Integrated models of transport and energy demand: A literature review and framework

Negar Rezvany [*] Tim Hillel [*] Michel Bierlaire [*]

July 2021

[*]École Polytechnique Fédérale de Lausanne (EPFL), School of Architecture, Civil and Environmental Engineering (ENAC), Transport and Mobility Laboratory, Switzerland, {negar.rezvany,tim.hillel,michel.bierlaire}@epfl.ch

Abstract

Energy and transport demand can both be considered as being derived from an individual's activity participation. As such, both energy and transport demand are inherently linked: completing activities inside the home generates residential energy demand, where completing activities outside the home generates transportation and non-residential energy demand. Whilst there are several works in the literature that focus on either energy or transportation demand, there remain very few studies which explicitly investigate their interaction. To address this need, in this paper we conduct in-depth literature review of transportation and energy demand modeling. The review analyses the methodologies employed within each domain in order to (a) establish the state-of-research for energy demand modeling and (b) identify the suitable opportunities for joining these two domains. Drawing on a review of the current papers, we identify four key areas of practice: (i) activity scheduling, (ii) building energy demand, (iii) transportation energy demand, and (iv) the integration of components. Finally, based on the findings from the review, we propose a new framework for joint building and transportation energy demand modeling at an urban scale.
Keywords: Energy demand framework; Transportation demand; Building energy demand; Activity-based; Literature review

Glossary

EM Engineering methods.

EVs Electric vehicles.

GDP Gross domestic product.

HVAC Heating, ventilation, and air-conditioning.

LUT Land use-transport.

SEM Structural equation model.

SM Statistical methods.

TUD Time use data.

TUS Time use survey.

UBEM Urban building energy modeling.

USEM Urban-scale energy modeling.

VBA Virtual Basic for Applications.

1 Introduction

Urban areas consume two-thirds of the global energy, which leads to over 70% of global greenhouse emissions (IEA. 2008). Governments worldwide have pledged for ambitious reductions in emissions in the short- to medium-term future. Achieving these targets will require a much deeper understanding of urban energy demand in order to manage and reduce consumption.

The energy consumption in cities can be largely categorised within three different sectors: (i) residential buildings, (ii) non-residential buildings, and (iii) transportation. Of these three sectors, transportation is now the largest emission producer in many countries worldwide, including Switzerland (European Commission 2021). The energy consumption across each of these sectors is inherently linked. Understanding urban energy demand as a whole therefore requires the interactions between each of these sectors to be considered. However, energy demand models used in practice typically only focus on one element, with separate models for domestic and non-residential buildings energy demand and transportation demand. There is therefore limited understanding of the interactions between these sectors.

In the context of urban energy, Urban-scale energy modeling (USEM) has been introduced as an integrating concept for joining energy models at an urban scale. As proposed by Sola et al. (2018), USEM can be simulated using an integrated platform consisting of five sub-models: (i) an urban meteorology model, (ii) a building energy supply model, (iii) a building energy demand model, (iv) a transportation energy model, and (v) an energy optimization model. One of the main challenges of USEM is studying the interdependencies of urban systems, which requires co-simulating urban system models and coupling methods (Hong et al. 2020). In this paper, we focus only on the energy demand elements of the USEM, specifically building energy demand (subdivided into domestic and non-residential buildings) and transportation.

In the current state of practice in building energy demand, two main approaches have been used:

1. building envelope models; in which the buildings energy consumption pattern is simulated directly from aggregate historic energy values (Oneal and Hirst 1980), and

2. active occupancy models; in which energy demand is modeled based on the number of active occupants (present and not asleep) in the buildings (Richardson et al. 2010; McKenna and Thomson 2016),

In this paper, we consider an alternative approach to building energy demand modeling, by modeling energy demand as resulting directly from people's desire to participate in different activities, either inside or outside the home. This extends the activity-based modeling paradigm typically applied to investigate transportation demand. The proposed framework explicitly models the energy demand in the three sectors as explicitly linked using the activity as the central unit of analysis as follows:

- Activities completed at home; such as cooking, cleaning, and laundry which directly use appliances resulting in direct domestic energy demand,

- Baseline domestic energy; lighting, hot water, space heating and cooling, ventilation, and air-conditioning indirectly dependent on in-home activities (from occupancy),

- Out-of-home activities directly generate transport demand in which the transport energy demand can be either directly dependent on travel demand (private transport) or indirectly dependent on travel demand (public transport),

- Non-residential energy demand; which is indirectly dependent on out of-home activities.

Human activity is the main connecting element between these energy consumptions in urban systems. Behavior is the key element affecting individuals' activity scheduling and thus, energy usage is highly dependent on individuals' behavior. For example in the case of residential buildings as one of the main energy consumption sources in urban areas, energy consumption can vary dramatically from one household to another even in similar buildings. This reflects the heterogeneity in occupants' needs, behavior, and preferences (Liu et al. 2019). Occupants' activity patterns also vary throughout the day and even days of the week (weekdays and weekends). Therefore, occupants' activity scheduling which is affected by individuals' behavior is a key input to domestic energy demand modeling. Out of home activity participation has already been modeled extensively for transport demand modeling in form of activity-based transport models in the last decades. Transportation modelers take advantage of daily activity scheduling of individuals for agent-based transport modeling in which the demand for travel is assumed to be driven by the need to complete activities which are distributed in space and time (Kay W. Axhausen and Gärling 1992). This implies that well-established activity-based transportation modeling tools are available. However, although behavior is the key element joining mobility and energy use, the human behavior element is frequently neglected in the energy demand literature (Sovacool et al. 2015) and the current energy demand models are mostly based on active occupancy concept.

In order to address this gap, we propose an integrated model of disaggregate energy and transport demand using activity-based approach to model complex individual behaviors due to the multiplicity of individual actors, their multi-criteria objectives, and the multidimensionality of relevant factors. By recreating individual activity schedules in a day, our research proposes an integrating framework to co-simulate and study the interdependencies of energy demand and transport modeling. This new modeling paradigm, can be used to directly model both energy demand and transport demand derived from in-home and out-of-home activity participation.

To this aim, the following are the gaps in knowledge we need to address for our framework to work, however, they are not the same as the review questions, but can be used to help form them:

- How to incorporate in-home and out-of-home activity scheduling in a single scheduling model?

- How to derive both direct and indirect domestic energy demand from in-house activities?

- How to derive direct and indirect transportation energy consumption from travel demand?
- How to derive indirect non-residential energy demand from out-of-home activities?

The literature review aims to answer the following questions:

- What approaches have been used to model transportation and building energy demand?
- What is the relation between building and transportation energy demand?
- How can we link building energy demand modeling to transportation energy demand modeling?
- To what extent, the activity-based modeling has been applied to energy demand modeling in fields of transportation and building energy modeling?

The remainder of this manuscript is structured as follows. In the following section, a brief review of the existing literature on activity scheduling of individuals and energy demand modeling is presented. Section 3 presents the proposed integrated framework. Finally, the concluding remarks and opportunities for future research are presented in section 4.

In the remainder of this manuscript, the following terminology has been used for *household*, *building*, and *domestic/residential energy demand*. *Household* refers to the occupants living together in a housing unit. *Building* includes both residential and commercial building stock and refers to the building structure and its contents such as appliances and other plug loads. *Domestic/residential energy demand* refers to energy used in residential buildings including lighting, Heating, ventilation, and air-conditioning (HVAC), and appliances.

2 Literature Review

The aim of this section is to review the current literature on on activity scheduling as well as transport and energy demand modeling.

Activity-based models have been developed and extensively used over the past 50 years in transportation modeling (Chapin 1974; Hagerstrand 1970; Horni, Nagel, and Kay W Axhausen 2016; Roorda, Miller, and Nurul Habib 2008; Scherr et al. 2020). Also, activity-based models have been used in integrated land use-transport models (Miller et al. 2004; Waddell 2002), which can predict travel and activity patterns of all agents in the study area at high levels of spatial and temporal resolution, in a behaviorally realistic and policy sensitive manner. These integrated models present new opportunities for utilizing an activity-based approach in energy demand modeling (Keirstead, Jennings, and Sivakumar 2012) as there have been limited attempts to model electricity and heat demand using these approaches (Bustos-Turu et al. 2016). Extending such demand models to all energy resources is one of the most promising opportunities in the field of urban energy system modeling (Keirstead, Jennings, and Sivakumar 2012).

Moreover, occupants' behavior is a substantial source of uncertainty in buildings energy modeling as it can influence the energy consumption by as much as 100% for a given dwelling (Clevenger and Haymaker 2006; Emery and Kippenhan 2006; Masoso and Grobler 2010; Seryak and Kissock 2000; Yu et al. 2011; Palacios-García et al. 2018). Therefore, it is crucial to take into account the difference in individuals' daily behavior to avoid peaks in energy consumption at unrealistic point in time (Wang et al. 2018).

In spite of the similarities between activity-based transport modeling and building energy demand modeling, these two problems have not yet been considered together and there is not an integrated framework.

In this section, we have conducted an extensive review into energy demand modeling. To identify relevant papers, we search across three primary topics: building energy demand modeling, transportation modeling, and activity-based modeling. We then review the literature which attempts to bridge these three topics. We first discuss eight review papers in transportation modeling, building energy modeling, and the current approaches to integrate these two domains in section 2.1. Then, section 2.2 presents the existing research on energy demand modeling and is subdivided into two areas; building energy demand models (section 2.2.1) and transportation energy demand models (section 2.2.2). In section 2.3, a review on activity-based models and scheduling is provided, followed by section 2.4 which presents the current literature on integrating transportation and building energy modeling.

The review methodology of this review paper is such that we have identified the key papers in this field through an unstructured search by following the references from the key papers. The review is the exploration of the key themes and not an exhaustive review.

2.1 Summary of eight review papers in the field

In this subsection, eight review papers in transportation and building energy modeling and the existing attempts to integrate these two domains are discussed. Table 1 provides a summary of the key findings of these review papers. Then, based on the findings of these reviews, we provide a high-level scheme of a framework that serves as a guide in reviewing the papers to reach our ultimate goal (Figure 1).

Kotusevski and Hawick (2009) provide a thorough review of some of the available traffic simulator software packages discussing their applications, their features and characteristics as well as their short comes. Insights from this paper can be useful for selecting the most appropriate simulation tool for traffic system simulation and thus mobility energy demand. In the paper by Mahmud and Town (2016), the authors focus on Electric vehicles (EVs). They propose a thorough literature review on many of the current simulation tools for energy requirements of EVs and their impact on power distribution networks. Their contribution can assist us in selecting appropriate tools when integrating various means of transportation including EVs, which are becoming more and more popular these days, in an integrated energy demand modeling framework.

Swan and Ugursal (2009) provide a critical review on various residential sector energy consumption modeling techniques; top-down and bottom-up approaches. They observe that bottom-up engineering methods are the most suitable for examining different energy policies and strategies as they have the capability to determine the impact of new technologies and discontinuities on building energy demand. Li et al. (2017) provide a more up-to-date review of the urban buildings' energy modeling. Compatible with the conclusion of Swan and Ugursal (2009), they also state that as the bottom-up engineering approach

Table 1: Summary of existing review papers

Topic	Key findings	Citation
Traffic simulator softwares	Applications, features and short comes of traffic simulator softwares	(Kotusevski and Hawick 2009)
Review on modeling and managing impact of EVs on power distribution networks	125 simulation tools identified and 67 summarized, enable researchers select mix of tools to for their objectives.	(Mahmud and Town 2016)
Domestic energy modeling techniques	Bottom-up approach is suitable for examining energy policies and the impact of discontinuous advances in technology	(Swan and Ugursal 2009)
Urban buildings' energy modeling	Bottom-up engineering approach provide detailed information to evaluate impact of new technologies on building energy use	(Li et al. 2017)
Residential electricity demand modeling based on TUS data	Residential electricity demand is predominantly driven by the timing of occupants' activities that can be obtained from TUS data	(Torriti 2014)
Urban energy consumption	Integrated LUT modeling is highly relevant to urban energy systems but overlooked by the literature, activity-based approach is a promising integrating framework for future of USEM	(Keirstead, Jennings, and Sivakumar 2012)
Urban energy consumption	Activity-based approach can be a feasible solution to overcome the challenge of interconnected urban system modeling in UBEM	(Hong et al. 2020)
Classify the existing urban-scale energy systems simulation tools	Provide available resources for implementing new co-simulation approaches in USEM and reduce future modeling efforts	(Sola et al. 2018)

has a high temporal resolution (daily, hourly, and/or sub-hourly), it can provide detailed energy consumption information in order to establish a solid foundation for evaluating the impact of new technologies on buildings' energy use. Torriti (2014) proposes a focused literature review on residential electricity demand modeling based on Time use survey (TUS) data. Among the current approaches for residential electricity demand modeling, they rely on the assumption that residential electricity demand is predominantly driven by the timing of occupants' activities, which can be obtained from TUS data. These reviews, give us insight on possible data and methods used in time-use studies and building energy use modeling.

Keirstead, Jennings, and Sivakumar (2012) provide a comprehensive and diverse literature review on urban energy consumption which is of significant and growing interest. They claim that in spite of various models with different temporal and spatial scales, there has not yet been a piece of work that lightens up the full scope of activities in this area. The authors also point out the integrated Land use-transport (LUT) modeling as a field which is highly relevant to urban energy systems but overlooked by the literature. Moreover, they highlight that the future of urban energy systems modeling is in the use of an activity-based approach as an integrating tool. Hong et al. (2020) state that studying the interconnected urban system modeling is still one of the remaining challenges in Urban building energy modeling (UBEM). Therefore, tackling the challenges of using activity-based approach to couple and co-simulate urban system is still a gap which has not yet been filled by the existing research.

Sola et al. (2018) classify the existing urban-scale energy systems simulation tools according to their capabilities and the analysis area(s) they cover in the urban energy system with the goal of providing available resources for implementing new co-simulation approaches in USEM and reducing future modeling efforts.

Although these reviews point out to the potential of activity-based models as an integrating framework to co-simulate interdependent urban systems (transport and building energy demand), no one has done it so far. Therefore, in order to fill this gap, we have conducted a review on joint mobility and building energy modeling with a focus on activity-based approach as an integrating framework. Using these ideas from transport, energy demand, and activity participation, we come up with a framework that lastly generates buildings energy demand, transportation energy and transportation flows within the same activity-based model. Figure 1 illustrates the high-level scheme of the framework. This framework presents the building blocks together with the relationships we need to review in the literature to overcome the challenge of interconnecting urban system models using activity-based approach as an integrating tool.

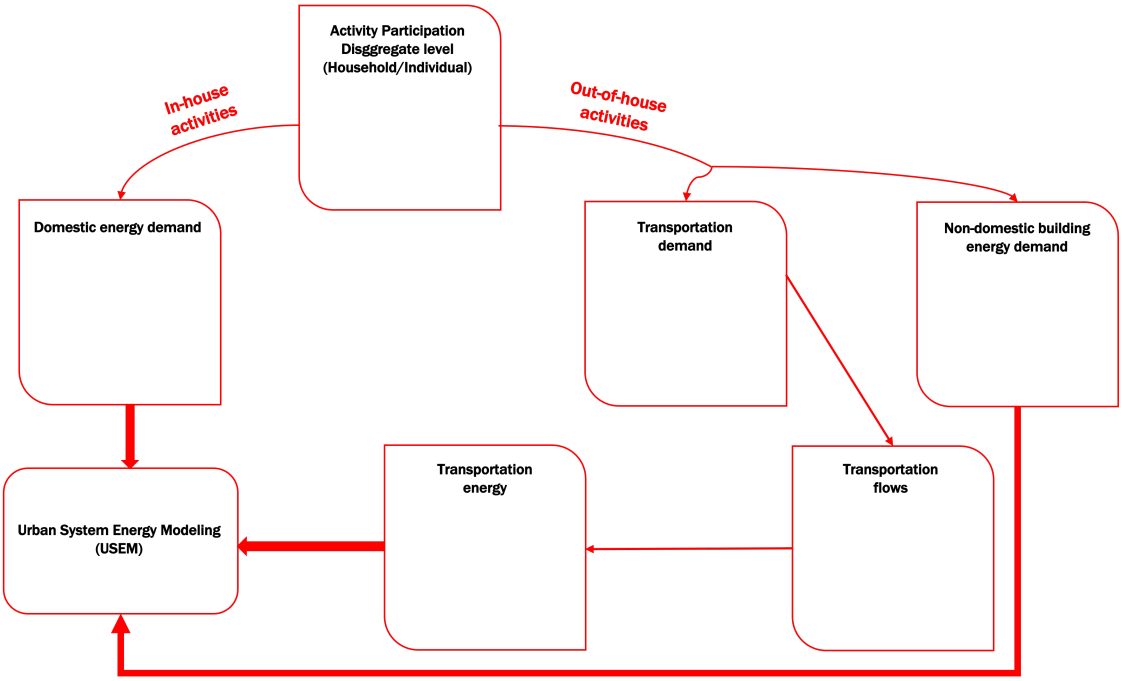

Figure 1: High-level scheme of the framework

2.2 Existing energy demand models

In this section, a review on the existing energy demand models is presented. The energy demand models are studied under two groups: building energy demand models (section 2.2.1) and transportation energy demand models (section 2.2.2), which are discussed in the remainder of this section.

2.2.1 Building energy demand models

Buildings are one of the substantial consumers of energy (Swan and Ugursal 2009); about 40% of global energy use (EIA 2020). By the term buildings, we refer to both residential and non-residential buildings. In this sub-section, we first review literature on domestic energy demand and then go over some available research on non-residential buildings energy modeling.

Buildings' energy use can be grouped as "active" energy use and "passive" energy use. People use certain appliances in order to do activities. Therefore, appliance energy use comes from individuals' daily activities such as using washing machine and dryer for doing the laundries. These building energy consumptions are categorized under the "active" energy consumption group. Passive energy consumption can be classified into two categories: the first category involves building energy use that does not directly depend on activities but rather depends on occupancy such as space heating, space cooling, ventilation, water heating, and lighting which control the indoor environment, and the second category are for the electrical appliances that operate all day without occupant intervention such as refrigerators and other cold appliances.

There are two general techniques for modeling residential energy demand namely “top-down” and “bottom-up” models (Swan and Ugursal 2009). Top-down models treat the residential sector as an energy sink and use historic aggregate total residential sector energy consumption together with some other high-level variables in order to compute the energy consumption of the housing stock as a function of its characteristics (Sola et al. 2018). The input data for developing these models include aggregate historic energy values, characteristics of the dwellings, occupants and their behavior, appliances' characteristics, general climate, and macro-economic indicators such as Gross domestic product (GDP), unemployment, and inflation (Muratori et al. 2013a). Time series stochastic approaches such as auto regressive moving average techniques can also be used to forecast domestic energy demand (Arghira et al. 2012). Although the top-down approach is simpler than the bottom-up approach and requires only widely available aggregate historic energy data, since it is mainly based on historical data, its predictions into the future is less appropriate and it cannot model discontinuous advances in technologies (Wang et al. 2018). Moreover, it lacks details regarding the energy consumption of individuals (Sola et al. 2018).

On the other hand, in the bottom-up models, the model calculates the energy consumption of individuals or groups of households and then extrapolate these results to a wider urban area by identifying the contribution of each end-use to the aggregate residential sector energy demand (Muratori et al. 2013a). This aggregation is accomplished using a weight for each simulated house or group of houses based on its representation of the sector (Swan and Ugursal 2009). This approach has two advantages: first, it can determine the total energy consumption of the residential sector without relying on historical data and second, its high level of detail which allows it to model the effects of technological improvements, policy decisions, and energy optimization techniques. The required input data for developing these models include explicit energy consumption of end-uses, building characteristics (e.g., size and layout, building materials, and characteristics of appliances), general climate, occupants' behavior and appliance usage, lighting use, and the characteristics of HVAC systems (Muratori et al. 2013a). Although the bottom-up approach has the aforementioned advantages, it has a great model complexity and requires more detailed input data compared to the top-down models.

The bottom-up approach can be sub-categorized into Statistical methods (SM) and Engineering methods (EM). SM rely on types of regression analysis to attribute the dwelling energy consumption to end-uses and climate. Once the relationships between end-uses and energy consumption have been established, the model can be used to estimate the energy consumption of dwellings representative of the residential stock. While EM explicitly account for the energy consumption of end-uses based on the building physics, power ratings, and usage of equipment (Swan and Ugursal 2009). Figure 2 presents a summary of techniques for building energy demand modeling.

Under the bottom-up engineering technique, there are mainly four approaches to quantify appliance energy consumption in buildings (Yamaguchi and Shimoda 2017; Yamaguchi, Prakash, and Simoda 2020); (1) building envelope models (2) occupancy-based, (3) activity-based, and (4) time-based approach. In the first approach, the behavior of energy consumption is simulated directly using real sub-metering data to derive diversity profiles of occupants energy use and then used to deduce buildings' energy consumption (Seryak and Kissock 2003; Yohanis et al. 2008). This approach ignores occupancy patterns, activities, and behavior.

In the second approach, the occupants' presence is modeled using Time use data

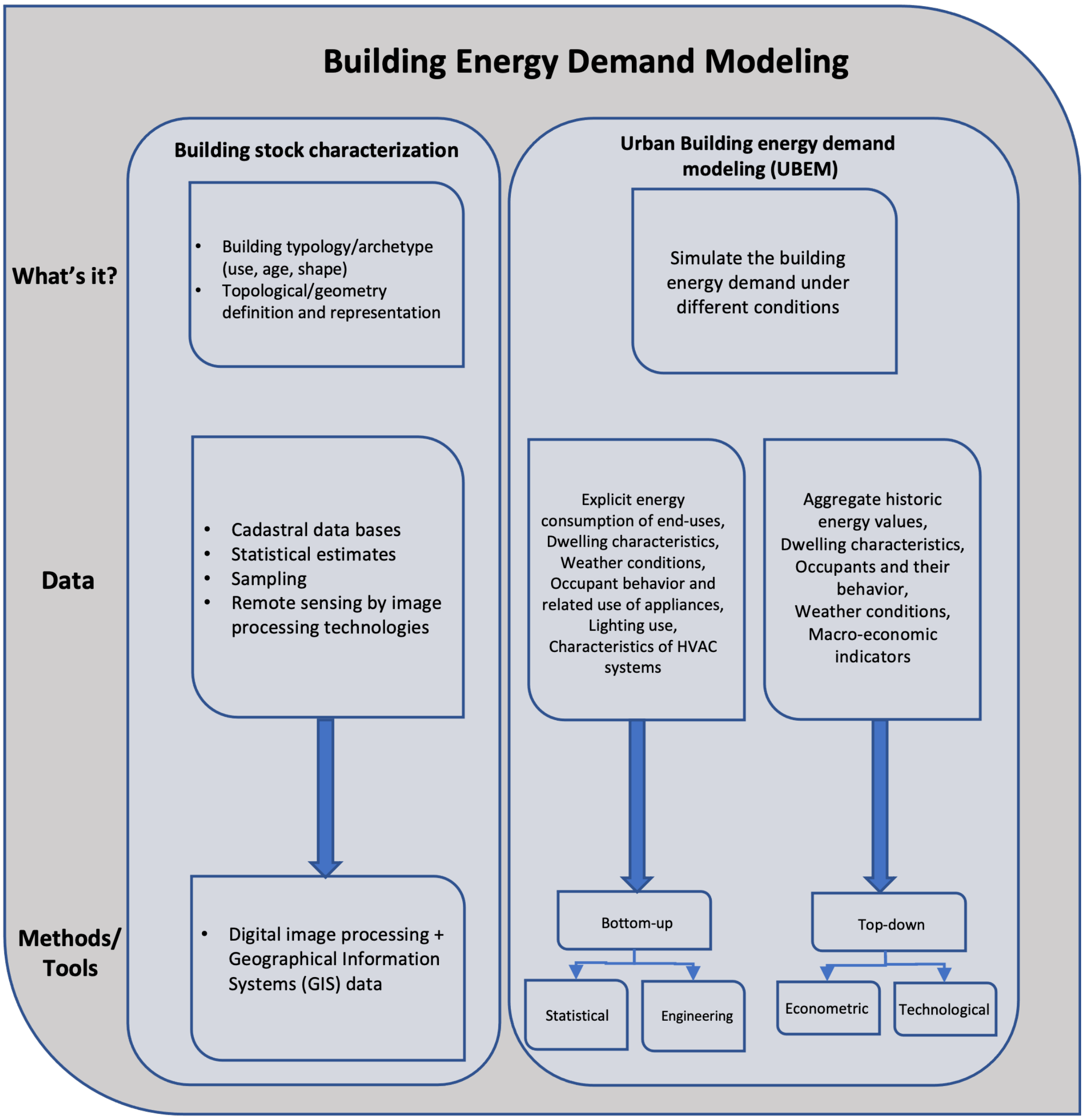

Figure 2: Building energy demand modeling

(TUD) and then converted into the operation of appliances. Therefore, occupant behavior is a critically important component to replicate the dynamic behavior and intensity of energy demand (Yamaguchi and Shimoda 2017). Richardson, Thomson, and Infield (2008) proposed an occupancy-based model for simulating domestic building energy demand. Their model has been expanded and frequently applied in buildings energy demand modeling (McKenna, Krawczynski, and Thomson 2015; Evins, Orehounig, and Dorer 2016). They established a discrete-time first-order Markov chain model dealing with the number of active occupants (being at home and awake) as transition states and developing transition probabilities, $N_{i,j}/N_i$ ($N_{i,j}$ is the number of samples whose state change from i to j, and N_i is the number of samples at transition state i), at each time step based on TUD categorised by household size. Therefore, first, a time series of changes in the active occupancy schedule is determined which is then converted into appliance switch-on probability. Appliance switch-on probabilities can be used for modeling the first category of building energy use: active energy consumption. Their model is developed using Excel Virtual Basic for Applications (VBA). Richardson et al. (2010) quantified the switch-on probability using appliance TUD and annual total electricity consumption, defining switch-on probability as the product of activity probability and a calibration scalar, adjusting the total number of switch-on events per year to avoid appliance use overestimation. Richardson et al. (2009) further used their occupancy model as an input to simulate lighting demand. The model accounts for shared light use, weekday and weekend pattern, and outdoor irradiance; so, it takes into account seasons. Richardsons' model is known as the CREST model. This approach can be applied to the first category of second group of building energy use: passive energy uses that depend on occupancy.

However, Richardson's model has the following opportunities to be improved: 1. it does not account for the heterogeneity between households, 2. variations in the number of switch-on events per day cannot be replicated, and 3. it is only for electrical and lighting energy demand. These limitations have been addressed by other researchers. Baetens and Saelens (2016) improved the model representing heterogeneity between households by categorising TUD based on occupancy pattern as well as household size. Flett and Kelly (2017) determine the number of switch-on events in a simulated day based on empirical data and then allocate them to the timeline based on occupancy. Therefore, they have addressed the second shortcoming. McKenna and Thomson (2016) extended the CREST model to integrate thermal demand to electric demand such that they are correlated.

Other authors such as Tanimoto, Hagishima, and Sagara (2008), Widén, Nilsson, and Wäckelgård (2009), Muratori et al. (2013b), and Subbiah (2013) have adopted occupancy-based approach as well. However, there are some drawbacks in the existing models using this approach:

- First, even though they correlate occupancy schedules to appliance use-patterns and consumption, neither of the existing approaches establish the link between occupants' daily living needs and their related energy consumption.

- Second, they do not generate energy demand profiles based on the activities performed in each household and by each household member. Therefore, they do not have the capability to depict use-situations such as sharing phenomena of appliance and activities.

- Third, they are not exhaustive in representing the household's socio-demographic attributes and the main variable considered in representing households is the number of active occupants.

- Fourth, the appliance use is modeled independently from other appliances resulting in unrealistic energy peaks and appliance use sequence.

Consequently, these models cannot assess the energy consumption variability between different population segments.

To overcome these limitations and enhance the flexibility in modeling households, activity-based approach explicitly simulate the activities of household members which are then converted to appliance switch-on occurrences. Widén and Wäckelgård (2010) and Widén, Molin, and Ellegård (2012) proposed a discrete-time Markov chain model with a number of activities are defined as transition states, which will be converted to appliance use. However, their model can not replicate activities' durations coherently since the durations are randomly determined as a result behavior transitions. Wilke et al. (2013) proposed a discrete-event model in which individuals' activities are simulated by selecting an activity to start at the first vacant slot and selecting its duration. They use multinomial logit models for the activities starting probability and predict their duration by means of survival analysis. Tanimoto, Hagishima, and Sagara (2008) proposed a discrete-event model in which activities' duration are determined based on a time-dependent probability equal to the ratio of TUD on each activity over the total number of TUD at each time of day. Moreover, Zaraket (2014) proposed an activity-based model which aims at forecasting occupant-related energy consumption in residential buildings while accounting for variability in consumption patterns due to heterogeneity in occupants' socio-economic and demographic profiles. This model is known as SABEC which stands for Stochastic Activity-Based Energy Consumption. Their model can be applied to active energy consumption in residential buildings.

The fourth approach for modeling energy consumption in buildings is the time-based approach. In the time-based approach neither the occupancy nor the activity is simulated. Instead, time is an indicator of activities and appliance switch-on probabilities. Authors such as Gruber et al. (2014) and Paatero and Lund (2006) have adopted this approach.

As such in residential buildings, there is a close relationship between occupancy patterns and energy consumption in economic sectors as well. Palacios-García et al. (2018) propose a stochastic model for the generation of daily occupancy patterns using a Markov Chain approach in nine economic sectors with a high temporal resolution. They distinguish between the type of day and type of working hours. Building occupancy data rather than activity data is the key input to simulating non-residential buildings' energy demand. This occupancy model is a stepping-stone for the estimation of energy demand in the commercial sector and the assessment of various energy policies.

In summary, considering all the aforementioned approaches in building energy demand modeling, activity-based approach provides a more accurate estimate of energy demand and has attractive qualities such as the ability to capture complex use situations (e.g., multi-tasking, interaction/sharing between the members of a household). Also, it enables predicting resource demand at high spatial and temporal resolutions to the extent of being able to produce building-by-building resource needs. It has the ability to predict resource demands along different dimensions while at the same time retaining the dependencies and links between these resource demands. Moreover, this approach enables us to observe the energy substitution effects between the use of different equipments and participation in different activities (Ghauche 2010). It also has the ability to capture the effect of temporal and cultural changes on human behavior which affects energy demand (Keirstead, Jennings, and Sivakumar 2012; Wilke 2013). A user-focused activity-based model which correlates occupants' profiles such as socio-demographics to activities, appliance ownership, and use trends is a suitable approach for an accurate and realistic estimation of building energy demand simulation and provides an effective test-bed for examining various scenarios.

2.2.2 Transportation energy demand models

Transportation modeling has been widely developed in the last decades. This implies that well-established transportation modeling tools are available. Although their focus is not on the modeling of transportation energy consumption, transportation energy demand can be quantified based on them. The models for simulating transportation energy demand can be classified in two groups (Sola et al. 2018): (1) vehicle-based models, in which energy consumption is calculated based on the outputs of a microsimulation transport model (such as multi-agent simulation and particle system simulation), and (2) macrosimulation models based on average speed philosophy and aggregate energy consumption data. Figure 3 presents this classification. In general terms, macroscopic models have low spatial and temporal resolution, while microsimulation modeling tools provide more accurate estimates of fuel consumption for a limited network application context. In any of the cases, this calculation is commonly done in an exogenous manner (as a post-process with the use of fuel consumption factors/ratios). To date, transportation modeling tools have been scarcely integrated into wider urban-scale energy models (Sola et al. 2018). The choice between both approaches will be based on the required level of details, data availability, computational time, and model accuracy (Sola et al. 2020).

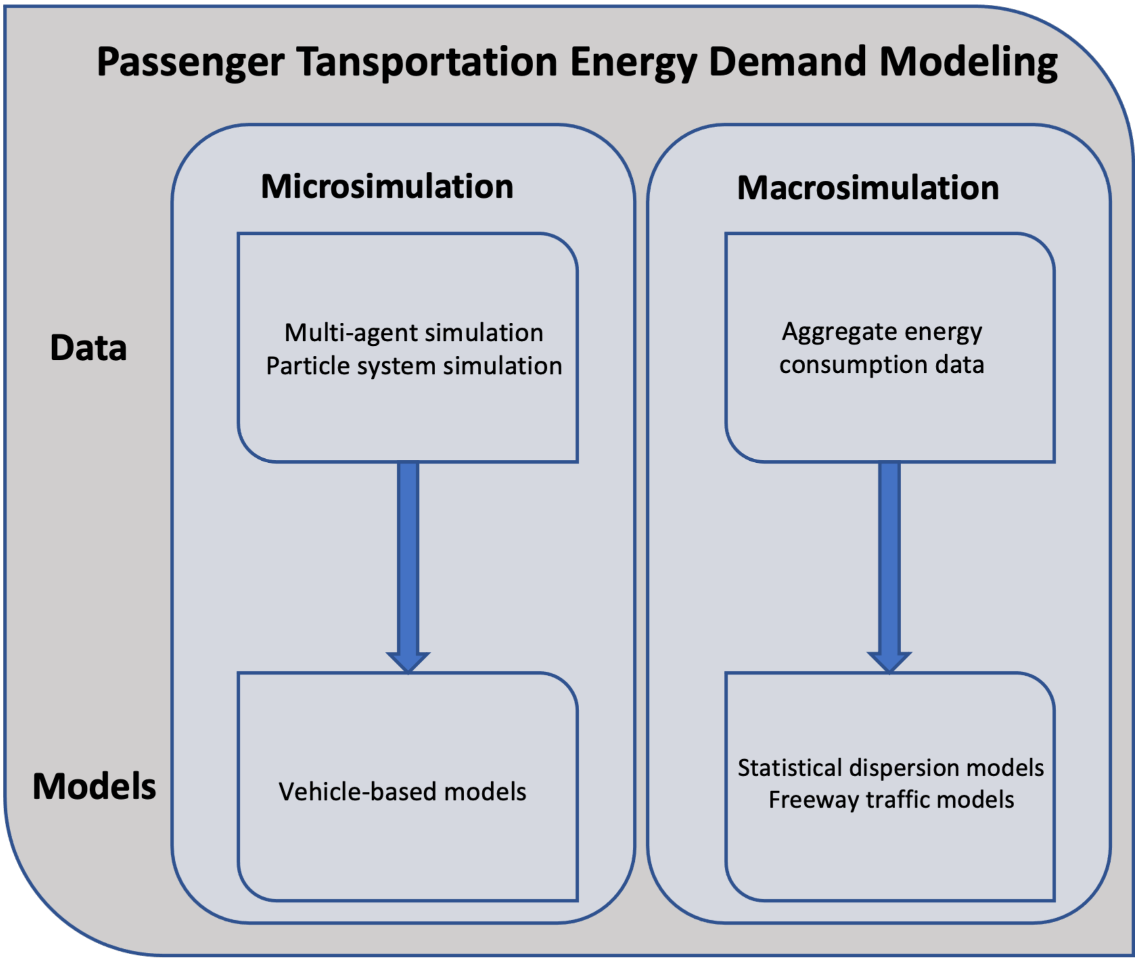

Figure 3: Passenger transportation energy demand modeling

In the microsimulation models, in order to calculate the transportation energy demand, we should first model travel demand. Travel demand models can be either categorised as (1) trip-based or (2) activity-based (Yamaguchi, Prakash, and Simoda 2020). Trip-based modeling has a top-down approach which uses the overall person trips in the studied area, disaggregated into trips with different characteristics such as origins, destinations, travel modes, and routes consisting of four sequential processes: trip generation, trip distribution modal split, and trip assignment.

While activity-based modeling has a bottom-up approach in which travel demand is modeled as an aggregation of trips made by individuals. Activity in transportation demand modeling is modeled as a sequence of in-home and out-of-home activities (Sivakumar 2013). In this approach, the decision to travel is considered as a choice among alternatives known as discrete choice set with a set of exhaustive and mutually exclusive alternatives. Discrete choice models such as multinomial logit, nested logit, and mixed logit models are used to model the likelihood of choosing an alternative based on certain input variables (M. Ben-Akiva and Lerman 1985). The influence of various factors such as socio-demographics and household type, land-use, and travel conditions can be included in the predicted likelihoods. Hazard-based models can be used for modeling the time to the next event. The models provided by Mannering, Murakami, and Kim (1994) for modeling travelers' home-stay duration, and the duration of shopping activity while returning from work to home are examples of this approach.

Activity-based approach has been developed and extensively used in transportation modeling over the past 50 years (Hagerstrand 1970; Chapin 1974; Roorda, Miller, and Nurul Habib 2008; Horni, Nagel, and Kay W Axhausen 2016; Scherr et al. 2020). Also, activity-based models have been used in integrated land use-transport models (Waddell 2002; Miller et al. 2004), which can predict travel and activity patterns of all agents in the study area at high levels of spatial and temporal resolution, in a behaviorally realistic and policy sensitive manner accounting for the constraints individuals encounter during travel activities. Activity-based approach has been also used in simulating trip-chains (Pitombo, Sousa, and Filipe 2009), which if known, will be useful for modeling more accurate transport energy consumption. Moreover, joint travels with other household members is another significant factor in modeling travel demand which has been studied in the literature (K. K. Srinivasan and Athuru 2005; S. Srinivasan and Bhat 2005a; Kato and Matsumoto 2009).

The advantages of the activity-based approach are as followed (Yamaguchi, Prakash, and Simoda 2020):

- It captures the link between activities and the need to travel,
- It captures relationships between various activities and dependencies between events,
- High temporal resolution,
- Complex behaviors such as joint travels can be considered,
- Decisions are analysed at the level of the household as opposed to seemingly independent individuals, and
- The effect of factors such as socio-demographics, built-environment, and travel conditions on individuals' travel decisions can be included.

Therefore, activity-based models are more behaviorally realistic than trip-based models. Activity scheduling is central to these models. However, whenever this approach has been used, either econometric models (random utility maximization) or empirical rule-based methods (using decision rules and heuristics) have been used to determine individuals' choice of activity schedules, instead of theory-driven behavioral models. These methods rather do not consider behavior explicitly but implicit to the full process (econometric models) (H. J. P. Timmermans 2003) or cannot be generalized to situations not observed in the data (rule-based models) (Joh, H. J. P. Timmermans, and Recker 2004).

2.3 Activity-based models and scheduling

Activity scheduling is a key input to the activity-based models. Individuals' activities have a strong impact on the energy consumption of a building and are a substantial source of uncertainty in building energy demand modeling. Daily scheduling of individuals also influences their travel behavior. This strongly influences the mobility energy demand. As such, individuals' behavior, including both in-house and out-of-house activity participation, is an integral input to energy demand simulation models in urban areas and is a key factor in understanding energy consumption (Kashif et al. 2013). Therefore, we divide this section into two sub-sections; we first discuss in-house activity schedule and occupants' behavior in Section 2.3.1. We then present the literature on out-of-house activity scheduling and travel behavior in Section 2.3.2.

2.3.1 In-house activity scheduling and occupants' behavior

In addition to the building physics, building energy consumption is highly dependent on the behavior of its occupants (Masoso and Grobler 2010; Palacios-García et al. 2018). Existing literature shows that energy consumption can vary dramatically from one household to another even in similar buildings, which reflects the heterogeneity in occupants' needs and preferences (Liu et al. 2019). Also, occupants' activity patterns vary throughout the day and even days of the week (weekdays and weekends). Therefore, occupants' activity scheduling is a key input to building energy demand modeling either for individual building or the whole building sector. It is noteworthy that individuals' activity data might not be easily accessible due to personal privacy issues and regulations (Liu et al. 2019). Therefore, simulating occupants' activity schedules is a viable way to generate user activities. We present some of the existing in-home activity scheduling models available in the literature.

Wilke et al. (2013) present a stochastic bottom-up modeling approach using a first-order in-homogeneous Markov process to predict the activities of occupants in a residential building based on time-dependent activity start probabilities and their corresponding duration distributions. A general model calibration based on individuals' behavioral homogeneity assumption is followed by successive refinements accounting for variations in the behaviors of sub-populations. It is notable that there is a strong correlation between households' attributes and domestic appliances ownership levels, energy rating, and use pattern. Therefore, socio-economic and demographic attributes that influence energy consumption trends should be taken into account when considering occupants' behavior for modeling occupant-related energy consumption. However, the authors have just accounted for a few socio-economic characteristics recorded in the TUS database influencing occupants' activities. Proposing sub-population dependent activity transition probabilities in addition to modeling concurrent and correlated activities between household members are among other opportunities for enhancing this model.

Yamaguchi and Shimoda (2017) propose a stochastic model to predict occupants' activities at home for community-/urban-scale energy demand modeling which is designed to overcome the two weaknesses of prevalent models; the consideration of interactions among household members and the enhancement of specificity and consistency in the generated occupant behavior.

Later, Liu et al. (2019) propose a stochastic model and a data generator which generates the activity sequences based on a Markov chain technique for residential households of one and two members. They suggest expanding the model to simulate a household of more than two members as a future research opportunity. Although their proposed model can generate an activity sequence of households of one and two members with high precision, there still is a gap in knowledge for generating activity sequence based on theoretical behavioral models rather than the rule-based Markov chain technique which will add a behavioral foundation to the simulated activity patterns. The rule-based models use hard-coded decision rules to derive feasible solutions. Although this makes them easier to implement, it limits their generalisation (Pougala, Hillel, and Bierlaire 2021).

In order to address the issues associated with Markov chain technique and capture the underlying behavior patterns that shape activity schedules, Ramírez-Mendiola, Grünewald, and Eyre (2019) propose a new approach in the form of a stochastic process with memory of variable length for modeling residential users activity patterns. They implement a new methodology for the analysis of empirical TUD with a view to identifying the behavioral patterns within them.

In summary, the studies that incorporate individuals activity scheduling into energy models, mainly use a rule-based Markov chain approach, which cannot fully capture the variability in activity patterns and their underlying behavioral patterns. Moreover, the current approaches to simulate the activity patterns focus on either time-use in home or out-of-home activities and not both.

2.3.2 Out-of-house activity scheduling and travel behavior

The demand for travel is assumed to be driven by the need to complete activities which are distributed in space and time (Kay W. Axhausen and Gärling 1992). When treating the demand for travel as being driven by the need or desire to conduct activities, activity-based travel demand modeling captures the relationship between activity and travel behavior (Fu and Juan 2017). Travel behavior provides information such as number of daily travels, distance traveled, and travel mode. The travel behavior of individuals is affected by their socio-demographics, which also affects their activity participation. According to Lu and Eric I. Pas (1999), we can explain travel behavior better if activity participation (activity scheduling) is included endogenously in the model rather than taking into account its effect through socio-demographics. To this aim, Lu and Eric I. Pas (1999) propose a structural equation model relating socio-demographics, activity participation, and travel behavior in which activity participation and travel behavior are endogenous to the model. Variables normally included in the existing travel behavior models can be broadly categorized into socio-demographics, household characteristics, travel conditions, and residence location and land-use accessibility (E. I. Pas 1984). In this sub-section, we point out to some of the existing activity-based travel behavior models in the literature together with their contributions and limitations.

Bowman and M. E. Ben-Akiva (2001) propose an activity-based discrete choice model system for integrated activity and travel schedule. One of the limitations of their model is that it lacks in-home activities. This limits the ability of the model to fully capture the activity basis of travel demand. In the paper by Fu and Juan (2017), the authors present a comprehensive framework using a Structural equation model (SEM) that accommodates the complex interactions among activity and travel choice dimensions. Their approach explicitly reveals the behavioral pattern underlying the activity-travel decisions. However, they have included only private cars and buses as transportation alternatives due to the computational complexity in SEM with a higher number of alternatives. More advanced models should be used to be able to incorporate more discrete alternatives. Moreover, a combination of personal and household characteristics has been developed and used in their model rather than incorporating them separately. This limits the information regarding the direct effect of specific socio-demographics and household characteristics on behavioral decisions.

Whilst these models provide detailed disaggregate simulations of people's travel behavior outside the home, there is little to no understanding of in-home activities from these models. This has two primary limitations: firstly, it is difficult to capture the trade-offs between in-home and out-of-home activities, which is relevant in the post-Covid era such as the increase in remote working from home. Secondly, they are of limited value for studying domestic energy demand, aside from for determining building occupancy.

2.4 Integration of components

Integrated transport and energy modeling can be established using consistent activities people are engaged inside and outside their homes. Most existing activity-based models have not been applied to integrated energy analysis between buildings and transportation as these two domains have been developed independently.

Among the current literature, we have identified three key papers trying to integrate mobility and home energy profiles in their energy simulation models, which are all for the very recent years. Kandler (2017) presents a modeling approach for the synthesis of electrical, thermal, and mobility-related energy profiles of households based on a German time-use analysis; MOHEMA; using a probability distribution instead of rule-based Markov chains for generating activity profiles. Muller, Biedenbach, and Reinhard (2020) develop an integrated and consistent model with a bottom-up approach with an activity model based on the Markov-chain process for simulating the electrical and thermal load profiles of private households and their mobility behavior. Yamaguchi, Prakash, and Simoda (2020) demonstrate an energy management system modeling approach integrating house and electric vehicles using consistent data between in-house and out-of-house activities taking a Japanese dataset as a case study.

We have identified two limitations across these works. First, from a methodological point of view, all of these works use empirical rule-based or randomized processes to determine individual choices and activity scheduling. Therefore, it cannot easily be generalized to situations not observed in the data. Second, the primary investigation of these papers is evaluating the effect of electrification of the mobility on the electricity load profiles of households and thus, they contain only the modal split to the journeys made by car. So, to the best of our knowledge, there is no integrated framework to predict the daily activity schedule of individuals and their mode choice behavior based on behavioral variations.

2.5 Summary

We have observed in the literature that while the motivation and fundamentals for activity-based transportation and energy demand models are closely linked, these two domains have not yet been modeled jointly. Therefore, the ultimate goal of this research is a joint simulation of transportation and domestic energy demand. To make this ultimate goal achievable, we have broken down the research into different work packages.

First, a general framework is needed, which provides a holistic perspective of the elements that should be considered in order to integrate transport and energy demand modeling. Therefore, in this manuscript, we first propose a general framework on integrated transport and energy simulation. This framework gives an overview on the components needed to integrate transport and energy as well as the relations between the components. Section 3 provides the details on this framework. The proposed framework is a guide throughout our research. We will then focus on a specific component in the next steps of the research.

3 Proposed Framework

In this section, we present our proposed framework for integrating transport and energy demand at an urban scale together with its details. Energy demand is derived from activity participation and travel between activities. Therefore, right at the centre of this framework is the *activity scheduling* module and all the energy demand (including both in-home and out-of home energy demand) is derived from activities and traveling between the activities which are distributed in time and space. Individuals' behavior affect their activity scheduling. Therefore, accounting for the heterogeneity in individuals' behavior give flexibility and viability to the energy demand profiles.

Figure 4 illustrates the outline of the proposed framework. Then, the detailed presentation of each module in the framework is provided in Figures 5 to 8. In Figure 4, the four modules present different elements of the proposed framework for urban system energy demand; among which the white modules illustrate different energy consumer layers and the green module represents the connecting element between these energy consumer layers: the *activity scheduling* module. In this section, we will introduce each module within the framework in detail. In this diagram we have first summarized different methodologies within the chosen approach in each module together with the one selected for our framework. In the proposed framework presented in figure 4, the orange arrows represent intra-level interaction which presents information flow between different modules in the framework. The purple arrows present the inter-level interactions between different parts within the same module. The interactions can be in one-way or both-ways. One-way interaction means that the results of one component affects the other component. This also can be considered as one component feeding the other. A two-way interaction between the components show that they both affect each other/ interact with each other. The black arrows show the information flow between the modules and the USEM platform.

The proposed framework has two dimensions. The first dimension presents the modeling layout. In this dimension, as in every modeling framework, the first step is gathering *data*. Then, these data will be used as input to the *models*. Lastly, the *outputs* of the models can be analyzed and used for testing and comparing various policies, strategies, and decision-making. The second dimension of the framework introduces different energy consumer sectors in an urban system, which can be categorised into *domestic buildings energy demand*, *non-domestic buildings energy demand*, and *transportation energy demand*; together with a connecting module between energy layers; *activity scheduling*. Therefore, different elements in the second dimension are connected via a common module called *activity scheduling*. *Activity scheduling* is at the core of the proposed framework, giving input data to all other modules. The outputs of the domestic, non-domestic, and transportation energy demand modules can be then used to estimate the *urban system energy demand*.

First, we go through the connecting module within the energy demand layers: *activity scheduling*. Figure 5 illustrates the *activity scheduling* module in details. In our framework, *activity scheduling* is at the center giving input to the energy consumer layer modules. This is based on the idea that energy-use comes from actions which are driven by the desire or need to pursue activities that are temporally and spatially distributed. Activity scheduling includes both *in-home* and *out-of-home* activities. Out-of-home schedule includes time passed traveling between consecutive activities which are not at the same location, as well as the time participating in out-of-home activities. In-house and out-of-house schedules are interconnected as spending more time on one can restrict the time budget for the other one. In addition, out-of-home activity schedule has a direct influence on the travel behavior of individuals as the out-of-house activities directly trigger travelling.

There are significant interactions between in-home and out-of-home activities (Lu and Eric I. Pas 1999; S. Srinivasan and Bhat 2005b) and thus, it is important to capture this trade-off. Daily activities can generally be categorized into three groups: subsistence (work, school, and business), maintenance (shopping, personal service, professional service, and medical care), and recreation (entertainment, religion/civil services, and visiting). As all types of in-home activity duration increase, out-of-home subsistence duration decreases (Lu and Eric I. Pas 1999). Interestingly, people who spend more time on in-home subsistence spend less time on out-of-home subsistence, however, individuals who spend more time on out-of-home subsistence also spend more time on in-home subsistence. This can be explained as the workaholic people tend to bring more work home. Furthermore, in-home maintenance is positively related to out-of-home maintenance but, individuals who spend more time on out-home maintenance, are likely to spend less time on in-home maintenance. Also, there is a strong interaction between out-of-home maintenance and recreation with out-of-home subsistence; the more time spent on out-of-home subsistence, the less time is spent on these two types of activities. This can be interpreted as considering the time budget, the workaholic people tend to spend most of their time on work and have less time to spend other activities. There also is a complex interaction between individuals' activity and travel choice dimensions (Fu and Juan 2017). For example, the mode choice for recreation activities are conditional on subsistence activities duration. Therefore, considering the interaction between in-home and out-of-home activities and the complexity in the activity-travel behavior patterns, they should be addressed within the same scheduling model. This scheduling model will then contribute to the transport and energy models. As such, this activity scheduling paradigm addresses the limitation in the existing research concerning the interaction between in- and out-of-home activities and their corresponding transport and energy demand.

Activity scheduling can be utilized for two applications: *energy modeling approaches* and *travel behavior modeling* approaches. In the former application (*energy demand modeling approaches*), TUS data is used as an input to the models. On the other hand, in the *travel behavior modeling* application, *historic trip diary data* is used as inputs to *activity-based transport models*. Finally, daily scheduling behavior of individuals including both in-home and out-of-home scheduling, as well as their travel behavior are estimated as the outputs of this module.

The scheduling module presented in this framework, captures the choice of a valid schedule for a day made by an individual as a member of a household. It is noteworthy to mention that although focusing only on one-day scheduling will ignore day-to-day correlations (Arentze, Ettema, and H. J. Timmermans 2011), the implementation and validation of single-day models are already complex. Additionally, the required information to implement multi-day schedule is usually not readily available and requires additional data collection and fusion of multiple data sources (Aschauer et al. 2019).

Next, we go through the *domestic building energy modeling* module presented in Figure 6. In order to translate the activities to energy demand in the buildings, we need to model how the activities are translated to energy usage. Domestic energy use can be grouped into *active energy consumption* (i.e., electricity consumption of appliances which is directly connected to occupants' activities) and *passive energy consumption* (i.e., building's baseline energy consumption which does not directly depend on occupants' activities). *Household and individuals' characteristics*, *appliance ownership*, and *appliance energy rating* influence the *active energy consumption*. While the *external environment*, *building characteristics*, and *domestic HVAC system and energy rating*, and *lighting system* are among the influencing factors of *passive energy consumption*. We should relate the usage of electrical appliances to the activities in order to determine the active energy consumption. This can be done using the existing approaches to relate the use of electrical appliance to the activities performed such as the one proposed by Wilke (2013). Finally, the output of the *domestic building energy modeling* module (total energy demand of domestic buildings in the simulated area) feeds into the USEM platform.

Next, we go through the *microsimulation transportation energy demand modeling* module presented in Figure 7. Among the existing approaches for transport modeling, we have chosen microsimulation in the proposed framework as microsimulation is at a disaggregated level and provides detailed energy demand profiles of vehicles. Therefore, the transportation energy demand model can be coupled with building energy demand models by utilizing the *activity scheduling* module as a linking element between these two energy consumption domains. Within the *microsimulation transportation energy demand modeling*, we see two predominant approaches: *top-down* and *bottom-up*, from which the latter is chosen for this framework. Activity-based models follow a bottom-up approach in which travel demand is modeled as an aggregation of trips made by the individuals. The input to these models is the travel behavior of individuals which is generated by the *activity scheduling* module. This input data is then fed into an agent-based transport simulator such as MATSIM (Horni, Nagel, and Kay W Axhausen 2016). The output of this module is the total transportation energy demand in the simulated area, which feeds into the USEM platform.

As presented in Figure 8, another module in this framework is the *non-domestic building energy demand*. In this module, the total energy demand of non-domestic buildings in the simulated area is estimated using out-of-house activity schedule as an input into the models of econometric analysis and end-use methods. Then, the output of this module feeds into the USEM platform.

The proposed framework presents seven key advantages compared to the already existing ones: (1) it integrates the human behavior to the models by including activity scheduling in the core so, it can be generalized to complex scheduling and mobility situations, (2) it captures the trade-offs between in-home and out-of-home activities and thus their corresponding energy demand, (3) it provides a detailed activity scheduling as an input to building energy demand simulators rather than using building occupancy profiles which will address the limitations of occupancy-based models in which behavior of individuals are lost, (4) it includes transportation energy demand which is most of the time disregarded in urban energy models (except the LUT models which also do not normally include engineering arguments and calculations) (Sola et al. 2020), (5) it is based on the activity-based modeling paradigm which is a significant new opportunity for the development of bottom-up urban energy demand models (Sola et al. 2020), (6) it is based on a bottom-up approach and thus, is suitable for future scenario testings; and (7) it uses co-simulation approach (instead of integrated approach) which reduces implementation and modeling effort and increases reliability as a result of using established packages for each module.

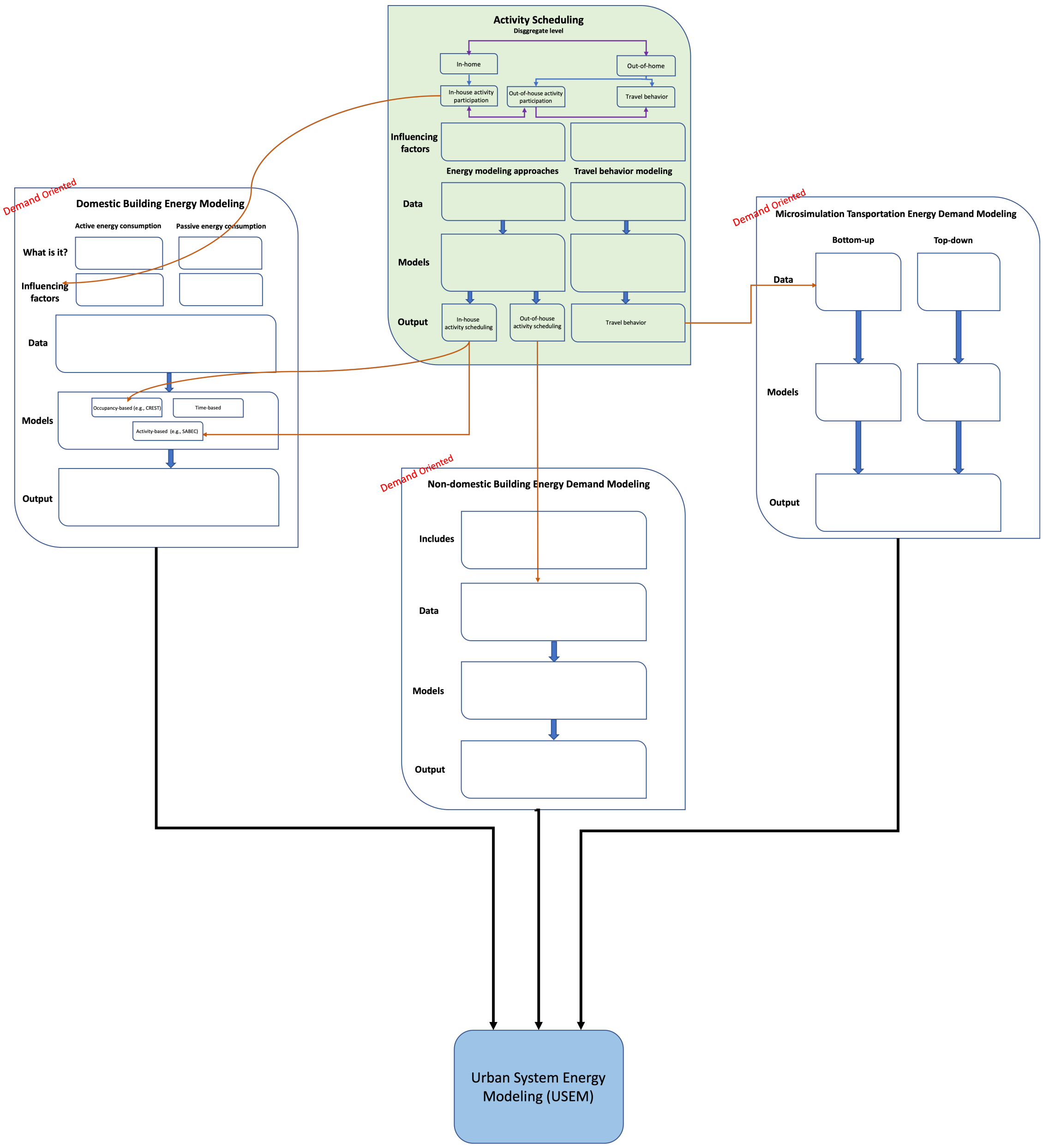

Figure 4: Urban system energy demand framework

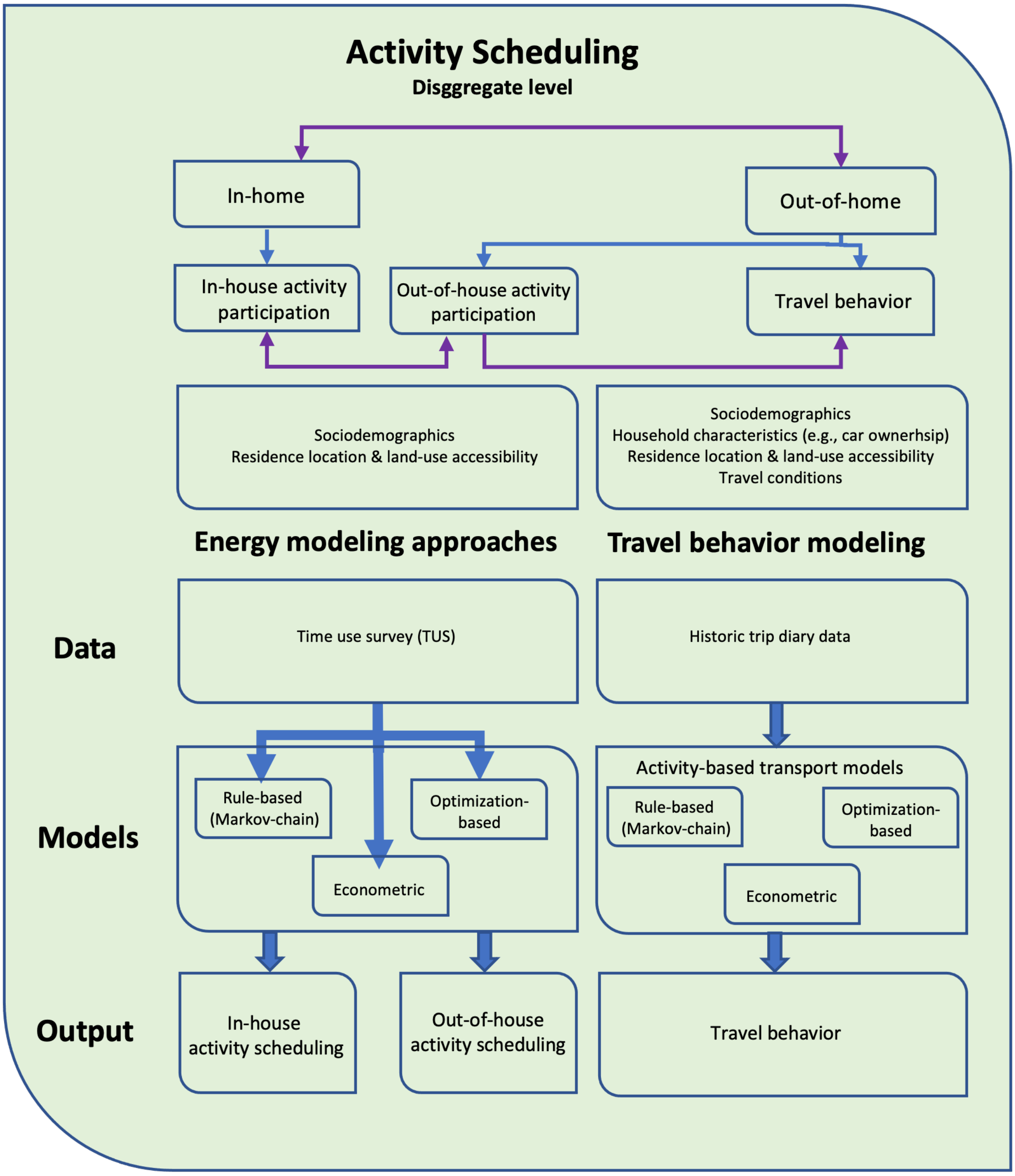

Figure 5: Activity participation framework

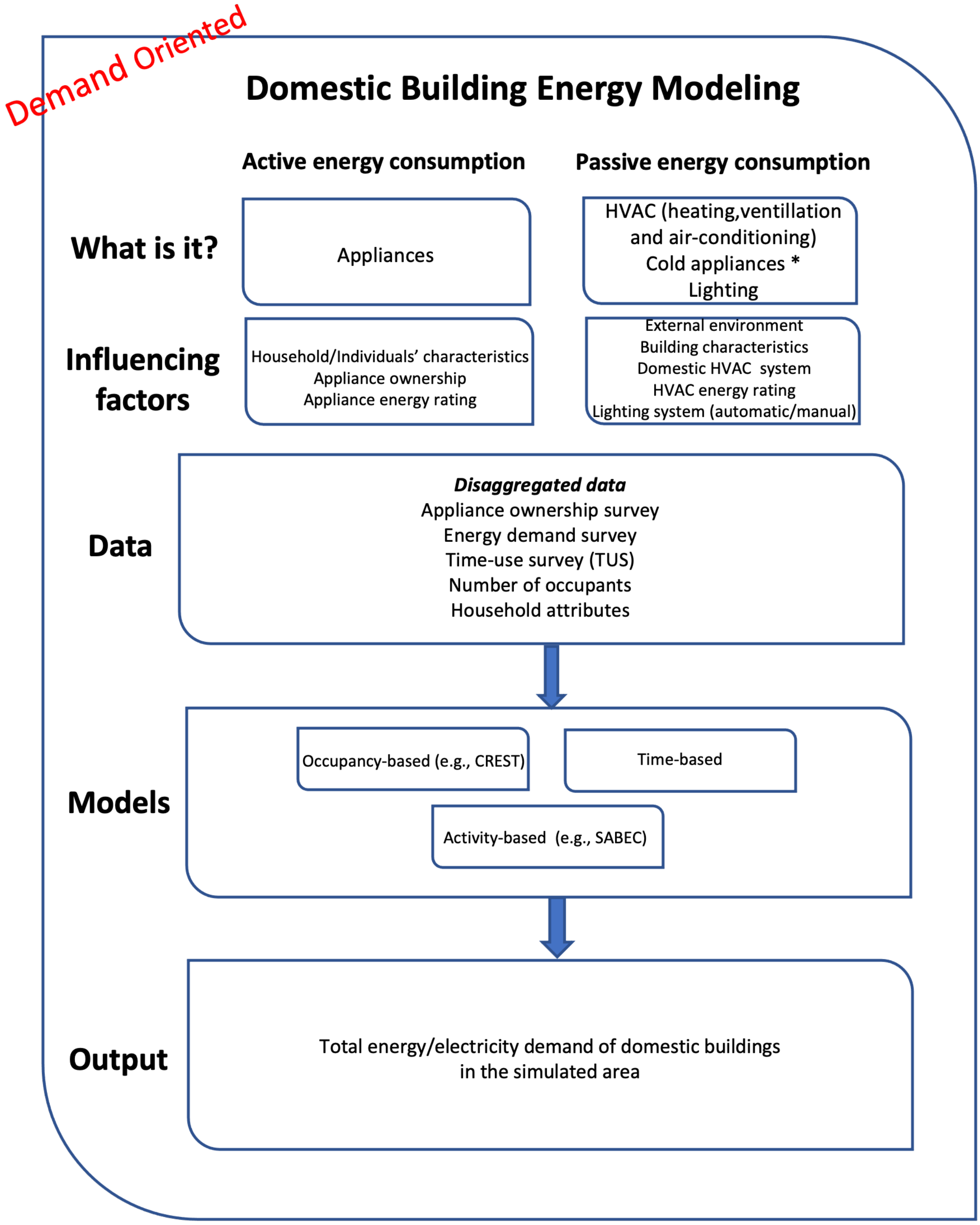

Figure 6: Domestic building energy modeling framework

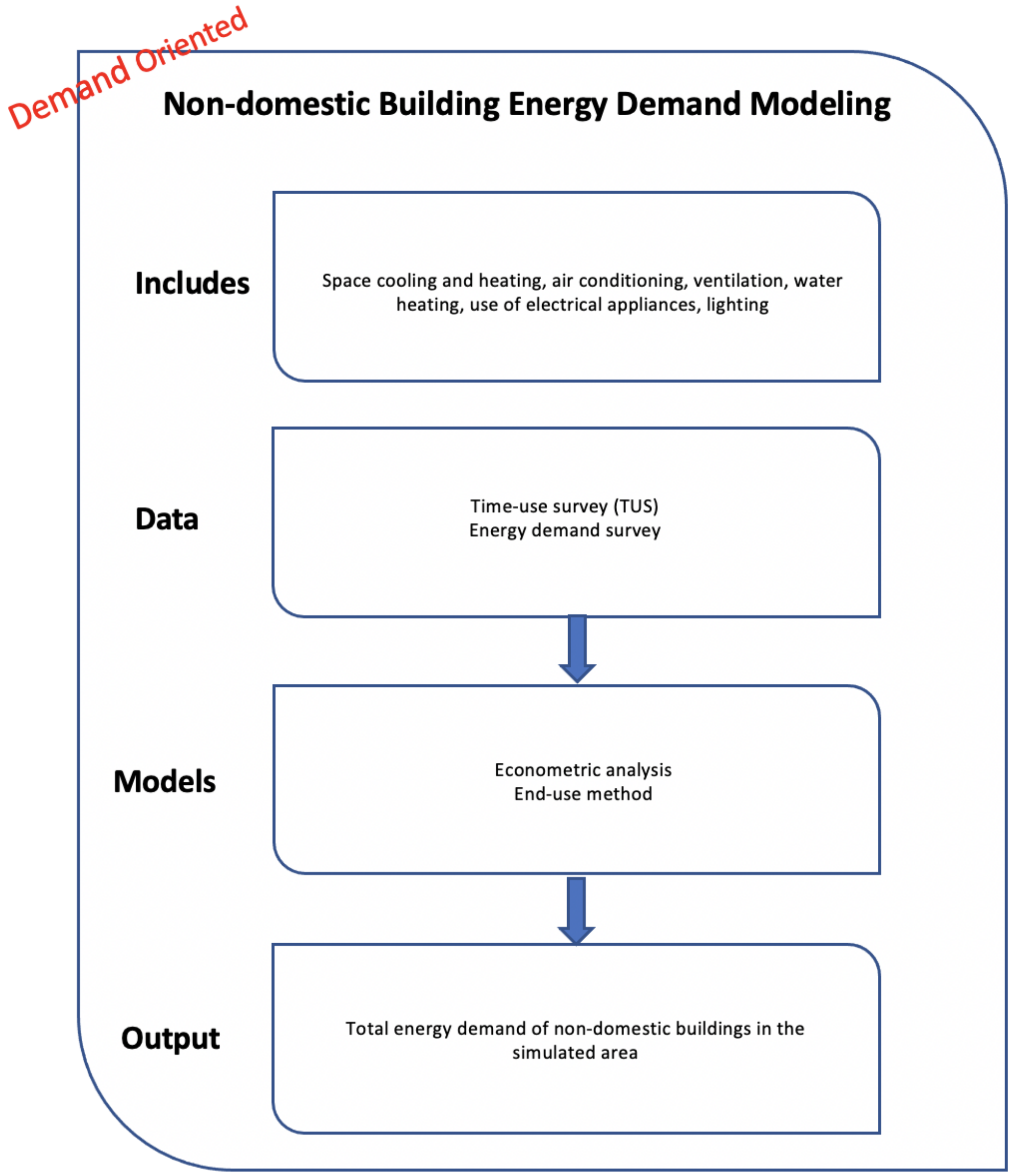

Figure 7: Non-domestic building energy demand modeling framework

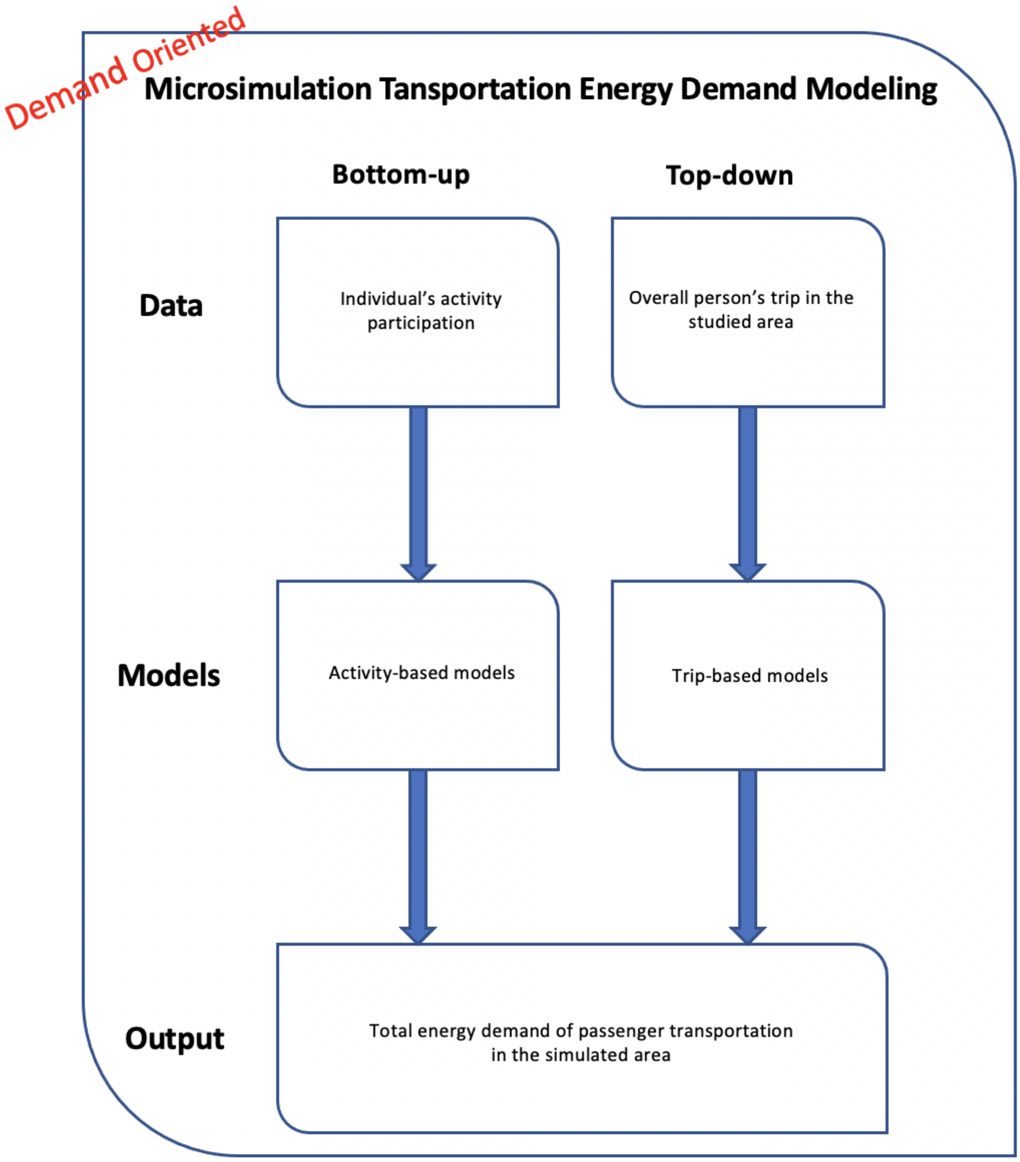

Figure 8: Microsimulation transportation energy demand modeling framework

4 Conclusion and Future Work

In this paper, we have reviewed the literature on transport and energy modeling. Through the review of the available literature, we have identified a lack of unified approach to simultaneously model transport and energy demand. In spite of a number of different methodologies to simulate each domain separately, there have not been a joint view on these two domains. We have identified an approach to co-simulate these two domains in order to capture their interdependence. Our proposed solution is using activity-based approach. We have seen that although activity-based models have been extensively used in transportation modeling, there have been limited attempts to model energy demand using this approach. This approach will enable us to assess the trade-off between in-home and out-of-home activities and their subsequent energy demand.

Then we have presented a holistic framework from an activity-based point-of-view for transport and energy demand modeling. Simultaneously with the literature review, the architecture and components of the framework have been set accordingly. We have introduced a new modeling framework for energy demand modeling, where the activity is the central unit of analysis. This framework bridges the traditional energy demand domains (domestic and non-domestic building) and transportation by incorporating a new element: activity scheduling. The contribution of this paper is to provide a holistic methodological map to joint transport and energy demand modeling, understand their inherent link, identify the existing approaches for each element, introduce a new modeling paradigm for integrating them, and identify the gaps in knowledge which should be addressed to get the framework running.

From the framework we can see that in order to fill the gap in joint modeling of transport and energy demand, first, an activity scheduling model which jointly model time-use in the home as well as the activities outside the home is needed. The sequential structure of econometric scheduling models does not represent the true nature of the scheduling process and makes it difficult to capture complex trade-offs and household interactions. Moreover, the hard-coded nature of rule-based scheduling models make them unable to generalise to situations which are significantly different to input data. Furthermore, the existing scheduling models focus either on in-home or out-of-home activities and not both.

Driven by the presented framework and gaps, we have identified the first research question that we should tackle next. The next step in this research is to formulate and implement a daily schedule model that covers both time-use whilst at home and activities outside the home. To achieve this, we plan to build on a current ongoing research at TRANSP-OR, which has developed an optimization-based scheduling model of time-use for out-of-home (Pougala, Hillel, and Bierlaire 2020a; Pougala, Hillel, and Bierlaire 2020b), by incorporating time-use for activities in the home (e.g., sleeping, cooking, showering, etc) as well. This approach treats individuals as maximising their total utility from completed activities in order to schedule their day, in which the first results show that this methodology is able to generate stable and reliable schedules for activities completed outside the home (Pougala, Hillel, and Bierlaire 2020a; Pougala, Hillel, and Bierlaire 2020b). There are a number of phenomena that should be addressed in this scheduling model such as the interactions between the members of a household, behavioral heterogeneity, and different behavioral patterns throughout times of the day and even days of the week. The model will be calibrated using detailed TUS data.

In the next steps, we will look for applying the model to the already existing energy simulation models and assess the effect of various policies, technological changes, and behavioral changes on energy demand.

It is noteworthy that this research intends to provide a generic framework for integrated transport and energy demand modeling. Therefore, the non-domestic building block has also been included in the framework to make it generic. However, in this research, transportation and in-house energy demand modeling have been chosen as the first sub-models to integrate. An in-depth investigation of integrating other sub-models of USEM such as industrial and commercial buildings' energy demand to the proposed framework, can be done in a future research.

References

Arentze, Theo A., Dick Ettema, and Harry J.P. Timmermans (2011). "Estimating a model of dynamic activity generation based on one-day observations: Method and results". In: *Transp. Res. Part B Methodol.* 45.2, pp. 447–460. DOI: 10.1016/j.trb.2010.07.005.

Arghira, Nicoleta, Lamis Hawarah, Stéphane Ploix, and Mireille Jacomino (2012). "Prediction of appliances energy use in smart homes". In: *Energy* 48.1, pp. 128–134. DOI: 10.1016/j.energy.2012.04.010.

Aschauer, Florian, Inka Rösel, Reinhard Hössinger, Heinz Brian Kreis, and Regine Gerike (2019). "Time use, mobility and expenditure: an innovative survey design for understanding individuals' trade-off processes". In: *Transportation (Amst).* 46.2, pp. 307–339. DOI: 10.1007/s11116-018-9961-9.

Axhausen, Kay W. and Tommy Gärling (1992). "Activity-based approaches to travel analysis: conceptual frameworks, models, and research problems". In: *Transp. Rev.* 12.4. DOI: https://doi.org/10.1080/01441649208716826.

Baetens, Ruben and Dirk Saelens (2016). "Modelling uncertainty in district energy simulations by stochastic residential occupant behaviour". In: *J. Build. Perform. Simul.* 9.4, pp. 431–447. DOI: 10.1080/19401493.2015.1070203.

Ben-Akiva, Moshe and Steven R. Lerman (1985). *Discrete Choice Analysis: Theory and Application to Travel Demand*. Cambridge, Massachusetts.: The MIT Press.

Bowman, J. L. and M. E. Ben-Akiva (2001). "Activity-based disaggregate travel demand model system with activity schedules". In: *Transp. Res. Part A Policy Pract.* 35.1, pp. 1–28. DOI: 10.1016/S0965-8564(99)00043-9.

Bustos-Turu, Gonzalo, Koen H. Van Dam, Salvador Acha, Christos N. Markides, and Nilay Shah (2016). "Simulating residential electricity and heat demand in urban areas using an agent-based modelling approach". In: *2016 IEEE Int. Energy Conf. ENERGYCON 2016*, pp. 6–11. DOI: 10.1109/ENERGYCON.2016.7514077.

Chapin, S. (1974). *Human Activity Patterns in the City: Thing People Do in Time and Space*. Wiley, New York, USA.

Clevenger, Caroline M and John Haymaker (2006). "The Impact Of The Building Occupant On Energy Modeling Simulations". In: *Jt. Int. Conf. Comput. Decis. Mak. Civ. Build. Eng.*, pp. 1–10.

EIA (2020). *Annual Energy Outlook*. Tech. rep.

Emery, A. F. and C. J. Kippenhan (2006). "A long term study of residential home heating consumption and the effect of occupant behavior on homes in the Pacific Northwest constructed according to improved thermal standards". In: *Energy* 31.5, pp. 677–693. DOI: 10.1016/j.energy.2005.04.006.

European Commission (2021). *Switzerland Energy profile*. Tech. rep. March.

Evins, Ralph, Kristina Orehounig, and Viktor Dorer (2016). "Variability between domestic buildings: the impact on energy use". In: *J. Build. Perform. Simul.* 9.2, pp. 162–175. DOI: 10.1080/19401493.2015.1006526.

Flett, Graeme and Nick Kelly (2017). "A disaggregated, probabilistic, high resolution method for assessment of domestic occupancy and electrical demand". In: *Energy Build.* 140, pp. 171–187. DOI: 10.1016/j.enbuild.2017.01.069.

Fu, Xuemei and Zhicai Juan (2017). “An integrated framework to jointly model decisions of activity time allocation and work-related travel”. In: *Transp. Plan. Technol.* 40.6, pp. 689–705. DOI: 10.1080/03081060.2017.1325145.

Ghauche, Anwar (2010). “Integrated Transportation and Energy Activity-Based Model”. PhD thesis. Massachusetts Institute of Technology, p. 141.

Gruber, J. K., S. Jahromizadeh, M. Prodanović, and V. Rakočević (2014). “Application-oriented modelling of domestic energy demand”. In: *Int. J. Electr. Power Energy Syst.* 61, pp. 656–664. DOI: 10.1016/j.ijepes.2014.04.008.

Hagerstrand, T. (1970). “What about people in regional science?” In: *Reg. Sci. Assoc. Pap.* 24.7.

Hong, Tianzhen, Yixing Chen, Xuan Luo, Na Luo, and Sang Hoon Lee (2020). “Ten questions on urban building energy modeling”. In: *Build. Environ.* 168. DOI: 10.1016/j.buildenv.2019.106508.

Horni, Andreas, Kai Nagel, and Kay W Axhausen (2016). *The Multi-Agent Transport Simulation MATSim*.

IEA. (2008). *World energy outlook*.

Joh, Chang-Hyeon, Harry J P Timmermans, and W W Recker (2004). “Measuring and Predicting Adaptation in Multidimensional Activity-Travel Patterns”. PhD thesis, p. 236.

Kandler, Christian (2017). “Modellierung von Zeitnutzungs-, Mobilitäts-und Energieprofilen zur Bestimmung der Potentiale von Energiemanagementsystemen in Haushalten [Time-use, mobility and energy modeling as part of an overall framework for evaluating the potential of home energy ma”. PhD thesis. Technical University of Munich, p. 251.

Kashif, Ayesha, Stéphane Ploix, Julie Dugdale, and Xuan Hoa Binh Le (2013). “Simulating the dynamics of occupant behaviour for power management in residential buildings”. In: *Energy Build.* 56, pp. 85–93. DOI: 10.1016/j.enbuild.2012.09.042.

Kato, Hironori and Manabu Matsumoto (2009). “Intra-household interaction in a nuclear family: A utility-maximizing approach”. In: *Transp. Res. Part B Methodol.* 43.2, pp. 191–203. DOI: 10.1016/j.trb.2008.05.006.

Keirstead, James, Mark Jennings, and Aruna Sivakumar (2012). “A review of urban energy system models: Approaches, challenges and opportunities”. In: *Renew. Sustain. Energy Rev.* 16.6, pp. 3847–3866. DOI: 10.1016/j.rser.2012.02.047.

Kotusevski, G and K A Hawick (2009). *A Review of Traffic Simulation Software*. Wellington, New Zealand.

Li, Wenliang et al. (2017). “Modeling urban building energy use: A review of modeling approaches and procedures”. In: *Energy* 141, pp. 2445–2457. DOI: 10.1016/j.energy.2017.11.071.

Liu, Xiufeng, Yanyan Yang, Rongling Li, and Per Sieverts Nielsen (2019). “A stochastic model for residential user activity simulation”. In: *Energies* 12.17, pp. 1–17. DOI: 10.3390/en12173326.

Lu, Xuedong and Eric I. Pas (1999). “Socio-demographics, activity participation and travel behavior”. In: *Transp. Res. Part A Policy Pract.* 33.1, pp. 1–18. DOI: 10.1016/s0965-8564(98)00020-2.

Mahmud, Khizir and Graham E. Town (2016). “A review of computer tools for modeling electric vehicle energy requirements and their impact on power distribution networks”.

In: *Appl. Energy* 172, pp. 337–359. DOI: 10.1016/j.apenergy.2016.03.100.

Mannering, Fred, Elaine Murakami, and Soon Gwan Kim (1994). “Temporal stability of travelers’ activity choice and home-stay duration: Some empirical evidence”. In: *Transportation (Amst).* 21.4, pp. 371–392. DOI: 10.1007/BF01110481.

Masoso, O. T. and L. J. Grobler (2010). “The dark side of occupants’ behaviour on building energy use”. In: *Energy Build.* 42.2, pp. 173–177. DOI: 10.1016/j.enbuild.2009.08.009.

McKenna, Eoghan, Michal Krawczynski, and Murray Thomson (2015). “Four-state domestic building occupancy model for energy demand simulations”. In: *Energy Build.* 96, pp. 30–39. DOI: 10.1016/j.enbuild.2015.03.013.

McKenna, Eoghan and Murray Thomson (2016). “High-resolution stochastic integrated thermal-electrical domestic demand model”. In: *Appl. Energy* 165, pp. 445–461. DOI: 10.1016/j.apenergy.2015.12.089.

Miller, Eric J., John Douglas Hunt, John E. Abraham, and Paul A. Salvini (2004). “Microsimulating urban systems”. In: *Comput. Environ. Urban Syst.* 28.1-2, pp. 9–44. DOI: 10.1016/S0198-9715(02)00044-3.

Muller, Mathias, Florian Biedenbach, and Janis Reinhard (2020). “Development of an integrated simulation model for load and mobility profiles of private households”. In: *Energies* 13.15, pp. 1–32. DOI: 10.3390/en13153843.

Muratori, Matteo, Michael J. Moran, Emmanuele Serra, and Giorgio Rizzoni (2013a). “Highly-resolved modeling of personal transportation energy consumption in the United States”. In: *Energy* 58, pp. 168–177. DOI: 10.1016/j.energy.2013.02.055.

Muratori, Matteo, Matthew C. Roberts, Ramteen Sioshansi, Vincenzo Marano, and Giorgio Rizzoni (2013b). “A highly resolved modeling technique to simulate residential power demand”. In: *Appl. Energy* 107, pp. 465–473. DOI: 10.1016/j.apenergy.2013.02.057.

Oneal, D. L.; and Eric Hirst (1980). “An energy used model of the residential sector”. In: *EEE Trans. Syst. Man, Cybern.* SMC-10, pp. 749–755.

Paatero, Jukka V. and Peter D. Lund (2006). “A model for generating household electricity load profiles”. In: *Int. J. Energy Res.* 30.5, pp. 273–290. DOI: 10.1002/er.1136.

Palacios-García, E. J., A. Moreno-Munoz, I. Santiago, J. M. Flores-Arias, F. J. Bellido-Outeiriño, and I. M. Moreno-Garcia (2018). “Modeling human activity in Spain for different economic sectors: The potential link between occupancy and energy usage”. In: *J. Clean. Prod.* 183, pp. 1093–1109. DOI: 10.1016/j.jclepro.2018.02.049.

Pas, E. I. (1984). “The effect of selected sociodemographic characteristics on daily travel-activity behavior.” In: *Environ. Plan. A* 16.5, pp. 571–581. DOI: 10.1068/a160571.

Pitombo, Cira, A. J. Sousa, and L. N. Filipe (2009). “Classification and regression tree, principal components analysis and multiple linear regression to summarize data and understand travel behavior”. In: *Transp. Lett.* 1.4, pp. 295–308. DOI: 10.3328/TL.2009.01.04.295-308.

Pougala, Janody, Tim Hillel, and Michel Bierlaire (2020a). “An Optimization Framework For Daily Activity Schedules”. In: *Proc. 9th Symp. Eur. Assoc. Res. Transp. (HEART), 3-4 Febr. 2021.* Lyon, France, pp. 1–13.

Pougala, Janody, Tim Hillel, and Michel Bierlaire (2020b). “Scheduling of daily activities: an optimization ap- proach”. In: *Proc. 20th Swiss Transp. Res. Conf. (STRC), 13-14 May*. May.

— (2021). *Capturing trade-offs between daily scheduling choices*. Tech. rep. Ecole Polytechnique Fédérale de Lausanne, p. 26.

Ramírez-Mendiola, José Luis, Philipp Grünewald, and Nick Eyre (2019). “Residential activity pattern modelling through stochastic chains of variable memory length”. In: *Appl. Energy* 237, pp. 417–430. DOI: 10.1016/j.apenergy.2019.01.019.

Richardson, Ian, Murray Thomson, and David Infield (2008). “A high-resolution domestic building occupancy model for energy demand simulations”. In: *Energy Build.* 40.8, pp. 1560–1566. DOI: 10.1016/j.enbuild.2008.02.006.

Richardson, Ian, Murray Thomson, David Infield, and Conor Clifford (2010). “Domestic electricity use: A high-resolution energy demand model”. In: *Energy Build.* 42.10, pp. 1878–1887. DOI: 10.1016/j.enbuild.2010.05.023.

Richardson, Ian, Murray Thomson, David Infield, and Alice Delahunty (2009). “Domestic lighting: A high-resolution energy demand model”. In: *Energy Build.* 41.7, pp. 781–789. DOI: 10.1016/j.enbuild.2009.02.010.

Roorda, Matthew J., Eric J. Miller, and Khandker M. Nurul Habib (2008). “Validation of TASHA: A 24-h activity scheduling microsimulation model”. In: *Transp. Res. Part A Policy Pract.* 42.2, pp. 360–375. DOI: 10.1016/j.tra.2007.10.004.

Scherr, Wolfgang, Patrick Manser, Chetan Joshi, Nathalie Frischknecht, and Denis Métrailler (2020). “Towards agent-based travel demand simulation across all mobility choices – the role of balancing preferences and constraints”. In: *Eur. J. Transp. Infrastruct. Res.* 20.4, pp. 152–172. DOI: 10.18757/ejtir.2020.20.4.4463.

Seryak, John and Kelly Kissock (2000). “Occupancy and Behavioral Affects on Rresidential Energy Use”. In: *Proc. Annu. Conf. Am. Sol. energy Soc.*

— (2003). “Occupancy and behavioral effects on residential energy use”. In: *Sol. Conf.* Austin, TX, pp. 717–722.

Sivakumar, Aruna (2013). “Activity-based modelling for urban energy systems”. In: *Urban Energy Syst. An Integr. Approach*. Ed. by James Keirstead and Nilay Shah. 1st ed. Routledge, pp. 204–217.

Sola, Alaia, Cristina Corchero, Jaume Salom, and Manel Sanmarti (2018). “Simulation tools to build urban-scale energy models: A review”. In: *Energies* 11.12. DOI: 10.3390/en11123269.

— (2020). “Multi-domain urban-scale energy modelling tools: A review”. In: *Sustain. Cities Soc.* 54, pp. 1–13. DOI: 10.1016/j.scs.2019.101872.

Sovacool, B. K. et al. (2015). “Integrating social science in energy research”. In: *Energy Res. Soc. Sci.* 6, pp. 95–99. DOI: 10.1016/j.erss.2014.12.005.

Srinivasan, Karthik K. and Sudhakar R. Athuru (2005). “Analysis of within-household effects and between-household differences in maintenance activity allocation”. In: *Transportation (Amst).* 32.5, pp. 495–521. DOI: 10.1007/s11116-005-5355-x.

Srinivasan, Sivaramakrishnan and Chandra R. Bhat (2005a). “Modeling household interactions in daily in-home and out-of-home maintenance activity participation”. In: *Transportation (Amst).* 32.5, pp. 523–544. DOI: 10.1007/s11116-005-5329-z.

Srinivasan, Sivaramakrishnan and Chandra R. Bhat (2005b). "Modeling household interactions in daily in-home and out-of-home maintenance activity participation". In: *Transportation (Amst).* 32.5, pp. 523–544. DOI: 10.1007/s11116-005-5329-z.

Subbiah, Rajesh (2013). "An activity-based energy demand modeling framework for buildings: A bottom-up approach". PhD thesis. Virginia Polytechnic Institute and State University.

Swan, Lukas G. and V. Ismet Ugursal (2009). "Modeling of end-use energy consumption in the residential sector: A review of modeling techniques". In: *Renew. Sustain. Energy Rev.* 13.8, pp. 1819–1835. DOI: 10.1016/j.rser.2008.09.033.

Tanimoto, Jun, Aya Hagishima, and Hiroki Sagara (2008). "Validation of probabilistic methodology for generating actual inhabitants' behavior schedules for accurate prediction of maximum energy requirements". In: *Energy Build.* 40.3, pp. 316–322. DOI: 10.1016/j.enbuild.2007.02.032.

Timmermans, Harry J P (2003). "Recent and Expected Direction in Modelling Transportation". In: *22nd Annu. South. African Transp. Conf.*

Torriti, Jacopo (2014). "A review of time use models of residential electricity demand". In: *Renew. Sustain. Energy Rev.* 37, pp. 265–272. DOI: 10.1016/j.rser.2014.05.034.

Waddell, Paul (2002). "Urbansim: Modeling urban development for land use, transportation, and environmental planning". In: *J. Am. Plan. Assoc.* 68.3, pp. 297–314. DOI: 10.1080/01944360208976274.

Wang, Danhong, Jonas Landolt, Georgios Mavromatidis, Kristina Orehounig, and Jan Carmeliet (2018). "CESAR: A bottom-up building stock modelling tool for Switzerland to address sustainable energy transformation strategies". In: *Energy Build.* 169, pp. 9–26. DOI: 10.1016/j.enbuild.2018.03.020.

Widén, Joakim, Andreas Molin, and Kajsa Ellegård (2012). "Models of domestic occupancy, activities and energy use based on time-use data: Deterministic and stochastic approaches with application to various building-related simulations". In: *J. Build. Perform. Simul.* 5.1, pp. 27–44. DOI: 10.1080/19401493.2010.532569.

Widén, Joakim, Annica M. Nilsson, and Ewa Wäckelgård (2009). "A combined Markov-chain and bottom-up approach to modelling of domestic lighting demand". In: *Energy Build.* 41.10, pp. 1001–1012. DOI: 10.1016/j.enbuild.2009.05.002.

Widén, Joakim and Ewa Wäckelgård (2010). "A high-resolution stochastic model of domestic activity patterns and electricity demand". In: *Appl. Energy* 87.6, pp. 1880–1892. DOI: 10.1016/j.apenergy.2009.11.006.

Wilke, Urs (2013). "Probabilistic Bottom-up Modelling of Occupancy and Activities to Predict Electricity Demand in Residential Buildings". PhD thesis. ÉCOLE POLYTECHNIQUE FÉDÉRALE DE LAUSANNE. DOI: 10.5075/epfl-thesis-5673.

Wilke, Urs, Frédéric Haldi, Jean Louis Scartezzini, and Darren Robinson (2013). "A bottom-up stochastic model to predict building occupants' time-dependent activities". In: *Build. Environ.* 60, pp. 254–264. DOI: 10.1016/j.buildenv.2012.10.021.

Yamaguchi, Yohei, Nikhil Prakash, and Yoshiyuki Simoda (2020). "Activity-Based Modeling for Integration of Energy Systems for House and Electric Vehicle". In: *Des. Anal. Distrib. Energy Manag. Syst.* Chap. 1.

Yamaguchi, Yohei and Yoshiyuki Shimoda (2017). "A stochastic model to predict occupants' activities at home for community-/urban-scale energy demand modelling". In: *J. Build. Perform. Simul.* 10.5-6, pp. 565–581. DOI: 10.1080/19401493.2017.1336255.

Yohanis, Yigzaw G., Jayanta D. Mondol, Alan Wright, and Brian Norton (2008). "Real-life energy use in the UK: How occupancy and dwelling characteristics affect domestic electricity use". In: *Energy Build.* 40.6, pp. 1053–1059. DOI: 10.1016/j.enbuild.2007.09.001.

Yu, Zhun, Benjamin C.M. Fung, Fariborz Haghighat, Hiroshi Yoshino, and Edward Morofsky (2011). "A systematic procedure to study the influence of occupant behavior on building energy consumption". In: *Energy Build.* 43.6, pp. 1409–1417. DOI: 10.1016/j.enbuild.2011.02.002.

Zaraket, Toufic (2014). "Stochastic Activity-based Approach of Occupant-related Energy Consumption in Residential Buildings". PhD thesis. ÉCOLE CENTRALE DES ARTS ET MANUFACTURES « ÉCOLE CENTRALE PARIS ».