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Design and Analysis of Distributed Energy Management Systems

Integration of EMS, EV, and ICT

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Preface

Smart grid infrastructure has attracted substantial interest for use as effective electric power management systems that work together with recently developed reciprocal communication networks. One of the most important considerations for smart grid systems is maximizing the use of renewable power sources such as wind and solar power, which are beneficial for the economy and sustainability. To achieve a balance of supply and demand with renewable energy sources, a dynamic pricing strategy intended to bring consumer demand more in line with supply has been proposed. However, the success of this strategy strongly depends on actual consumer response to time-varying prices. As can be imagined, having consumers be continuously aware of prices is generally inconvenient and impractical. Therefore, it is highly recommended to have a distributed energy management system (EMS) that can automatically regulate supply–demand imbalances with regard to user convenience and economy.

Additionally, demand for electric vehicles (EVs) and plug-in hybrid vehicles (PHVs) is expected to increase, making them important transportation means in a low carbon society. EVs and PHVs carry in-vehicle batteries of 20–30 kWh and 5–10 kWh, respectively. In addition, vehicles used for car sharing, customer transportation, luggage transportation, home delivery, and other such tasks will be electrified. Thus, there is little doubt that the market for EVs and PHVs will continue to develop. Setting the capacity, number, and arrangement of storage batteries and scheduling battery charging and discharging of batteries are important design points for realizing a distributed EMS that meets various requirements. As EVs and PHVs proliferate, in-vehicle batteries will not be used solely for transportation, but can be integrated into the customer's EMS. Effective use of in-vehicle batteries can be a key technology to realize a resilient community, particularly when supply and demand balance is significantly disrupted or when a disaster occurs. In consideration of these factors, in-vehicle batteries will play three roles in next-generation smart communities.

1. Power storage device for transportation
2. Power storage device for improving supply–demand balance in each customer's local EMS
3. Aggregated community virtual power storage used for power network stabilization

It is highly recommended to design charge–discharge scheduling of in-vehicle batteries to balance supply and demand in the local EMS and meet the community's power network stability requirements while considering the transportation demands of each user. Therefore, an energy–mobility integrated system model must be developed and fully exploited to design the future smart community. Based on these perspectives, this book addresses the following topics:

Part I Design and analysis of energy management systems considering consumer demand and use of electric vehicles

- Activity-based modeling for integration of energy systems for house and electric vehicle

This chapter introduces an activity-based approach to model home and transportation energy demand. This method simulates in-home and out-of-home activities and quantifies home and transportation energy demands accordingly. This method enables quantification of energy demand with realistic temporal variations. An important application of this method is analyzing the EMS that integrates the house and EV or PHV, which can be achieved when in-home and out-of-home activities are modeled consistently.

- Probabilistic model and prediction of vehicle daily use

To utilize in-vehicle batteries in an EMS, with consideration of user acceptance, the EMS must know when the vehicle is driven and parked, which can be represented by a departure, and travel time profile. This chapter presents a method to predict the most probable car use profile over 1 day based on a customer's daily car use statistics. The prediction method is formulated as a maximum-likelihood estimation, and the usefulness of the proposed method is evaluated using numerical experiments.

- Design of a home energy management system integrated to a vehicle (V2H + HPWH EMS)

This chapter proposes a home EMS (HEMS) that simultaneously controls an in-vehicle battery charge–discharge process and a heat pump water heater (HPWH) operation plan. The proposed control method iteratively calculates the in-vehicle battery charge–discharge plan and HPWH operation schedule to minimize the electricity bill considering both reverse surplus power as a penalty and vehicle usage as a constraint. The effectiveness of the proposed system is then verified in simulations using real household data.

- Range extension autonomous driving for electric vehicles based on optimization of velocity profile considering traffic signal information

In this chapter, a range extension autonomous driving system that considers traffic signal information is proposed. This proposed system optimizes the autonomous driving velocity profile based on precise vehicle loss models. The authors conduct simulations and experiments to prove the effectiveness of the proposed system in terms of mileage per charge.

Part II Synthesis of distributed energy management systems based on aggregation of local EMSs and vehicles

- Real-time pricing and decentralized optimization strategy for power flow balancing in EV/PHV storage management

This chapter investigates a decentralized energy management strategy for a community composed of households equipped with EV/PHV storage. The proposed real-time pricing strategy does not depend on the number of agents and allows plug-and-play type operations. This will address EV/PHV storage management problems as unpredictable connections or disconnections of vehicles may exist. Effectiveness of the proposed pricing-based decentralized management strategy is then evaluated using numerical experiments.

- A scalable control approach for providing regulation services with grid-integrated electric vehicles

Researchers at the University of Delaware are providing regulation services by controlling bidirectional power transfer between a fleet of EVs and the grid. As EVs become more popular, increasing the size of the EV fleet, large-scale control becomes an important challenge. Power transfer for thousands of EVs may need to be controlled, accounting for driver requirements while providing regulation services. To cope with this challenge, the authors propose a grid-integrated vehicle (GIV) control approach based on bins. Results show that their GIV control method can combine the good scheduling qualities of a centralized GIV approach with a distributed GIV approach's scalability.

- A continuum approach to assessing the impact of spatiotemporal EV charging to distribution grids

The assessment problem on how charging operations of a large population of EVs impact the spatial voltage profile of a power distribution grid is addressed. Unlike the conventional space-discretization approach, an alternative approach for the assessment based on a continuum representation of the distribution voltage profile is introduced. Continuum representation explicitly keeps spatial (or geographical) information on a distribution grid and thus enables us to quantify the spatial impact of EV charging.

Part III Toward dependable distributed energy management system using information and communication technologies (ICT)

- Cyber security for voltage control of distribution systems under data falsification attacks

This chapter provides an overview of recent research on false data injection (FDI) attacks on voltage measurements transmitted by sensors to a centralized controller. The approach is to first introduce an attack detection algorithm and then enhance the security level using a resilient controller that can perform regulation in the presence of attacks by utilizing detection results. We illustrate our methods using simulation studies on a realistic, small-scale distribution system.

- Machine learning based intrusion detection in control system communication

This chapter compares conditional random field-based intrusion detection with probabilistic model-based intrusion detection. These methods use control system communication network traffic sequence characteristics. Learning only utilizes normal network traffic data, assuming no prior knowledge on attacks in the system. We apply these two probabilistic models to intrusion detection in DARPA data and an experimental control system network and compared performance differences.

Lastly, this work was supported by many collaborative researchers and executed as one of the projects in the Core Research for Evolutional Science and Technology (CREST) program of the Japan Science and Technology Agency (JST), and we deeply appreciate these contributions.

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Part I
Design and Analysis of Energy Management Systems Considering Consumer Demand and Use of Electric Vehicles

Chapter 1
Activity-Based Modeling for Integration of Energy Systems for House and Electric Vehicle

Yohei Yamaguchi, Nikhil Prakash, and Yoshiyuki Simoda

1.1 Introduction

Energy is consumed to sustain everyday human activities. People use appliances for various purposes such as cooking and entertainment, and use cars to travel to work and other places. Thus, home and transportation energy consumption has been understood, analyzed, and modeled in relation with people's activity. Activity-based modeling generally assumes that energy consumption is derived from the activity of simulated individuals. Thus, activity is dealt with as a core of modeling, which enables replication of the structure determining energy demand. According to Sivakumar [58], activity-based modeling is distinguished from agent-based modeling simulating the actions of individuals or a group of individuals because not all agent-based models are activity-based. In this chapter, we present activity-based modeling techniques to model energy systems integrating houses and electric vehicles.

There have been several activity-based models developed to model home and passenger transportation energy demand. Integrated modeling between homes and passenger transportation can be established using consistent activities people engage in inside and outside their homes. Most existing activity-based models have not been applied to integrated analysis between home and transportation because these domains are developed independently. However, there is an increasing need for integrated analysis for various purposes, such as design of home energy management systems (EMSs) for minimizing household electricity cost because of the emergence of electric vehicles (EVs). In the power system management field, EVs are recognized as a source of flexibility to levelize electric power demand and

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improve power system performance [6]. Several studies have analyzed integrated home EMSs considering EVs [14, 22, 42–44, 67].

Existing activity-based models are characterized by methods in which activity and appliance and car use among other factors are modeled. This chapter introduces a method for classifying activity-based energy demand modeling techniques developed for home energy systems (Sect. 1.2) and transportation energy systems (Sect. 1.3). Section 1.4 presents an activity-based model developed for integrated analysis between homes and EVs.

1.2 Energy Demand Modeling for the Residential Sector

Household electrical appliances can be classified into three groups based on their use [17]. The first group operates all day without occupant intervention such as refrigerators and network routers. The second group includes appliances operated by occupants for certain activities, such as washing machines and televisions. The third group involves heating, air conditioning, and lighting, which are operated to control the indoor environment depending on home occupancy. Based on this understanding, appliance energy consumption has been modeled to realize a relationship with occupancy and activity of people in the house. Established models use a variety of methods to generate occupancy and activity and determine appliance use as explained below.

1.2.1 Occupancy-Based Approach

Richardson et al. [54] established an occupancy-based method for modeling residential energy demand, which has been frequently used to model for dynamic energy demand for residential buildings. The number of active occupants is considered as transition states and a random trial is conducted at each time step to determine the occurrences of transition between transition states. For this process, the Markov property is assumed as the transition probability defined as $N_{i,j}/N_i$, where N_i is the total number of samples at transition state i and $N_{i,j}$ is the number of samples whose state changes from i to j. Transition probability is defined for each time step, and by evaluating with random numbers, a time series of changes in the number of active occupants is first determined.

Time use data (TUD) is generally used in this process. TUD is generally collected by time use surveys, in which respondents are asked to submit time use diaries that describe how they spent their time on survey days. In their model, TUD is classified by respondent household size of when transition probability is quantified.

After generating an occupancy schedule, occupant appliance use is determined. For appliances in the aforementioned second category, a so-called switch-on probability, which is the probability of a switch-on event of an appliance occurs, is used. In Richardson et al. [54], the switch-on probability was quantified using appliance TUD and annual total electricity consumption. They assumed the switch-on probability to be proportional to the probability of activities being undertaken (referred to as activity probability) quantified for each time of day based on the TUD corresponding to the number of active occupants. It should be noted that activity probability is different from switch-on probability. If activity probability is used as switch-on probability, appliance use will be overestimated because switch-on events do not occur at every time step when activity is undertaken [69]. A calibration scalar is thus used to avoid such overestimation. Switch-on probability is defined as the product of activity probability and the calibration scalar, which adjusts the total number of switch-on events per year to replicate the appliance's annual total electricity consumption.

In Richardson et al. [53], this approach was applied to model lighting use. The only difference in this approach was that the lighting model considered natural light depending on outdoor irradiance. This approach can be applied to appliances categorized in the third category operated to control the indoor environment depending on occupancy. This approach has several applications.

Richardson's model has been further extended. For instance, McKenna and Thomson [41] integrated modules to quantify energy demands for both water heating and space heating to cover energy demand for all end-uses. Baetens and Saelens [3] proposed accounting for occupancy patterns [2] to classify TUD, which was originally classified solely by household size. This contributed to improve the model's ability to represent heterogeneity among households. Yamaguchi et al. [69] proposed using a calibration scalar dependent on time of day to improve the representation of appliance use time variation.

One of the shortcomings of Richardson's model is that variations in the number of switch-on events per day cannot be replicated because switch-on events occur as a result of random trials made at each time step. Flett and Kelly [18] overcame this weakness by first determining the number of switch-on events for a simulated day based on empirical data. Switch-on events are then allocated to the timeline considering occupancy.

1.2.2 Activity-Based Approach

The second type of model explicitly simulates household member activities, such as watching television and cooking. Simulated activity classification depends on available TUD. Activities are then converted to switch-on event occurrences. There are two approaches that can be considered for this model type. First, Widen and Wackelgard [64] and Widen et al. [65] proposed a discrete-time Markov chain model in which activities are defined as transition states. Random trials of transitions from one state to another are conducted in each time step.

Secondly, Wilke [66] proposed a discrete-event model in which household member activities are simulated by repeating the following two processes: selecting an activity starting from the examined time of day and selecting the selected activity's duration. For activity selection, the starting probability, at which each considered activity starts, is calculated using multinomial logit models developed for each time of day. Markov chain transition probability can also be used to model the sequence of discrete activities as transition probabilities from one activity to another and is quantified based on TUD as a semi-Markov process. Tanimoto and Hagishima [62] proposed to use the activity probability. Yamaguchi and Shimoda [68], whose work is explained in detail in Section 4, proposed a similar approach and compared how model design influences activity modeling performance.

An appliance switch-on event occurrence is examined in relation to the stochastically determined activity, and both discrete-time and discrete-event trials can be adopted for this process. In discrete-time trials, switch-on event occurrence is examined at each time step during an activity. In a discrete-event trial, occurrence is examined only once during an activity, such as at the activity's beginning or end.

The most important difference between occupancy-based and activity-based approaches is that in an occupancy-based approach, appliance use is modeled independently from other appliances, thus possibly resulting in an unrealistic appliance use sequence. One extreme example is that all appliances in a house are operated simultaneously. In contrast, such unrealistic sequences do not occur in activity-based approaches, as a sequence of activities is generated before a switch-on event occurrence is examined.

1.2.3 Time-Based Household Energy Demand Model

There is another model variety that does not simulate occupancy and activity. In these models, time represents household member activity by assigning appliance switch-on probabilities as a time-dependent quantity. To construct a model, switch-on event occurrence is identified from measurements of appliance power demands (i.e., empirical data). For example, Yilmaz et al. [70] constructed a cumulative distribution function (cdf) for the number of switch-on events for a simulated household. The number of switch-on events is first assigned each day using this cdf. Then the switch-on event occurrence time is randomly determined based on the switch-on probability, which is the sum of observed "switches on" divided by the total number of days. This improves modeling accuracy in terms of the daily number of switch-on events and includes variations in the number of switch-on events for different days within the same household. Paatero and Lund [46] and Gruber et al. [23] developed similar models.

1.2.4 Important Factors in Energy Demand Modeling

Yamaguchi et al. [69] conducted a cross-analysis of these existing household appliance use modeling methods and found that model performance depends heavily on modeling contexts. A model developed based on empirical data of appliance use can replicate household-specific characteristics in appliance use, including both intra/inter-household variation as these variations can be captured from empirical data. However, empirical data availability is limited in many modeling contexts, which is critical when the developed model is applied to contexts outside of where empirical data were collected. TUD-based models have advantages in this aspect, as their analyses revealed that demographics and household characteristics significantly influence household appliance use. Thus, considering their significance will improve model performance. The ability of TUD-based models to reflect demographics and household characteristics enables models to be applied to areas where such conditions are available. In contrast, it is difficult to address cross-area variation in models based on empirical data if empirical data lacks information on demographics and household characteristics.

1.3 Energy Demand Modeling for Transportation

Activity in transportation demand modeling is modeled as a sequence of in-home and out-of-home activities [58]. Activity-based transportation implies that travel derives from daily activities. For example, a person leaves home for work in the morning and travels to an office. That person then leaves the office in the evening and travels back home. Typical activity-based models simulate such sequences, including timing, location, and mode of travel. Transportation energy demand can thus be quantified based on this information.

Transportation research has a long history of modeling travel demand considering the influence of socioeconomic conditions and land-use configuration [4]. Earlier travel demand research focused on evaluating long-term investment-based capital improvement to execute regional planning strategies. Since 1970, attention has shifted to short-term behavior analysis to understand travel schedules of individuals to frame congestion management policies.

Travel demand modeling can be broadly classified into two categories: trip-based modeling and activity-based modeling. Trip-based modeling relies on a top-down nature as it uses overall person-trips in the studied area and is disaggregated into those with different trip origins, destinations, modes, routes, and so on. In contrast, activity-based modeling relies on a bottom-up nature as travel demand is modeled as an aggregation of trips made by independently modeled individuals.

1.3.1 Trip-Based Modeling

Trip-based modeling evolved tremendously in the early days of travel demand modeling [13]. This approach uses trip data collected by individuals, known as person-trip data, and consists of four sequential processes: trip generation, trip distribution, modal split, and trip assignment [45]. Trip generation estimates the number of person-trips emanating from or terminating at an aggregated level of zones. The trip distribution process distributes person-trips from each origin to various destinations. The modal split process assigns travel modes to person-trips with origin-destination pairs. Lastly, the trip assignment process assigns network links or routes to each person-trip. The results illustrate traffic volume on all roads in a traffic network link. This four-stage approach has been widely used for congestion management in transportation planning.

1.3.2 Activity-Based Modeling

The travel activities of individuals can be identified in terms of time, origin, destination, purpose, mode, and route of travel. An activity-based modeling approach considers the decision to travel as a choice among alternatives known as a discrete choice set with alternatives that are exhaustive and mutually exclusive. Discrete choice models are used to model such decision-making and predict the likelihood of an alternative to be selected based on certain input variables. Examples of the most frequently used models are multinomial logit, nested, and mixed logit models [1, 7, 16, 28, 34, 35]. A hazard duration-based model is also often used to model the time until an event is of interest. Mannering et al. [37] developed hazard-based models to analyze time spent by individuals at home before conducting another trip. Bhat and Koppelman [5] analyzed the duration of shopping on the way to work.

Activity-based approaches consider travel a derived demand. The most important feature of discrete choice models is that various factors' influence can be reflected in predicted likelihoods. The seminal works of Chaplin [8], Hagerstrand [24], and Cullen and Godson [11] were based on travel activity analysis and revealed that travel demand is complex and elucidates the relationship between land-use and transportation demand in association with constraints individuals encounter during a particular travel activity. The following factors have been recognized as significantly influencing many papers: socio-demographics and household type and [31, 36, 38–40, 47, 61, 63], land-use and built environment and [12, 16, 32, 49, 55], and travel conditions, including activity duration and [19, 33, 50].

Structural equation modeling, a multivariate statistical technique, is also used for activity modeling. This technique assumes a hierarchical structure among influencing factors, which are classified as exogenous and endogenous variables. This approach considers the influence of exogenous variables on endogenous variables. Activity-based travel demand models are used extensively as this approach captures

(1) direct relationships between activity demand and the need to travel and (2) relationships between participations in various activities. It is also advantageous in modeling joint demand for activity duration and travel [21, 29]. Lu and Pas [36] developed a structure equation-based activity-based travel demand model to analyze the influences of socioeconomic variables on in-home and out-of-home activities.

Conducting higher activity participation within a stipulated time period requires the combination of several trips in a single journey. Such a sequence of activities is described by a trip chain [25, 57]. Henser and Reyes [25] considered seven different trip chains that originated and ended at home that had simple to complex combinations of work and non-work travel alternatives to demonstrate the influence of trip chains on the likelihood of using public transit. Pitombo et al. [48] developed 14 distinct trip chain combinations using activity sequence (home, work, school, and other activities), travel mode sequence (private, public transit, and non-motorized), and the distance between the destination and home traffic zone centroids. This approach is beneficial as energy demand can be quantified more accurately if data describing trip chains are available.

In recent years, interpersonal dependencies among household members have been recognized as a significant factor in modeling travel demand as some travel activities are conducted jointly with other members of the family. In their research, Srinivasan and Athuru [59] investigated the activity allocation and participation of household members for maintenance activities, examining whether an activity is conducted alone or jointly with other household members. They found that gender, working status, household role, and presence/absence of children were significant factors determining joint or solo travel. Srinivasan and Bhat [60] examined the role of intra-household interactions on time consumed by household heads on maintenance activities and household chores in nuclear family households. They observed that gender plays a significant role in executing in-home activities, with non-working women undertaking a considerable share of such activities and that resource constraints such automobile availability are of significant importance in deciding whether an out-of-home maintenance activity is undertaken jointly or individually. An interesting outcome of Kato and Matsumoto [27] revealed that having more children in a household increases the likelihood of conducting joint husband and wife out-of-home leisure activity. Additionally, more non-working days for husbands tends to lower the likelihood of individual out-of-home leisure activities.

Some models constituting sets of rules to establish condition-action pairs have been implemented on an urban scale to schedule traffic volume in congestion management-related studies. CARLA [9] and STARCHILD [51] and [52] were among some of the earliest scheduling models developed for this purpose. CARLA uses a complex combinatorial algorithm based on spatio-temporal and interpersonal constraints to model scheduled activities and their associated durations to decide viable activity patterns. STARCHILD also employs a combinatory approach to select activities before applying a logit choice model to devise the highest utility activity pattern choices. Other models that have been widely accepted are SCHEDULER [20], SMASH [15], and AMOS [30].

As described above, the activity-based approach models travel demand as an accumulation of trips made by individuals. The advantages of an activity-based approach can be summarized as follows: (1) the relationship between trips and factors such as demographics and land-use accessibility can be addressed; (2) the approach provides an effective way to analyze travel demand by aggregating demand considering factors such as travel purpose, travel mode, and locations; (3) it enables consideration of complex behavior such as intra/inter-households activity participation and joint travel decision-making; (4) temporal resolution is well-defined, with activities spread over 24 h in a continuous manner; and (5) travel and energy demands are quantified at various scales from a single house to a community to a nation.

1.4 Case Study

This section presents an activity-based modeling example in which household member activities are randomly simulated for integrated analysis considering a house and an EV. In the analysis, household member daily activities, including those undertaken inside the house and outside the house, are simulated, enabling the energy demand of the house and EV to be quantified in a consistent manner. Activities conducted inside the home such as sleeping, laundry, and cooking are designated as "in-home" activities, whereas activities conducted outside of the home such as leisure outings, going to the supermarket, and commuting to the office are designated as "out-of-home" activities. In the model, out-of-home activity is categorized into two sub-types: home-work-home (HWH) and home-other-home (HOH) as listed in Table 1.1. HWH refers to daily travel related to job, work, or school that originates and terminates at home after conducting the activity. HOH signifies activities other than HWH that originate from and terminate at home.

Figure 1.1 provides an overview of the modeling framework, which consists of the household generation model, the in-home activity model, and out-of-home activity model. The household generation model generates simulated households living in a simulated area based on population census data published in e-Stat [56], which has various datasets available at different spatial boundaries from postcode zone, city, and prefecture to nationwide [26]. Generated households are modeled as a combination of household members to which specific demographic conditions, listed in Table 1.2, are assigned. To assign demographic conditions and combinations of household members, various probability distributions were

Table 1.1 Definition of out-of-house activities

Purpose of travel	Description
Home–work–home (HWH)	Going for work/school and returning back to home
Home–others–home (HOH)	Going for other activities and returning back to home

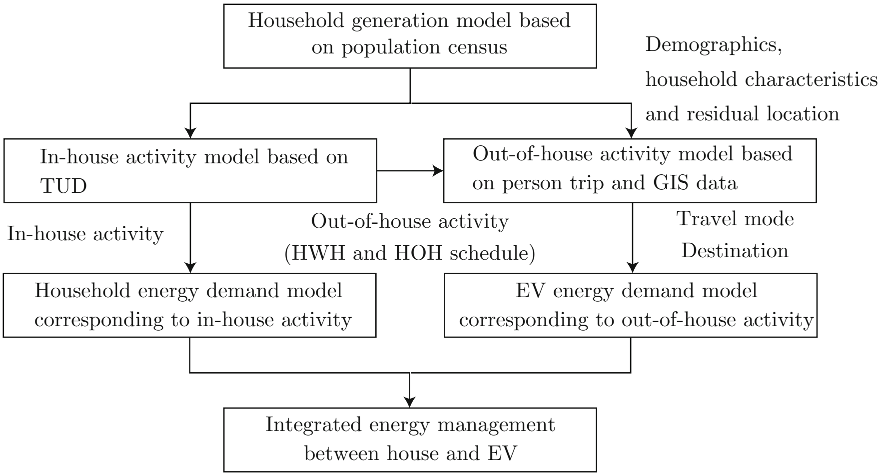

Fig. 1.1 Framework for the activity-based modeling

Table 1.2 Demographics and household characteristics

Category	Item	Note
Demographics	Age	Categorized with 5-year age range
	Gender	Male or female
	Employment type	Full-time, part-time, and unemployed
	School status	Preschool, elementary, junior, and high school, and university
	Occupation	Occupational category
Household characteristic	Member composition	One-person, couple, couple with children, one person with children, couple with parents and children
	Existence of children	Existence of school child, Existence of preschool child
	Household size	Number of household members
House specification	Ownership	Owner or renter
	Housing type	Single detached house or multi-family building
	House size	Total floor area of house
Residence location	City size	Population size of city
	Land use and accessibility to public transport of the area	Population, bus stop and train station density (number of unit per land area)

developed based on population census data. The conditions listed in Table 1.2 are used to select a dataset for the in-home activity model that generates in-home HWH and HOW activities with 5 min intervals for a given period. The in-home activities profile is used in the household energy demand model that quantifies the simulated