]	3 455	6 400
Canada	TUS CA 15-16	Rueda [82], Osman [186]	?	17 390
Denmark	TUS DK 08/09	Foteinaki [181]	4 679	9 640
France	TUS FR 98/99	Wilke [161]	7 949	15 441
Germany	HETUS DE	Fischer [167]	5 200	14 000
		Fischer [168]	7 200	32 000
	TUS DE 12/13	Müller [182]	5 000	11 000
		Barsanti [188]	4 021	10 364
		Yu [189]	5 040	12 000
	TUS DE 01/02	Kleinebrahm [63]	5 443	11 921
	MID 08/09	Fischer [169]	20 000	40 000 (70 000 trips)
	MID 17	Müller [182]	5 000	11 000
	MOP 01-17	Kleinebrahm [63]	900–1 900	1 500–3 100
	MOP	Müller [182], Yu [189]	?	?
Italy	TUS IT 08/09	Bizzozero [172], Gruosso [173]	?	?
	TUS IT 13	Bottaccioli [134]	27 000	60 000
Japan	TUS JP 06	Yamaguchi [179], Taniguchi [132]	7 681	18 291
Netherlands	TUS NL	Nijhuis [171]	?	2 042
	TUS NL 05	Flett [177] (only validation)	?	?
Sweden	TUS SE 96	Widen [158], Grahn [159]	169	431
		Widen [128], Sandels [160]	179	463
	TUS SE 07	Widen [128, 158] (only validation)	5	13
United Kingdom	TUS UK 00	Richardson [152, 153], Collin [166], Good [154], McKenna [155, 156]	?	?
		Flett [175–177]	?	20 000
	TUS UK 05	Flett [175] (only validation)	?	5 000
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