4 Empirical Analysis of Behavioral Variability

In western culture it is common to view humans and by extension human behavior as highly individual. This view often ensues a perspective on behavior that emphasizes its high variability between individuals. When it comes to including information on human behavior in energy models, how to deal with such variability is often viewed as an important challenge. This can be exemplified by a statement from Swan and Ugursal (2009; p. 1828) in their review on modeling of end-use energy consumption in the residential sector: "…, the EM [engineering method] has the highest degree of flexibility and capability with regard to modeling new technologies which have no historical consumption data. However, occupant behavior must be assumed. As occupant behavior varies widely, this is difficult to estimate." In other words, the inclusion of information on energy using behavior is viewed as complex due to its high variability. On the one hand, describing variability of behavior is an essential question also in engineering methods of modeling energy demand, which makes it a relevant interdisciplinary intersection, and on the other hand, behavioral analysis of behavior suggest a "handling" of variability which advocates its usefulness and relevance for understanding determinants of behavior and emphasizes the importance of environmental contingencies structuring behavior instead of factors attributed to an individual. The perspective on behavioral variability is thus different. The empirical analysis of degrees of freedom in appliance using behavior from a behavior theoretical perspective is the overarching goal in this section.

To characterize degrees of freedom in distributing behavior and options for flexibility of appliance using behavior one can look at variability of behavior in terms of homogeneity within individuals and between individuals. Behavior variability within individuals over time could give insights to variations in distributing behavior during a day for different time spans like multiple days, weeks, months

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or years. Behaviors subject to less variability within individuals would thus indicate a functional relation to regularly occurring contingencies for that organism. Variability in distribution of behaviors between individuals over the course of a day (or other time spans) could indicate shared regularly occurring contingencies and thus indicate time spans available for a "free" distribution of appliance using behavior for groups of individuals under similar contingencies. To analyze such variabilities in behavior, one needs information on the timing of behavior of individuals.

Empirical information on when people do what over the course of a day can be obtained from Time Use Surveys (TUS). TUS exist for many countries across the world. In a study from 2015 (updated in 2016), Charmes (2015) counts 65 TUS, which are based on a diary, albeit with different time intervals (10, 15, 30 or sometimes 60 min), with classifications of time of use activities (in different detail, but at least ten activities) and a national scope of analysis. In the last data collection period from 2008 to 2015 within Europe, 18 countries, among them Germany, participated in collecting time budget information following in principle the Harmonised European Time Use Survey (HETUS) 2008 guidelines (Eurostat, 2009) (Eurostat, 2018b).

4.1 Describing the German Time Use Survey 2012 / 2013

The survey data, which is being used to analyze variability in energy using behavior comes from a representative quota sampling procedure from German private households based on the Mikrozensus 2012 (Statistisches Bundesamt, 2016). Participants with a main place of residence and at least ten years of age were eligible to take part in the survey (Statistisches Bundesamt, 2016). Time of data collection was August 1st 2012 until July 31st 2013. On a voluntary basis, participants filled out an activity diary[1] for three days, including two consecutive weekdays and one weekend day (L. Maier, 2014). Information about 5040 private households with 11,371 individuals and 33 842 diary days was recorded concerning the time budget for primary and secondary activities throughout the day (Statistisches Bundesamt, 2016). Activities are diverse and range from sleeping, food consumption and personal hygiene to time spend on education, work, hobbies or chores (Theisen, 2017). Data collection was done in pen and paper format without interviewer and consisted of three questionnaires: a household questionnaire, a personal questionnaire and a diary (L. Maier, 2014). As part of the household

[1] An example of the employed diaries is included in Statistisches Bundesamt (2016).

questionnaire, family relations, composition of individuals in a household, and socio-demographic characteristics such as age, gender and nationality were collected (Theisen, 2017). The personal questionnaire included socio-demographic and socio-economic information on for example marital and family status, occupation, work hours, educational qualification and voluntary work, as well as questions on quality of life aspects such as subjective sense of time, like experienced time pressure or conflicts in allocation of time (Theisen, 2017). The diary had a table structure beginning at 4:00 a.m. in the morning and ending at 3:59 a.m. the following day with one row representing a ten-minute interval, where participants could freely write in their activity description (Theisen, 2017). For some activities, such as media use via smartphones or comparable devices the ten-minute format is assumed to lead to an underrepresentation of such activities because they are often associated with shorter usage times (Theisen, 2017). The diary data for the primary and secondary activities is categorized hierarchically into 165 activity categories, consisting of nine main categories and 48 sub categories within which the specific activities are coded (Theisen, 2017).

Through this survey design, it is possible to analyze what types of activities are performed, the frequency and duration of different behavioral activities in certain time intervals with a precision to ten minutes, the timely distribution of behaviors over the course of a day and the sequence of different behaviors (all referred to under the broad term of 'activity pattern' or 'behavior pattern', which are used synonymously). Additionally, one can analyze similarities within individuals in such activity patterns for weekdays and weekend days, as ideally three days are collected per person, as well as similarities between persons in activity patterns. As socio-demographic and socio-economic data is also collected, differences in activity patterns between groups of different socio-demographic or –economic background would be possible. Furthermore, due to information from the household questionnaire, an analysis of similarities between persons of one household in comparison to similarities between persons of different households would be possible. Even though Time Use Data (TUD) is not a measurement of observed behavior, I assume that, due to its diary style with short time intervals, it can provide close enough information on when certain behaviors occur during the day to treat it as information on the rate of behavior. Thus, it seems a suitable source of information to analyze variability of behavior.

4.2 Time Use Data for Energy Behavior Modelling

TUS were designed to mainly focus on assessing lifestyles, the time spent on leisure, transport and commuting as well as differences for example between genders in paid and unpaid work (Charmes, 2015). This focus is also reflected in the last report form the conference proceedings on the German TUS in 2016 (Statistisches Bundesamt, 2017). Despite this different original focus, the available information from TUS data and the quality of the data provided allow to also address other questions.

In relation to problems of climate change, the possibilities of integrating TUD into quantitative frameworks have been discussed in the context of sustainability research, where it is applied, for example in lifestyle oriented approaches in the analysis of household consumption activities (e.g., Minx & Baiocchi, 2009; Schipper, Bartlett, Hawk, & Vine, 1989; Weber & Perrels, 2000) to better integrate social and behavioral aspects in estimations of environmental impact of energy using behavior. In the context of energy behavior modelling, two approaches of integrating TUD are interesting for the question of shifting energy using behavior. One focusses on demand modelling as part of a (engineering) bottom-up modelling of energy using behavior and the other on analyzing time dependence of practices as part of a social practice-oriented theory approach.

In energy building analysis, user behavior is most often conceptualized as part of occupant behavior and often limited to modelling presence and absence in fixed schedules (deterministic approaches), which is regarded as limitation because it does not capture variations of behavior (review by Delzendeh et al., 2017). The target behavior for this investigation, using of appliances, is often just one source of energy consumption from occupant behavior which is modelled in building models. Other modelled sources of energy demand are using of lightning and solar shading, using of HVAC (heating, ventilation and air conditioning) systems and set-points, using of hot water and using of openings such as opening and closing windows (Delzendeh et al., 2017). A simplified view on occupant behavior in energy models is said to be one of the main reasons for an observed discrepancy between estimated energy demand in buildings and observed energy consumption (e.g., Delzendeh et al., 2017; Happle, Fonseca, & Schlueter, 2018). One suggested possibility to describe occupant behavior more accurately is to use probabilistic profiling approaches of energy behaviors, which predict the probability that a behavior occurs and thus model more of behavioral variation than fixed schedules. Another suggestion is to adjust occupancy profiles based on rules relating to other model parameters, like, for example, room temperature (Delzendeh et al., 2017). As stated before, the question of how to handle variability in energy using behavior has been an important research topic within the technical approaches of building models.

One main approach from building models which model energy using profiles in more detail, are bottom-up models in comparison to top-down models. The distinction refers to the direction in which the model is set up to describe energy demand for a region, state or other area specification of interest. While top-down models start with highly aggregated input data and break it down to factors relevant for energy consumption, bottom-up models start with the input data from the smallest units of the energy system and aggregate it to estimate consumption of areas (Swan & Ugursal, 2009). For an overview, further distinctions between top-down and bottom-up modelling approaches and their pros and cons see e.g., Kavgic et al. (2010), Li et al. (2017), Swan & Ugursal (2009).

One advantage of engineering bottom-up models in comparison to statistical bottom-up models is their possibility to integrate detailed information on energy using behavior. Information from energy suppliers' billing data as it is commonly used in statistical bottom-up models (Swan & Ugursal, 2009) or the data electric utilities typically have on residential electricity consumption which is aggregated for multiple households without knowledge about activities or fluctuations in energy consumption within households (Paatero & Lund, 2006) is not detailed enough for generating diverse electrical power profiles. Even though standard or average electrical power profiles do not offer enough information, when it comes to evaluating shifting potentials of electrical consumption within households which is attributable to user behavior, most policy-makers and energy suppliers base their policies and tariffs on average electrical power profiles (Torriti, 2014). In bottom-up household energy engineering models, different ways of incorporating more detailed information of appliance end-use are pursued, one of them being the generation of diverse electrical power profiles based on TUD.

A good opportunity to integrate information about behavioral variability is to combine the behavioral analysis of appliance using behavior with an engineering bottom-up modelling technique. This combination can describe the consequences of degrees of freedom of appliance using behavior on the energy system level[2] and thus link it to questions of supply and demand. The fact, that TUD is already employed as input data and that TUD potentially offers valuable information for analyzing behavior beyond generating fixed occupancy schedules for certain socio-demographic groupings, makes it a good interdisciplinary intersection

[2] When talking about the consequences of modeling energy using behavior as part of a bottom-up approach, the term "energy system" is employed in an abstract meaning which encompasses all possible aggregation levels from households to grid sections, to areas and so forth.

between electrical engineering and behavior analysis for addressing questions of describing and shifting appliance using behavior in households.

4.3 Changing Focus on Variability of Appliance Using Behavior

Bottom-up models have been used to generate diverse energy using profiles for buildings. They are principally suited to this task because they start building their models from the smallest units of the energy system and can incorporate different groupings and variations in user behavior profiles. But as the engineering simulation perspective traditionally focuses on modelling physical units of the energy system, their approach towards user behavior in the early years consisted in closely remodeling the (physical) characteristics of energy demand associated with behavior without consideration of theoretically justified groupings of user groups or meaningful descriptions of variability of the modelled behavior. In more recent approaches which use TUD to describe behavior this focus has shifted towards a stronger emphasis on using variability of behavior as an important characteristic to describe behavior and towards theoretical considerations. Although in this work a different theoretical approach is proposed, the meaningful description of behavioral variability and its implications for shifting user behavior are the important points of discussion in an interdisciplinary field that tries to profit from both, knowledge on modelling building models and knowledge on energy using behavior.

One way of integrating appliance using behavior, is to model appliance using behavior in households from TUD. The basic idea is to combine activity data from TUSs and appliances' electrical consumption to estimate energy demand for a household. The possibility of engineering bottom-up models to integrate information about user behavior is viewed as asset and at the same time as difficulty within the field. One discussed drawback is the necessity to make assumptions about occupant behavior because it is mostly perceived to vary widely and at the same time to significantly impact energy consumption (Swan & Ugursal, 2009). Thus, even though information about behavior is integrated in bottom-up models to estimate energy demand, a theoretically meaningful and useful description of behavior in terms of variation still appears to be missing. This is something an analysis of behavior can provide.

In a review of time use models of residential electricity demand by Torriti (2014), he includes seven studies (Capasso, Grattieri, Lamedica, & Prudenzi, 1994; Richardson, Thomson, & Infield, 2008; Richardson, Thomson, Infield, &

Clifford, 2010; Torriti, 2012; Widén, Lundh, et al., 2009; Widén & Wäckelgård, 2010; Wilke, Haldi, Scartezzini, & Robinson, 2013), which develop occupancy and / or appliance use models for households by generating occupancy profiles based on TUD and then linking them with electrical consumption information. As underlying assumption of all TUD approaches Torriti (2014) identifies that household electricity demand is influenced by the timing of human activities and most essential for the timing of energy demand. The point is made that high homogeneities between individual energy use patterns lead to peak loads in the transmission grid, which poses a problem for the energy supply system due to increased carbon emissions and system costs (Torriti, 2014). Even though not stated, the relevance of timing of energy using behavior has become even more important in recent years due to increasing amounts of VRE in the energy system. The question of timing of energy demand is especially relevant for the problem of discrepancies between energy supply and demand because this discrepancy refers to specific time points and not absolute amounts of energy supply or demand.

The studies on integrating TUD in engineering bottom-up models identified by Torriti (2014) take into account variability in energy using behavior by reproducing aggregate variations in occupancy states over a day as described by TUD. Using mostly Markov-Chain Monte Carlo methods, synthetic demand profiles are generated and validated against other measurements of electricity demand. The focus of those studies is a close matching of aggregate synthetic load profiles and distribution of diurnal energy demand as it can be expected in a building or grid section. With the exception of Torriti (2012), the focus is not an analysis of variations in energy using behavior but a close enough modelling of variations to capture important average peak demand characteristics. Even though connecting (theoretical) analysis of variability in appliance using behavior and bottom-up engineering modelling is possible, in those early studies TUD was merely used as input data to predict energy demand and peak loads. The general approach of coupling appliance and using patterns is well exemplified by the early study from Capasso et al. in 1994. Even though it might be considered an out of date study, it highlights aspects still relevant for the current discussion. Capasso et al. (1994) combine engineering data on appliances and "lifestyle and habit" related "psychological data" based on the Italian TUS 1988 / 1989 and a Household Consumption Survey on national-users' electric energy consumption and its relationship with socio-economic, demographic and regional conditions in order to develop an end-use energy model for the residential sector. The validation of their simulated load profiles against measured load profiles shows good approximations and the authors conclude this then new bottom-up approach with inclusion of behavioral and engineering functions as promising due to its flexibility in adjusting probability functions. As a development goal they see (among others) also the possibility to evaluate various load management policies.

The elementary units of Capasso et al.'s (1994) model are appliance and household member, which together produce different demand profiles, which are aggregated on the level of individual households and then various households' load profiles are aggregated to generate energy consumption for an area (Capasso et al., 1994). Their so named "behavioral functions" are availability at home of each member of the household (a histogram gives the percentage values for time intervals), home-activities involving electrical appliances (housework, personal-hygiene, cooking, leisure), proclivity for home-activities (each household member is assigned a percentage availability for each home-activity depending on the average participation of a household member with characteristics like gender according to TUD), human resources (eyes, ears and hands which are used to allow or deny simultaneous use of certain appliances) and appliance ownership (set of appliances in a household determined by a parameter depending on features such as assumed income, number of members, socio-economic characteristics of the end-use area and so forth; not all are given) (Capasso et al., 1994). The central ideas for describing energy using behavior from TUD are to define availability for using appliances at home, define activities which are associated with using electrical appliances, define the probability to perform a certain activity, account for simultaneous use of appliances (and in later studies sharing between household members) and to define the appliance stock. Availability at home is later on mostly modelled as occupancy with the differentiation of absence, active occupancy and passive occupancy (Torriti, 2014).

Concerning Capasso et al.'s (1994) modelling of appliance using behavior, it is interesting, that the probability functions for using an appliance are grouped according to socio-demographic data from the TUS (only gender is clearly identifiable form the article). They state that "household energy usage is intimately linked to life-style-related psychological factors that are, of course, extremely subjective and not easily defined with any degree of precision." (Capasso et al., 1994, p. 957). This could mean, that they assume (all) those socio-demographic features to theoretically influence behavior. If that is the case, they offer no further reasoning for this assumption. But it could also mean assuming that socio-demographic characteristics are suitable groupings to generate profiles of energy demand because they differentiate groups of people with different energy consumption (e.g., Frederiks et al., 2015) and thereby increase the diversity of energy demand profiles, which on an aggregate level match aggregated measured load profiles. A behavior analysis perspective would suggest to first analyze the variability and then functionally relate similarities in variability to other characteristics, instead of summarizing it without some theoretical idea of why certain variability is related to some characteristics. This is the intersection where interdisciplinary work, also from other theoretical perspectives, is needed.

Capasso et al. (1994) problematize another aspect about the approach to define "standard behavior of the various types of customer through statistical correlations within the framework of load-research […] (which is that) it fails to consider the random variability of the demand." (p. 957). It seems that in their view socio-demographic differentiated profiles do not model enough variability of behavior and maybe also not adequately. If one assumes high amounts of randomness in energy demand caused by energy related behavior, which cannot be sufficiently explained by statistical relations between variables without further meaning in relation to a description of the world, one could investigate the variability more closely and then try to theoretically relate behavior and other things in the world. It seems adequate to say that variability in behavior as exemplified by this engineering perspective, even though very important in order to predict energy demand with relatively parsimonious models, is not analyzed from a theoretical perspective. Variability in behavior is important in both perspectives, engineering bottom-up modelling and behavior analysis, but its treatment is different. If the main aim is improving prediction of energy demand, theory lacking statistical prediction models to group energy demand to increase diversity in profiles seems to suffice because model validations in the here referenced studies are judged to be good. But when it comes to deriving evaluations for DSM programs which are related to user behavior, which is so often stated as a goal and advantage of bottom-up modelling approaches, the connection to (behavior) theory is essential. Without it, variability is underrecognized in its importance for shifting user behavior, categorizations of behavior variability remain meaningless and can give no useful guidance on possibilities for influencing behavior.

Until Torriti's study in 2012, the other referenced studies also employing TUD as empirical input to model appliance using behavior are unchanged in the basic approach and idea as described for the study of Capasso et al. (1994) except that they mostly employ a Markov-Chain Monte Carlo (MCMC) method to generate synthetic load profiles from TUD based on occupancy pattern description.

Richardson, Thomson, and Infield (2008) present this method description for generating synthetic occupancy profiles based on UK TUD from 2000. The premise being, that taking account of occupancy patterns improves the modelling of variability in energy demand profiles, they aim to develop a method which can produce synthesized occupancy data without reference to detailed appliance load (i.e., electrical power curve) measurement or reliance on statistical averages on consumption data. They view the high time resolution from TUD as an asset for applications in building domestic energy models as well as designing and evaluating DSM systems. In comparison to Capasso et al.'s (1994) model which does not take the chronological sequence of activities during the day into consideration, when allocating loads from electrical appliances to time intervals, the first order non-homogeneous MCMC method used by Richardson, Thomson, and Infield (2008) captures time dependence of activities by defining different transition probability matrices for each of the 144 time steps (24 h day divided into ten minute intervals) based on the relative frequencies of activities in TUD. The synthesized occupancy profiles are produced by using a random number at each time step to determine, together with the transition probability matrix and the occupancy state at the current step, the state at the next time step. Variation between different runs of a simulated household for a weekday or weekend day is modelled by using random numbers in generating one specific time-series of occupancy. To validate the model, a large number of occupancy profiles were generated and the sample statistics of this output compared against original TUD with good correspondence in terms of overall proportion of active occupants in each time interval for weekday and weekend data. Intra-individual day to day dependencies in occupancy patterns or reasons for variability in occupancy patterns are not addressed by this approach as the main aim was to establish the feasibility of the method for engineering bottom-up simulation. Building on this occupancy model, a model including the coupling of activities and appliance using behavior in households was developed later (Richardson et al., 2010). Other validations of this general approach were done by Widén, Nilsson and Wäckelgård (2009) and Widén and Wäckelgård (2010).

In Widén, Lundh et al. (2009) the idea for incorporating TUD into a bottom-up modelling approach is laid out. The purpose being to better model the behavior component in residential energy use and to complement or even substitute cost intensive measurements of direct high-resolution appliance energy end-use in households. They view as advantages the possibility to model time-use profiles for individual household members. Thus, instead of the building, the individual becomes the smallest unit of analysis and different types of activity patterns can be identified and connected to household categories (Widén, Lundh, et al., 2009). To model electricity demand in households, they employ as input data a subset of 432 persons in 169 households from a pilot survey of time use by Statistics Sweden in the autumn of 1996 considering only activities performed at home in 5-min intervals. The electricity demand model (Widén, Lundh, et al., 2009) can generate output for electricity demand (Power in Watt) per household or per individual or per another household grouping criteria form the available socio-economic data over the course of a day. For three household sizes (two-, four- and six- person household) they exemplary display electricity demand per household, concluding that differences in peak power demand can clearly be seen. Differences between load profiles, variability in behavioral patterns and load shifting possibilities are not considered. Instead, the focus lies on validating the approach of using TUD in bottom-up energy modelling to generate household energy load profiles. They show that sufficiently accurate load curves can be generated when comparing modelled load curves with measured load curves from the same five households in respect to reproducing overall differences between different days and households and the number of peaks and their magnitudes. Furthermore, by comparison with measured load profiles on an individual appliance level by the Swedish Energy Agency collected between 2005 and 2007, they show that average load curves generated from the TUD model correspond well to average measured load curves. In sum, the general idea to use TUD to model appliance using behavior and couple it with appliance load features to derive energy demand profiles can be considered legitimate.

As argued before, an analysis of variations between individuals is central to determining possibilities for shifting user behavior. Torriti (2012)[3] highlights this point by showing with the HETUS data reduced for single-person households that there exists a high similarity in peak loads for the activities TV, DVD and video watching between 8.20 p.m. and 8.30 p.m. This marks a shift in attention towards analyzing variability of appliance using behavior within the application of TUD, which was not identifiable in the earlier studies and which according to the more general reviews on building models (compare e.g., Delzendeh et al., 2017; Li et al., 2017; Swan & Ugursal, 2009) is not a common perspective. Analyzing

[3] In the 2012 article Torriti analyzes for 15 European countries variations in occupancy levels and aims to deduce DSM strategies for shifting user behavior. Although to my knowledge this is the first study to introduce a concept of occupancy variation, unfortunately, the study does not offer (theoretical) ideas on the meaning of variability and how its related to energy using flexibility. Furthermore, the used indicators for behavioral variability and deduced DSM strategies are not well justified. The proposed indicator for flexibility is peak variance and given for two time periods within a day which are identified as peak events. Peak variance is calculated for peak events restricted to 40 min for each period per country between 7 a.m. and 8 a.m. and 19:30 p.m. and 20:30 p.m. (exact times per country not reported) according to the following formula:
$\mu_{T,T+1} = \frac{\omega_T}{\omega_{T+1}}$ where ω_T is the level of occupancy in time period T (Torriti, 2012, p. 201).

As this indicator gives the changes in occupancy status from one time period to the next, it does reflect variation in behavior sequences in a peak event period in relation to the following time period but it seems not suitable as indicator of behavioral flexibility. This is because variation in occupancy status gives the amount of changes occurring in occupancy but cannot relate whether or not those changes are timely fixed changes in a behavior. High variance in peak periods means that it is more likely that changes in occupancy status and thereby in electricity consumption occurs but an aggregate description of variation cannot indicate flexibility of behavior in that time period because nothing is known about the possible restrictedness or structure of individual behavior sequences.

occupancy patterns from Spanish TUD (2009–2010) López-Rodríguez, Santiago, Trillo-Montero, Torriti and Moreno-Munoz (2013) derive suggestions for manual and incentive-based DSM of appliance-related activities for the evening peak following the same approach of in-homogenous MCMC bottom-up stochastic modelling as described above for an active (at home and awake) and inactive (outside household or asleep) state for one to six person households on weekdays and weekend days (e.g., Richardson et al., 2008; Widén & Wäckelgård, 2010). Peak occupancy variance is operationalized analogous to Torriti (2012) and as such the argument for preferring manual and incentive-based DSM during the evening peak is that occupancy variance is lowest during that time period, indicating that people are at home and able to respond to such DSM measures. One of their assumptions on which they build their analysis of peak variance is not well argued from a behavioral point of view: "If the main objective is to shift loads to off-peak hours, the choice of DSM programs should be based primarily by what happens in the peaks of occupancy" (López-Rodríguez et al., 2013, p. 749). As behavior analysis suggests, when a behavior is performed depends on the determining context structure and the regularities in contingencies and the relation of those for alternative behaviors at a certain time point. Thus, what lies outside the time period of peak demand is essential in understanding the potential for shifting behavior because it is what determines appliance using behavior distribution in time. This chosen focus on peak events will not be shared in this analysis of behavioral variability.

Torriti (2014) later emphasizes that occupancy patterns are not as variable as sometimes assumed (also compare references above to widely varying energy using behavior) and suggests a connection between similarity in behavioral patterns and energy econometricians' description of the residential demand curves as rigid against time and price (Torriti, 2014). This last idea is interesting to follow up upon because it also links behavioral variability and flexibility.

So far, TUS data has been used to describe and model appliance using behavior to describe electricity load profiles with less cost intensive synthetic profile generation, to reproduce observed peak demands in average demand and improve informational basis for energy demand management (but only few studies make suggestions for DSM). A further development to better model variations in energy using behavior was made, when clustering algorithms were added to the MCMC method of generating occupancy profiles for engineering bottom-up simulations to sort occupancy patterns according to similarity in occupancy patterns and not according to socio-demographic groupings. This appears advantageous because one does not have to assume a theoretically meaningful relationship between socio-demographic variables and energy using behavior, but instead can focus on describing the observed behavioral variability in the data to arrive at theoretical interpretations of the observed variability.

Aerts, Minnen, Glorieux, Wouters and Descamps (2014) build on some of the previous occupancy models (e.g., Richardson et al., 2008; Wilke et al., 2013)[4]. They include three states: at home and awake, sleeping, absent. The reasoning behind choosing occupancy states as basic categorization to model energy using behavior is that many of the "explanatory variables" that are discussed in the literature for energy consumption such as surface area of the dwelling, household composition and appliance holdings are directly or indirectly related to the number of people and the amount of time spent at home (Aerts et al., 2014). Although the rational for focusing on occupancy states is well supported by correlational empirical data, for the purpose of describing and explaining energy using behavior this categorization is too undifferentiated because except for the category sleeping, it is not informative enough about activities performed during absence or awake presence time. If the aim is to analyze behavioral variability in appliance using behavior, other activities available in the TUD should also be subject of analyzing similarities between individuals as they also theoretically influence the timing of appliance using behavior.

Aerts et al. (2014) found in an earlier study that variation in behavioral patterns when described for different categorizations of household types (e.g., number of adults, employment type, presence of children) remains large. Using such categorizations as predicting variables for energy using patterns is argued to be insufficient because it does not capture differences in behaviors. In order to remedy this shortcoming, they propose a probabilistic bottom-up engineering model which incorporates categorizations based on observed differences in occupancy patterns derived from hierarchical agglomerative clustering of occupancy states as derived from TUD. Except for the reliance on occupancy states this appears to be very helpful for an analysis of behavior. From a behavioral theory perspective, analyzing behavior from different individuals in terms of their similarity and dissimilarity (and in case of large numbers using a method such as clustering to help see order in the data) is useful because it will help analyze the degrees of freedom of behavior.

Somewhat in contradiction to Aerts et al.'s (2014) own statement that focusing on behavior variation directly instead of relying on assuming correlations

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[4] Aerts, Minnen, Glorieux, Wouters and Descamps (2014) reference a third influential occupancy model developed by Widén, Nilsson and Wäckelgård (2009), which is excluded in the above list of bottom-up simulations using TUD for modelling household appliance using behavior because it models lighting demand.

to socio-economic variables in order to model energy using behavior is advantageous, they argue in favor of such an option when it comes to describing intraindividual seasonal and weekly variations in behavior patterns in order to construct yearly behavior patterns from the clustered daily behavioral patterns: "The presented patterns represent an observed behaviour, whilst an individual's year should be seen as a series of behaviours. Clearly, this behaviour may vary considerably throughout the week and throughout the year. This is confirmed by the analysis of individuals with the same socio-economic characteristics, which indicates that an individual may fit into more than one pattern." (p. 75). The argument that by showing that individuals with same socio-economic characteristics fit into more than one pattern, it can be deduced that individuals vary considerably during a week or season is flawed. It is so because it presupposes that socio-economic variables determine behavior patterns and that differences in patterns within the "same socio-economic" individuals are attributable to within-individual differences and not external variations. In light of (current) literature on the importance of contextual factors in influencing behavior and the conceptualization of socio-economic variables in energy research as mostly statistical indicators without further theoretical meaning, both assumptions are considered wrong. The assumptions on intra-individual variation during a week and different seasons should really also be analyzed empirically. Unfortunately, the possibilities to analyze intra-individual seasonal variations are not given by the current design of TUD. Data are collected throughout a calendar year, covering all seasons with roughly the same number of people, but as they are different people, seasonal variations could only be described by inter-individual variations. Intra-individual weekly variations, however, could be addresses by the German TUD set, as it collects three different days in a week per individual.

Following the same approach of clustering behavioral occupancy patterns in TUD to build a bottom-up engineering model, a k-modes clustering algorithm has been proposed as more suitable to handle categorical activity data than a hierarchical clustering approach (Diao, Sun, Chen, & Chen, 2017). Using American TUS data, they show that the proposed behavior model based on behavior classification and simulation offers more accurate and reliable prediction on energy loads than the standard schedule from the American Society of Heating, Refrigerating, and Air-Conditioning Engineers. While estimating and predicting energy demand with this approach is well developed at this point and the described literature has shown the validity and usefulness of this approach for predicting residential energy demand, it could be enriched by focusing on analyzing the variability in behavior instead of mainly using it to improve prediction. This focus is important because in order to deduce opportunities for shifting user behavior more needs to be known about the structuring context of appliance using behavior or more generally determinants of appliance using behavior. Although the application of such bottom-up engineering models to inform DSM has been stated as an important advantage, with the exception of research from López-Rodríguez et al. (2013) and Torriti (2012) analysis of DSM opportunities has been scarce in the here described research. Another potential enrichment, which could also help with informing DSM interventions, could come from relying on behavior theoretical principles to describe behavior instead of following an a-theoretical empirical approach.

A number of recent studies address some of these potential enrichments for describing and analyzing appliance using behavior. They also use TUD to come to better descriptions and understandings of variability in appliance using behavior. For example, the importance of a theoretical perspective is introduced by Torriti (2017). Assuming that energy demand in households is determined by time dependence of social practices, he proposes a social practice theory perspective and analyzes time dependence of social practices at specific points of day and time dependence variation across days of the week and seasons employing the 2005 UK Time Use Survey data. This study moves away from describing behavior by occupancy categorizations and looks at six activity codes which can be associated with appliance use: preparing food and drinks (including cooking, washing up); washing (including dressing/undressing); cleaning (including tidying house); washing clothes (including ironing or mending clothes); watching TV (including videos/DVDs, listening to radio or music); using a computer. As non-household related behavior also determines the allocation of appliance using behavior, future analysis of behavioral variability should further extend analyzed activity categorizations to include outside of household activities. Time dependence is defined as "high occurrence of the same practice over the same periods of the day. Practices which repeatedly take place at the same time of the day are said to be time dependent."[5] (Torriti, 2017, p. 38). A high time dependence could also be interpreted as indication of low behavioral flexibility, if one assumes that time dependence occurs due to common structuring context shared by multiple individuals. Even

[5] Time dependence is operationalized by (Torriti, 2017, p. 39) as follows:

$$T_{DEP} = \frac{Max[x_i - m(X)]}{m(X)}$$

where x_i is the number of minutes associated with the practice x at the time of the day i and $m(X)$ is the mean number of minutes of practice x.

though stating that differences in residential loads between weekdays and weekend days are one important variation, Torriti (2017) argues to limit the time dependence analysis to week days because of the focus on peak demand issues. While this is a reasonable focus for peak demand analysis, in order to analyze behavioral variability and shifting potentials, the differences between weekdays and weekend days seem necessary considerations. Conclusions encompass a highest time dependence for washing, followed by relatively similar time dependence values for cleaning, preparing food, watching TV and washing clothes. In comparison a relatively low time dependence is reported for using a computer, which takes place more or less at any time of the day. For all practices, the highest time dependencies for weekdays occur on Tuesdays, Wednesdays and Thursdays. This is thought to be a result of higher levels of working from home on Mondays and Fridays. Seasonal variations in social practices are also observed like e.g., that in November watching TV is more spread out across the day than in February, June and September and that preparing food has the lowest seasonal variation (Torriti, 2017). Analyzing variability of energy related activities empirically, as done here by use of an indicator reflecting time dependence of social practices, is one important aspect in describing energy demand, but it does not offer explanations for the timing of energy behavior, which is essential for identifying potentials for DSM. Torriti (2017) discusses causal influences such as the role of working, the structuring effect of family commitments and internal synchronization in a social space.

The importance of structuring factors such as timing of work and services in regard to activities "that the individual controls" (Palm, Ellegård, & Hellgren, 2018, p. 101) and the importance of analyzing sequences of behavior are also highlighted by a proposed time-geography perspective for analyzing flexibility of energy using behavior. The idea that analyzing similarities between behavioral sequences by using a cluster analysis reoccurs in this study. In contrast to the described previous work within energy building simulation, it chooses to separately analyze laundering, watching TV and cooking for weekdays and weekend days in Swedish TUS data from 2010 / 2011, coding all other activities as "other" in activity sequences. As results they describe timely distributions of activity sequences in the derived clusters (selection criteria not specified) for different gender and age groups. Although arguing that those socio-demographic groupings are not used for "analytical purposes" (p. 103) but for facilitating interpretation, testing for differences between such groupings and writing as if they were meaningful factors seems problematic as it obscures the focus of just describing the observed variations between clusters. The connection between description of clusters and behavior shifting opportunities is not discussed in this paper, but is the next important step.

What remains open at this point is a better understanding of the connection between behavioral variability as observed in TUD and behavioral flexibility. The possibility for deducing potentials of shifting appliance using behavior has been numerously stated in the bottom-up engineering perspective of building modeling as well as in practice theory-oriented descriptions of TUD. But apart from general suggestions like whether manual or (semi-) automated DSM strategies are more appropriate for a certain region or user group (e.g., López-Rodríguez et al., 2013; Torriti, 2012), theoretical arguments for linking behavioral variability, shifting behavior and interpreting options for changing behavior as part of DSM are not reported. While the operationalization of peak occupancy variance does not seem a helpful indicator for analyzing behavioral variability, time dependence of activities as a concept does reflect variability of behavior as high time dependence in TUD should also be an indicator of common structuring context. The results of Torriti (2017) should thus be theoretically consolable with results of this analysis of behavioral variability.

Common grounds from the studies on describing appliance using behavior with TUD so far seems to be that analyzing behavioral variability does provide information for analyzing behavioral flexibility in scenarios of peak load shifting and smart grid optimizations as it is associated with structuring factors, that it is an approach allowing detailed energy load modelling as done in the engineering perspective which improves on standard load profiles and that in principle a connection between a theoretical approach to analyzing TUD and then modelling energy demand by coupling appliance use behavior information with appliance load information is feasible. Especially this last integration is worth pursuing because it will allow describing behavior variation meaningfully beyond energy demand prediction (which is missing in the engineering perspective) and make the consequences of a certain theoretical perspective visible for the energy system (which is missing without connecting the analysis of variability in behavior to building modelling). Building on the developed insights into appliance using behavior so far, inter-individual variability as well as intra-individual variability should be analyzed, the categorization of behavioral activities into occupancy states should be given up in favor of a more comprehensive analysis of variability in behavioral patterns, the meaningless summary of variation into socio-demographic or socio-economic groupings should be given up in favor of a summary of behavioral variability based on behavior sequences and a-theoretical description should be given up in favor of theoretical analysis of behavior.

As my understanding of the subject matter so far is that behavioral theory can explain how structuring factors or material arrangements, alas structuring context selects the behavioral sequences, while I do not see such an explanation in social practice theory, the current analysis is a behavior theoretical analysis. As the insights into the descriptions of TUD from other perspectives show, there is enough common ground in the empirical approach to describing activity sequences and the aim to understand determinants of shifting appliance using behavior for DSM purposes as well as in the value placed on the TUD itself to work on further knowledge integration in this field.

4.4 Behavior Theoretical Analysis of Behavior Variability in Time Use Data

To arrive at a detailed meaningful description of appliance using behavior, data from the latest German Time Use Survey from 2012 / 2013 (FDZ der Statistischen Ämter des Bundes und der Länder, n.d.) is analyzed. In relation to and extension of previous work on describing energy demand by use of TUD, appliance using behavior is analyzed with a behavior theoretical approach. As much information as possible in terms of types of activities is integrated because limiting the analysis to appliance using behavior or to summarizations into occupancy categories is insufficient for describing behavioral variability because the selection of a behavior at a certain time point influences the distribution of other behaviors and occupancy status is not differentiated enough to relate it to structuring contingencies. Furthermore, as previous descriptions suggest there exist differences between weekdays and weekend days in timely distribution of certain behaviors, for example later decline of sleeping activity in the morning hours on weekends than on weekdays (Palm et al., 2018) or time dependence for different days of the week (Torriti, 2017), a separate analysis for weekdays and weekend days is performed. This differs from argumentations, which sometimes focus only on weekdays because during weekdays instances of problematic peak events occur. Since the mismatch problem is tried to be mitigated by shifting energy using behavior, a focus on just peak events or weekdays is too narrow because the degrees of freedom of behavior outside those time periods of peak events are essential for describing shifting possibilities. At this point a summary into weekdays and weekend days seems a useful simplification when thinking about the necessary connection to a building model and reasonable when one assumes more homogeneous context constrictions during weekdays due to the structuring element of work. Following existing approaches of describing appliance use behavior, a cluster analysis method is employed to order behavioral sequences according to similarities, before analyzing behavioral variability and interpreting it in relation to common structuring context contingencies.

4.4.1 Behavioral Similarities Between Individuals

A separate cluster analysis for weekdays and weekend days (Saturday, Sunday and national holidays) is performed. In the TUS, participants filled out three diary days and it occurred that people had two data entries for a weekday or a weekend day. One data entry for weekdays and one entry for weekend days was randomly selected. So that for weekdays a total of $n = 10{,}589$ subjects had to be clustered and $n = 10{,}654$ for weekend days.

4.4.2 Groupings of Activities

One advantage of employing the German TUD to describe behavior patterns is the richness of available information in form of more than 165 activities. Even though the richness of information on behavior is an advantage, it also poses a problem for the application of clustering algorithms. Too many categories could lead to similarity measures between different objects with a narrow range of values and thus limiting the ability of clustering methods to identify groups of objects, which are more similar to each other than to objects from other groups. Thus, some sort of summarization of this very detailed description of different behaviors is necessary. Since the activities are organized hierarchical (L. Maier, 2014), one can reduce the categories by summarizing lower levels of hierarchy. But still the non-trivial question remains how to categorize the coded activities.

It is an important question because choosing a categorization should ideally already hold information about theoretical relevant structures of the things one wants to describe. For questions of describing appliance using behavior this would imply categorizations meaningful for describing behavior, if this is the focus of investigation. Many categorizations of activities from TUD or in general for modelling energy demand so far are designed from a technical perspective and thus focus on relating the structure of the physical characteristics of appliances. Examples for this are categorizations which distinguish between cold, active, standby and continuous appliances (Firth, Lomas, Wright, & Wall, 2008). Activities from the TUD which can be associated with appliances falling into those categories are grouped based on the type of electric load that is generated by the appliance (e.g., cold appliances are characterized by cyclic load resulting from thermostatic temperature control in freezers and fridges) and not by the behavioral function it serves. In some cases, this might fall together. Opening and closing a fridge or a freezer both have as a common consequence a longer preservation of food supplies. But active patterns of appliance use (characterized by active switching on or off by householders and no standby mode), which group activities such as using kettles and electric showers together, result mostly in different consequences and should thus not be analyzed as one group when the focus is to describe behavior.

In a technical perspective behavior of household members is often described by occupancy categorizations because occupancy is empirically associated with energy demand in households and due to few different occupancy states relatively easy to handle in simulation models. This is not a hindrance for bottom-up building models which generate energy demand profiles which's main focus is to improve upon standard energy load profiles or enable analysis of small-scale distributed power generation, it is just a hindrance, when those models are supposed to be useful for analyzing aspects of behavior such as flexibility. At this point models do not only need to predict average energy demand profiles but the categories making up the activity patterns which are matched to electrical loads should share communalities in terms of degrees of freedom or flexibility so that simulations altering parameters for those activities are rooted in variability schemes of behavior. Arriving at a suggestion for such a categorization after analyzing behavioral variability in the TUD would be a valuable outcome as it can open up a debate about flexibilities in behavior and potential of DSM approaches based on behavior information.

That categorizations are important in respect to what statements can be derived about behavior is also evident from the way in which categorizations can steer the focus of an analysis. For example, in demand control programs appliance using behavior is often categorized into controllable and non-controllable appliances (Parisi & Christensen, 2011) from the perspective of a smart device scheduler or grid controller. While this is very useful for modeling appliances which are currently available for automated or semi-automated control, it can obscure potentials for shifting appliance using behavior. This is because potential is analyzed in terms of what is technical possible and not what is possible or promising in terms of behavior. An activity such as watching TV is mostly categorized as un-controllable and thus excluded from DSM programs while the empirical analysis from López-Rodríguez et al. (2013) shows, that consumption due to watching TV during the evening peak can be substantial and that thus DSM should consider TVs to participate in DSM strategies. Choosing categorizations for activities should thus not only be based on practical and technical energy building considerations.

From behavioral theory it is known that the relevant categorization of behavior is not in terms of its topography, i.e., whether the behavior is holding a tablet or looking at a TV, but in terms of its consequences, i.e., in both cases getting

Table 4.1 Summarization of TUD Activities into 22 Activities

		Frequency in %[2]	
Description of activity	Code number[1]	Weekday	Weekend
sleeping	11	34.04	38.85
physiological recreation like food and drink consumption and washing oneself	12, 13	10.25	11.75
occupational activities	2	12.42	2.35
education and further education in school, college or at the university	31–34	3.14	0.09
other education related activities like homework, studying	35, 36	1.19	0.83
preparing meals and cleaning up afterwards	41	2.48	2.96
chores at home	42	1.74	2.01
doing laundry, mending textiles	43	0.82	0.77
gardening and animal care	44	1.34	1.43
handicraft activities	45	0.42	0.55
shopping and use of services not at home	46	2.48	1.77
childcare at home	47	1.19	1.20
care and support of adult household members	48	0.09	0.08
other housekeeping and support activities for the family	49	1.11	1.36
volunteer work	5	1.07	1.26
social activities and cultural entertainment	6	5.53	8.97
hobbies, sports, game playing	7	3.62	5.24
reading	81	1.93	2.34
watching TV, DVD etc	82	7.43	9.31
listening to radio and music	83	0.30	0.36
using computer or smartphone	84	1.52	1.62
travel and commute activities	9	5.88	4.89

Note [1] original upper code number from Time Use Survey ("Aktivitätenliste" 2017, pp. 398–400)

[2] relative frequency of an activity across all 10-min time intervals for weekdays (n = 10,589) and weekends (n = 10,654). (FDZ der Statistischen Ämter des Bundes und der Länder, n.d., own calculations).

information on soccer scores from today's matches.[6] As such, a categorization of activities should come as close as possible to a functional perspective of behavior categorization. As the TUD is pre-categorized by the Statistisches Bundesamt and the descriptions in the diary are in most cases made more in terms of what was done instead of what were the results of a certain behavior, a behavior theoretical categorization is not possible without some effort. Adjusting TUD diary instructions to include descriptions of the consequences of behavior could be an interesting possibility to come closer to a behavior theoretical perspective[7]. The chosen summary of activities into certain groupings is a compromise between the available data, the idea to include all activities from the TUS and the need to get detailed information on appliances that were used in the building model from the project partner.

The original activities in the German TUD are described by Statistisches Bundesamt (2017). The summarization into categories is presented in Table 4.1 and gives 22 activities. The original code number from the TUD is given for tracking purposes as well as the frequency of those activities separated for weekdays and weekend days. These activity categories are the basis for applying a clustering method.

4.4.3 Organizing Similarities in Behavior Patterns: Cluster Analysis

One essential aspect of appliance using behavior which has to be analyzed when addressing problems of shifting behavior in order to mitigate problems of discrepancies between energy supply and demand due to increasing shares of renewable energy generation is the degrees of freedom in distributing behavior over the course of a day. Degrees of freedom in distributing behavior is related to behavioral variability in a way that low variability in terms of fixed times for when a certain behavior is performed implies contingencies which are structured in a way that the selection of an operant falls into certain time bands. Or in other words is restricted to certain time periods. In principle, degrees of freedom in distributing behavior over a day can be looked at form an intra-individual perspective over multiple days or from an inter-individual perspective over multiple people.

[6] Operant is the theoretical term for behavior which is defined by its consequences (as was described in the section theoretical analysis of behavioral variability).

[7] A verbal description of consequences is also not the correct way to identify operants in a behavior theoretical analysis, but in keeping with the advantages of the TUS, it is a compromise which could improve upon the information one can obtain from TUSs.

While the intra-individual perspective can inform possible patterns of individually relevant contingencies and the importance of past contingencies for selection of behavior, the inter-individual perspective can inform possible patterns of relevant common contingencies, which at this point of discussion might be more helpful to derive general ideas for DSM strategies in the sense of shifting appliance using behavior.

To get a first impression of inter-individual behavioral variability for the randomly selected subset of $n = 10{,}589$ subjects for weekdays and $n = 10{,}654$ for weekend days one can visualize the activity sequences for each individual for the 22 activity categories and look when during the day different activities are performed, view Figure 4.1. On the x-axis time of day is indicated from 04:00 a.m. to 03:50 a.m. with a precision of ten-minute intervals as available from the TUD. On the y-axis each individual is displayed sorted beginning with the person having the longest sequence of the activity which is the first entry in the data set. In this case the data is sorted beginning with the sleeping activity. From this visualization already a few things about the distribution of behavior and the variability in behavioral sequences between individuals becomes evident. In the upper display of activity sequences for weekday data, sleeping is the most common activity and due to the sorting of data it can also be seen that in the morning hours people do differ considerably concerning the timing of when the activity sleeping ends, as can be seen by the “s” shape dividing the bright red sleeping area from the beginning other activities. The same “s” shape divides sleeping and other activities for the weekend data with a difference being that a larger area is covered by the sleeping activity, indicating that more people sleep longer on weekends. Furthermore, for weekdays and weekend days a similarity is that sleeping (bright red) is often followed by physiological recreation (dark red) in the morning and also dominates the evening and nighttime hours. Visible is also a large amount of working activity (light green) for the weekdays. But this is not true for all behavioral sequences. Several do also consist of notable amounts of educational activities (dark blue) in the morning and midday hours. On the weekend those activities are not as dominant, instead the activity sequences appear more diverse and more dominated by social activities (yellow) throughout the day. For both weekdays and weekend days watching TV (plum) in the evening is a common activity. The results in terms of the activities sleeping, watching TV, work and education are similar to the descriptions of Swedish TUD 2010 / 2011 from Palm et al. (2018) and to the description of watching TV on the basis of United Kingdom TUD 2005 from Torriti (2017).

To gain further insights into the distribution of activity patterns and make them better describable, the activity sequences for weekdays and weekend days

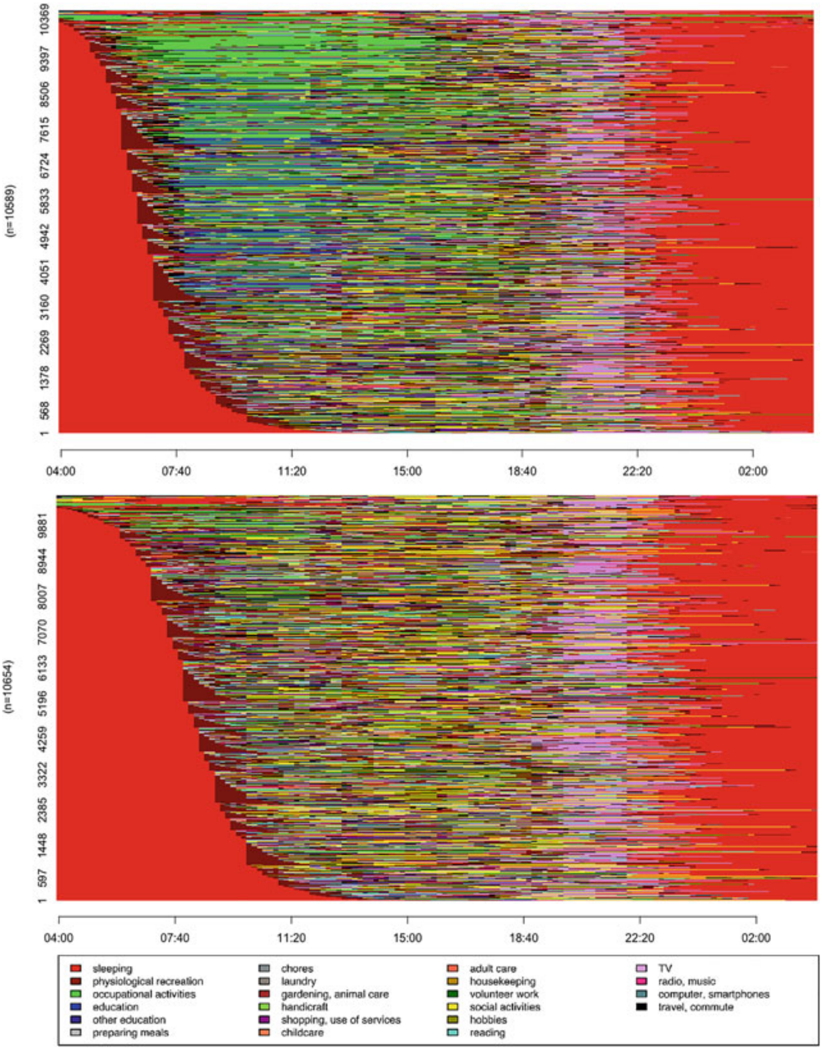

Figure 4.1 Activity sequences for weekday (top) and weekend (bottom) data (FDZ der Statistischen Ämter des Bundes und der Länder, n.d., own calculations). Visualization done with the TraMineR Package in R (Gabadinho, Ritschard, Müller, & Studer, 2011)[8]

[8] A display of frequency distributions for the 22 activities for weekday and weekend data is given in Appendix A.

are ordered by a clustering algorithm according to their similarity in the pattern of activities over a day, so that similar activity patterns can be described together. Apart from a social practice proposition that in principle forms of energy consumption can be understood as outcomes of related patterns of social practices such as working, visiting friends and family, shopping, going to school and more (Shove, Watson, & Spurling, 2015) and empirical descriptions of TUD which lead to assuming an importance of working schedules for energy using behavior (e.g., Palm et al., 2018; Torriti, 2017) there is no theoretical assumption about the number of groups of activity patterns. It is thus an exploratory approach using unsupervised clustering to identify groups of behavioral patterns.

The 22 activity categories (Table 4.1) are used to cluster the different behavior patterns. For weekdays a total of n = 10,589 subjects were clustered and n = 10,654 for weekend days. The distance between the subjects is measured using a type of edit distance called Levenshtein Distance[9] (Levenshtein, 1966), which typically and also here means that when comparing two strings or in this case the sequences of activities in the 144 time slots between each pair of subjects to derive the distance measures, the cost for each edit necessary to transform the sequence of one subject to the sequence of another subject is set to one (instead of for example assuming different costs for insertions, substitutions or deletions) (Aerts et al., 2014).

In previous studies, several clustering methods were used to recognize occupancy patterns. D'Oca and Hong (2015) for example clustered occupancy patterns in office buildings by k - means clustering, in the residential sector, an agglomerative hierarchical clustering method was applied to TUD to recognize occupancy patterns (Aerts et al., 2014) as well as a k-modes clustering algorithm (Diao et al., 2017), which is more appropriate for a categorical data structure like TUD activities.[10] Hence a k-modes clustering method called Partitioning around Medoids (PAM) (Kaufman & Rousseeuw, 1990) is employed in R (PAM package cluster version 2.0.6). The general idea of the PAM algorithm is that it clusters objects by taking k representative objects referred to as medoids and then assigns each remaining object to the nearest medoid such that the sum of dissimilarities of

[9] The distance matrix is calculated using the stringdist R package version 0.9.5.2 (van Der Loo, 2014).

[10] The TUD analysis by Palm et al. (2018) also used a clustering method, but from their description it is not clear which method they employed: "The clustering was done in R version 3.2.3 (R Core Team, 2014) using Ward's distance and the TraMineR (Gabadinho, Ritschard, Müller, & Studer, 2011) and WeightedCluster (Studer, 2013) packages." p. 102. It is probable that they used the ward method for clustering, leaving the distance measure unspecified.

the medoids to all other objects in the same cluster is minimized (Kaufman & Rousseeuw, 1990).

Based on the validation criterion average silhouette width (range $-1 \leq s_i \geq 1$; Kaufman & Rousseeuw, 1990) which is shown in Figure 4.2, a cluster-solution with three groups seemed preferable for the weekday data. If the average silhouette width takes on large values close to 1, it means that the within cluster dissimilarity is much smaller that the smallest between cluster dissimilarity indicating a good classification. If the value is near 0, then on average objects lie equally far away from the cluster they are assigned to and the nearest other cluster. A value near -1 indicates that objects on average lie closer to another cluster than the one they have been assigned to (Kaufman & Rousseeuw, 1990). For the weekend data in terms of silhouette width there is no unambiguous solution, so a six-cluster solution was chosen due to similar cluster sizes and preferable separation values (the five-cluster solution had two clusters with comparatively very high but also low separation values and the seven-cluster solution had two relatively small sample sizes) (view Appendix B for an overview of cluster sizes and validity indicators). As can be seen, for weekday data and for weekend data, the average silhouette width values are positive, but very close to zero, indicating that within-cluster cohesion is only slightly larger than between clusters. Since the validation criterion average silhouette width has values closes to zero which according to Kaufman and Rousseeuw's (1990) "subjective interpretation" is indicative of a situation in which "no substantial structure has been found" (p. 88), their suggestion is followed and different clustering algorithms applied to the data. As can be seen in Appendix B for a selection of best alternatives for agglomerative hierarchical methods, solutions are not preferable to the PAM algorithm, so the solution of the PAM algorithm is kept. It is assumed that the validity indicators are insufficient because of the relatively large amount of activities chosen for clustering. Nonetheless, the grouping can be helpful for the organization of activity patterns and analysis of activity distributions in the chosen cluster, if it is able to order subjects according to differences in some of the 22 activities which are already visible in the activity sequence plots (Figure 4.1).

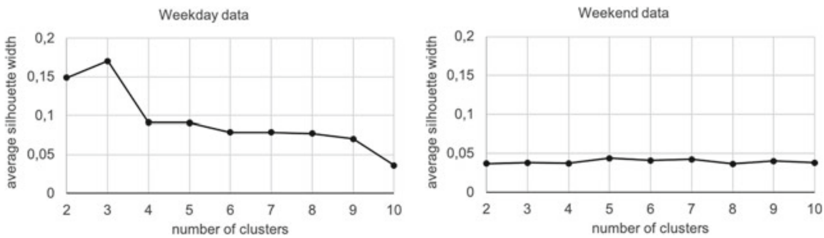

Figure 4.2 Selection criterion average silhouette width for weekday data (left side) and weekend data (right side). (FDZ der Statistischen Ämter des Bundes und der Länder, n.d., own calculations)

For an overview of cluster sizes for weekday and weekend data, view Table 4.2. As can be seen, the clusters are large enough in order to be useful for simulation purposes in the building model.

Table 4.2 Cluster Size for Weekday and Weekend Clusters

day type	cluster 1	cluster 2	cluster 3	cluster 4	cluster 5	cluster 6
weekday	4325	1991	4363	–	–	–
weekend	1278	1946	2482	1260	2738	950

4.4.3.1 Timely Distribution of Behavior in Chosen Cluster Solution

An important property to describe behavior is rate of behavior. This makes TUD a good data base for a behavior analysis as it captures frequency of behavior in relation to time. For describing multiple people with an inter-individual perspective, this property of behavior is summarized as relative frequency of a behavior in each ten-minute time interval as probability of an activity in that time interval within a cluster. Based on this indicator common structures of activity patterns as well as the differences separating the three weekday and six weekend clusters are described. Plotting the results for the chosen cluster solution gives the behavioral activity patterns displayed in *Figure 4.3* and *Figure 4.4* for weekday data and in *Figure 4.5*, *Figure 4.6*, and *Figure 4.7* for weekend data. In each figure, the x-axis displays the time of day in 2-h intervals with precision to 10-min intervals and the y-axis displays the percentage of an activity within a cluster for all 22 activities.

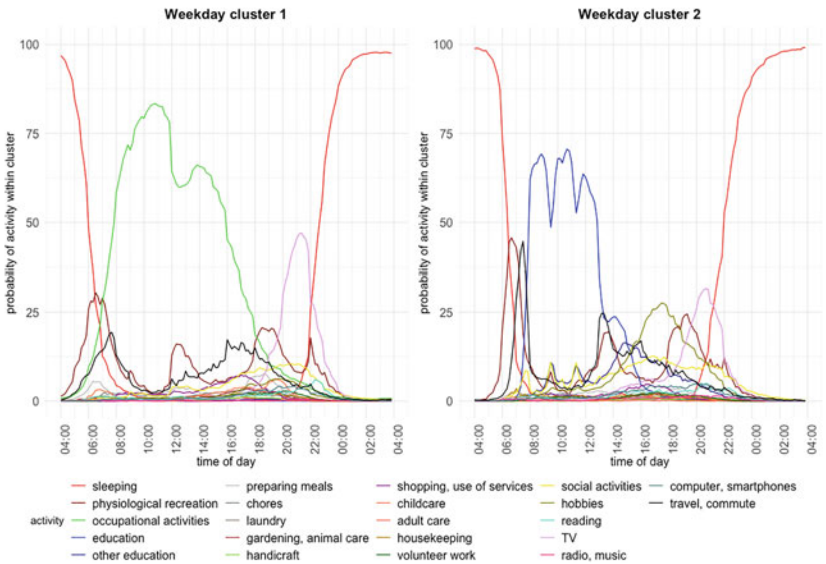

Figure 4.3 Behavioral activity patterns for weekday data in cluster 1 ($n = 4235$) and cluster 2 ($n = 1991$). (FDZ der Statistischen Ämter des Bundes und der Länder, n.d., own calculations)

An inspection of the results shows a strong communality in form of a homogeneous shape of the sleeping curve across all weekday and weekend clusters, which only differ in slope and horizontal position. In weekday cluster 1 more than 90% are sleeping until 04:40 and less than 10% are sleeping at 07:20. In weekday clusters 2 and 3 more than 90% are sleeping until 05:40 and 05:50, respectively and less than 10% are sleeping at 07:10 and 09:50, respectively. On the weekends more than 90% are sleeping approximately one to two hours later in comparison to weekday clusters 1 and 2 (except weekend cluster 6: 04:50). In the evening more than 10% are sleeping in weekday clusters 1, 2 and 3 beginning at 21:50, 20:50 and 21:50 and more than 80% are sleeping beginning at 00:00, 23:50 and 00:50. On the weekend evenings more than 10% are sleeping in clusters 1, 2, 3, 4, 5 and 6 beginning at 22:20, 21:30, 21:50, 23:20, 21:50 and 22:10 (in same order) and more than 80% are sleeping beginning at 01:20, 00:00, 00:00, 02:00, 00:00 and 01:10 (same order) so that especially cluster 4 has a later beginning of the sleeping activity.

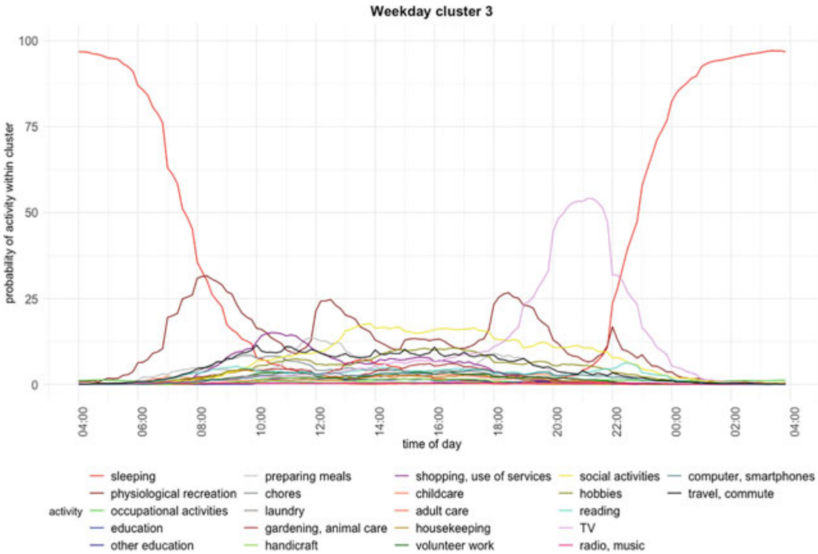

Figure 4.4 Behavioral activity patterns for weekday data in cluster 3 ($n = 4363$). (FDZ der Statistischen Ämter des Bundes und der Länder, n.d., own calculations)

For weekdays, the main difference between clusters consists in the difference of frequency of occupational activities and education. In weekday cluster 1 occupational activities are predominant with a mean occupational activity frequency of 30.04% ($SD = 11.13\%$) across all time intervals, while in cluster 2 and 3 the mean activity frequencies are 0.41% ($SD = 2.57\%$) and 0.80% ($SD = 4.11\%$) respectively. In weekday cluster 2 education is dominant ($M = 16.29\%, SD = 2.57\%$ in comparison to cluster 1 with $M = 0.05\%$, $SD = 0.88\%$ and cluster 3 with $M = 0.14\%$, $SD = 1.46\%$) and in cluster 3 neither of those two activities have a high frequency. Instead, the frequencies of other activities such as physiological recreation, social activities, preparing meals, shopping and watching TV are slightly higher (for an overview of all mean activity frequency values and standard deviations view Appendix C). It appears that for the weekday data the cluster algorithm has sorted the activity sequences according to the differences also visible in the activity sequence plot: absence and presence of occupational and educational activities.

In weekday cluster 1 occupational work activity is distributed in a way that beginning from 06:40 until 19:00 more than 10% is occupational activity and from 08:00 until 15:50 more than 50% is occupational activity. A noticeable

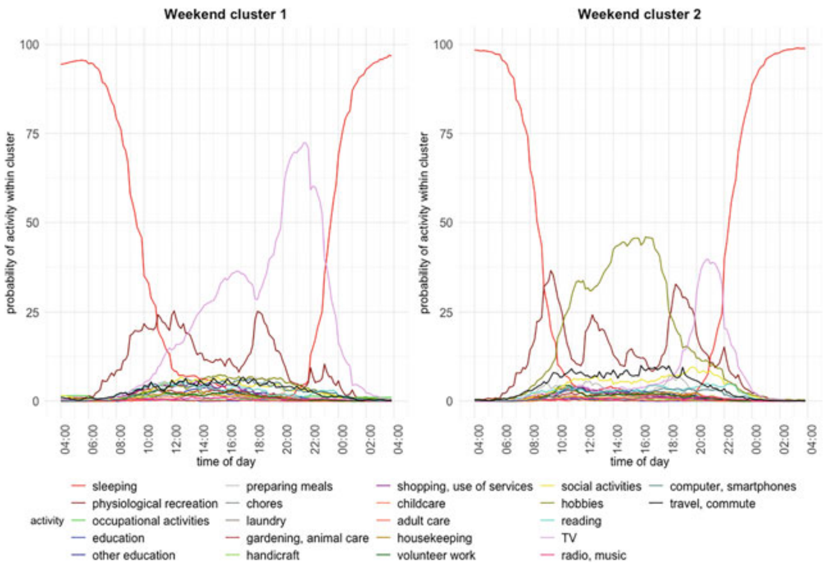

Figure 4.5 Behavioral activity patterns for weekend data in cluster 1 (n = 1278) and cluster 2 (n = 1946). (FDZ der Statistischen Ämter des Bundes und der Länder, n.d., own calculations)

drop in occupational activity frequency for cluster 1 is observable around midday around 12:30 / 12:40 which is something that was also described by Palm et al. (2018) for Swedish TUD as "The majority of the individual activity sequences also include work/school activities (red) during daytime hours with a lunch break at noon." (p. 103). In regards to educational activities which is predominant in weekday cluster 2, it seems however, that around midday the supposed "lunch break" is not a break but that the frequency of educational activity ends for about half of the individuals. From 12:50 on 50% or less is educational activity in weekday cluster 2. In comparison to weekday cluster 1 and 2, it can be seen in *Figure 4.4* that the social activity is distributed more evenly over the course of the day within periods of low sleeping activity, while for clusters 2 and 1 social activities increase toward the late afternoon and evening hours.

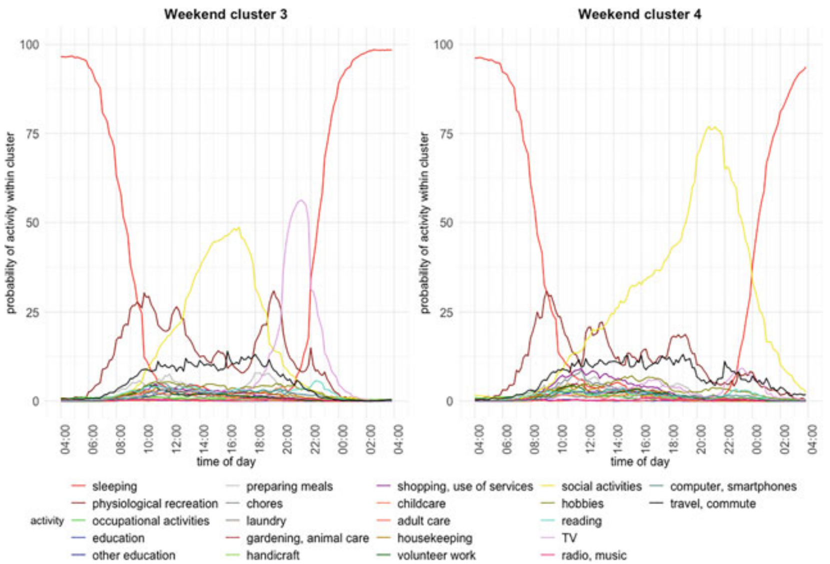

Figure 4.6 Behavioral activity patterns for weekend data in cluster 3 ($n = 2482$) and cluster 4 ($n = 1260$). (FDZ der Statistischen Ämter des Bundes und der Länder, n.d., own calculations)

The weekend data is not as homogeneous as the weekday data since there are six instead of three clusters, thus showing more diversity in the activity sequences, which was also visible in the activity sequence plot. What was not identifiable, is what communalities exist in the structure of activity sequences. According to the cluster solution for the weekend data, the similarities in activity patterns within clusters or in other words, what about activity sequences differentiates most noticeably between the six weekend clusters are social activities (weekend clusters 3 and 4), hobbies (weekend cluster 2) and occupational work (weekend cluster 6), while there are two weekend clusters (1 and 5) which are distinguished by a comparatively low frequency of those activities and a high frequency of the activity watching TV with a higher overall and midday frequency in weekend cluster 1 ($M = 21.26\%$, $SD = 9.88\%$) compared to weekend cluster 5 ($M = 10.21\%$, $SD = 6.51\%$). In weekend cluster 5 also the activities doing chores with its peak probability at 10:00 and preparing meals with its peak probability at 11:50 are different from the other weekend clusters. Weekend

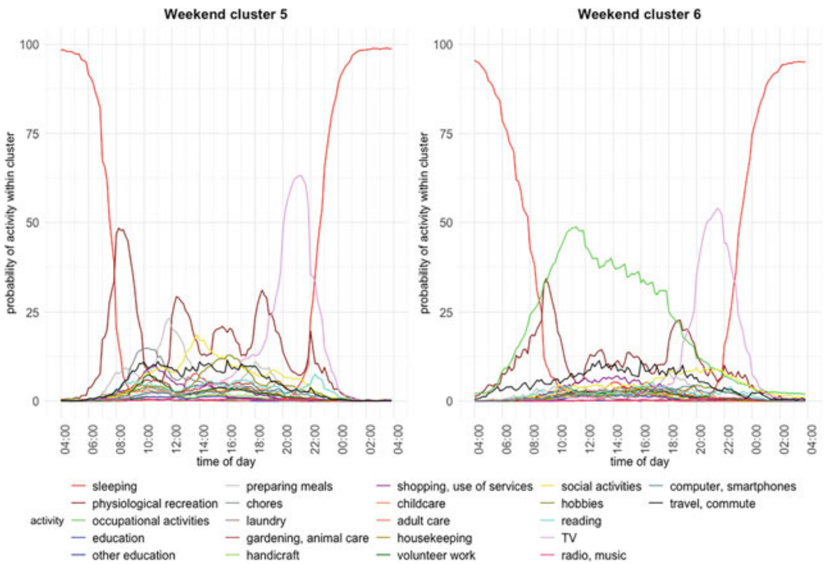

Figure 4.7 Behavioral activity patterns for weekend data in cluster 5 ($n = 2738$) and cluster 6 ($n = 950$). (FDZ der Statistischen Ämter des Bundes und der Länder, n.d., own calculations)

clusters 3 and 4 are both dominated by a high frequency of social activities (cluster 3: $M = 13.58\%$, $SD = 8.23\%$); cluster 4: $M = 25.76\%$, $SD = 11.25\%$), but the timing of this activity differs between clusters. For weekend cluster 4 the social activities have a peak towards the evening hours at 21:20, while cluster 3 has a high frequency of social activities more around the late afternoon between 16:00 and 17:00 with a broader not skewed activity curve. Weekend clusters 2 and 6 differ concerning the frequency of hobbies and occupational activities, respectively, in comparison to the other weekend clusters as can be seen in Table 4.3. Another frequent activity in all weekend clusters is physiological recreation (dark red) which encompasses eating and drinking as well as washing oneself and which differs in the timely distribution as can be seen by the different amounts of peaks and where in the day they are situated. For example, weekend cluster 5 has five prominent peaks spreading across all time slots with little sleeping activity, while weekend cluster 6 with occupational work on weekends, has two major peaks which fall at the time of rising and falling of occupational work in the morning

Table 4.3 Selection of Activities: Differences in Mean Frequencies and Standard Deviations for Weekend Cluster Solution in %[1]

	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
Description of activity	*M (SD)*	*M (SD)*	*M (SD)*	*M (SD)*	*M (SD)*	*M (SD)*
sleeping	41.85 (8.95)	42.22 (7.87)	41.65 (8.31)	33.19 (8.48)	36.65 (5.88)	34.44 (7.69)
physiological recreation	9.89 (4.87)	11.83 (5.46)	11.78 (5.48)	10.71 (5.12)	13.62 (5.72)	10.07 (4.53)
occupational activities	0.72 (4.28)	0.29 (2.14)	0.68 (3.44)	1.26 (5.00)	0.36 (2.20)	20.28 (16.20)
preparing meals, cleaning	2.35 (3.15)	2.06 (3.04)	2.49 (3.25)	2.17 (3.51)	5.05 (4.65)	1.89 (2.67)
chores at home	1.60 (2.97)	1.18 (2.21)	1.64 (2.81)	1.92 (3.31)	3.40 (4.28)	1.38 (2.66)
social activities	2.82 (4.02)	3.76 (4.72)	13.58 (8.23)	25.76 (11.25)	5.41 (5.02)	3.89 (5.85)
hobbies, sports	3.06 (5.16)	15.84 (9.54)	2.58 (4.20)	2.77 (5.08)	3.52 (4.53)	1.69 (3.76)
TV, DVD etc	21.26 (9.88)	6.65 (6.05)	7.96 (5.89)	2.55 (4.10)	10.21 (6.51)	8.54 (6.34)
travel and commute	2.91 (4.74)	4.34 (5.63)	5.43 (6.57)	6.77 (6.61)	4.78 (6.65)	5.11 (5.92)

Note [1] Full table with all 22 activities is in Appendix C.

hours at around 09:00 and the evening hours at around 19:00[11]. Besides sleeping, a communality between all weekend clusters which can be seen from *Figure 4.5*, *Figure 4.6*, and *Figure 4.7* appears to be (at this level of visualization) the almost even spread of the travel and commute activity across the day between approximate times of 11:00 and 19:00. The other activities displayed in the plots of probability of an activity within a cluster are too low in frequency to describe behavioral patterns at this level and have not been decisive in establishing an order in behavioral patterns by means of the employed clustering algorithm.

In summary, the main difference between the clusters arises from differences in frequency and the timely distribution of certain activities. For weekday data, those are occupational and educational activities and their absence in weekday cluster 3, as well as differences in slope and beginning rises and declines in the probability of the sleeping activity. In shape, the activity sleeping curve is very homogeneous for all weekday and weekend clusters. The main differences between the weekend data stem from the sleeping activity, occupational activities (weekend cluster 6), hobbies (weekend cluster 2), social activities (weekend cluster 3 and 4) and watching TV (weekend cluster 1 and 5). Looking at the social activities and watching TV, it becomes clear, that what mainly differentiates the clusters is not only the overall probability of this activity within a cluster, but their timely distribution over the course of a day. In terms of variability in behavioral patterns between individuals these results indicate that during weekdays the variability in behavioral patterns is smaller than on weekend days as there are three instead of six different clusters identifiable. Although with an amount of 22 activities in 144 10-min time slots the clustering algorithm is only able to order behavioral sequences according to major differences in activity sequences, the established order points towards a relative homogeneous structure in behavioral activities such as sleeping, working, educational activities, hobbies, social activities and watching TV.

[11] The graphical display has the advantage of relating the frequency of the differentiating activities to time of day, which is an important feature for interpretation and also for recognizing differences, which might be unseen in comparison of mean values in activities between clusters. Nonetheless mean values, standard deviations and results of a robust ANOVA for trimmed means (Wilcox, 2012) for all activities for weekday and weekend data are reported in Appendix C. The results are in accordance with the description of the plotted activity patterns pointing towards the same significant differences in activities between clusters. That is, occupational and educational activities and sleeping for weekday clusters and occupational and social activities, hobbies, watching TV and sleeping for weekend clusters.

4.4.3.2 Variability in Behavior Given the Chosen Cluster Solution

One aspect which has become clear is that some of the 22 activities are so frequent and distinctly distributed in time that they potentially structure at what times other behaviors are performed. Hence, the variability of those structuring behaviors is relevant for questions of degrees of freedom of distributing behavior across the day because their variability indicates how flexible those behaviors are themselves but also in what ways they might limit the times in which other behaviors can be performed.

A challenge in describing behavioral variability for aggregate data of activity sequences as ordered by the cluster algorithm and summarized into probabilities of behavioral activities in certain time slots, is that the way in which to describe variability is dependent on theoretical assumptions. For instance, summarizing variability of behavioral sequences (be it occupancy states or appliance using activities) into socio-demographic and socio-economic groups implies assumptions such as "the characteristics age and income of a person (causally) influence presence and absence times at home or appliance using behavior". Even in cases where such groupings are made to only summarize observed variability without assumptions of causal influence (e.g., Palm et al., 2018 state to do this), the question remains why use a way of describing behavior which is assumed to be irrelevant for behavior? In cases where the theoretical basis is a descriptive theory, such as social practice theory in Torriti's (2017) analysis of UK TUD the indicator remains also descriptive: the constructed indicator time dependence captures one variability aspect of appliance using behaviors which is high occurrences of the same activity over the same time periods. This aspect of variability of TUD can also be analyzed as was done in the previous section when describing high frequencies of activities for the different behavioral clusters with the difference that not only appliance using behavior was clustered. In order to establish a link between behavioral theory and an indicator which describes behavioral variability in the aggregate descriptions of activity sequences ordered by the cluster algorithm and summarized into probabilities of behavioral activities in certain time slots, assumptions need to be made relating the information available from the plots of activity curves and contexts-as-structure of contingencies.

The basic behavior theoretical premise is that context in the sense of context-as-structure of contingencies selects behavior by constituting the contingencies between stimuli, responses and consequences and by restricting the variability of behavior. In the first case, if one assumes an established context structure, the regularities determining different consequences are what mainly alters the functional relations of the three-term contingency throughout a day. Restrictions by regularities (also referred to as constraints) influence behavioral variability by setting the conditions of when a behavior is followed by certain consequences.

If an operant cannot be performed at any time throughout a day with a similar consequence, then the behavior is referred to as having low degrees of freedom in being distributed freely across the day because the changing contingencies select specific time periods for performing a behavior. A behavior with high degrees of freedom can be described by contingencies which remain similar across a day, meaning that the consequences of performing a behavior are approximately the same independent of when a behavior is performed. In the second case, context-as-structure can restrict the variability of behavior by setting boundary conditions. Although, strictly speaking restrictions by regularities also restrict the variability of behavior by setting the time limits of when certain behaviors will be followed by a consequence, the description "restricting the variability of behavior by boundary conditions" refers to the case in which an analyzed behavior is restricted by other behaviors. This means that context structure as boundary condition influences behavioral variability by limiting possible times of performing a behavior because behaviors with low degrees of freedom can only be performed at specific time points selecting them in competition to other behaviors in those time periods. Behaviors with unchanging contingencies throughout the day and very little restrictions by other behaviors can thus be regarded as having high degrees of freedom. While these described relations between context-as-structure and operant are grounded in behavioral theory, the suggested reference points for different degrees of freedom allow a categorization of activities in terms of behavioral variability. An indicator which describes behavioral variability for clustered TUD activities should try to capture the described relations between behavior and context-as-structure. The main difficulty is that while the relations are clear, they cannot be inferred with certainty from the available inter-individually aggregated data as it is available from the TUD. Thus, further assumptions have to be made on how to describe behavioral variability in clustered TUD.

It is assumed that changes in frequencies (positive or negative slopes) are indicative of changes in contingencies in behavior. That context-as-structure influences the distribution of behavior by either providing restricting regularities or by limiting the distribution due to other behaviors which have more dominant contingencies in a time period. When many people perform a behavior at similar times it is assumed that context-as-structure must be very selective of this behavior at that time and contingency structures are invariant across people, thus indicating societal restrictions. So, when changes in frequencies over a day are large, it is assumed that the context structure is very selective and restricts behavior to those time periods with very high in comparison to very low frequencies (constraints). Those activities are viewed as having low degrees of freedom and that they can restrict the distribution of other behaviors. Furthermore, it is assumed that activities which have little changes in frequency over the course of a day (few positive and negative slopes and longer time periods with close to zero slopes) have unchanging contingencies. If relatively infrequent activities for which unchanging contingencies can be assumed show changes in frequency over the course of a day, it will be assumed that this is due to the restriction of other behaviors. The idea for an analysis of variability in the selected clusters is illustrated by a hypothetical activity curve in *Figure 4.8*.

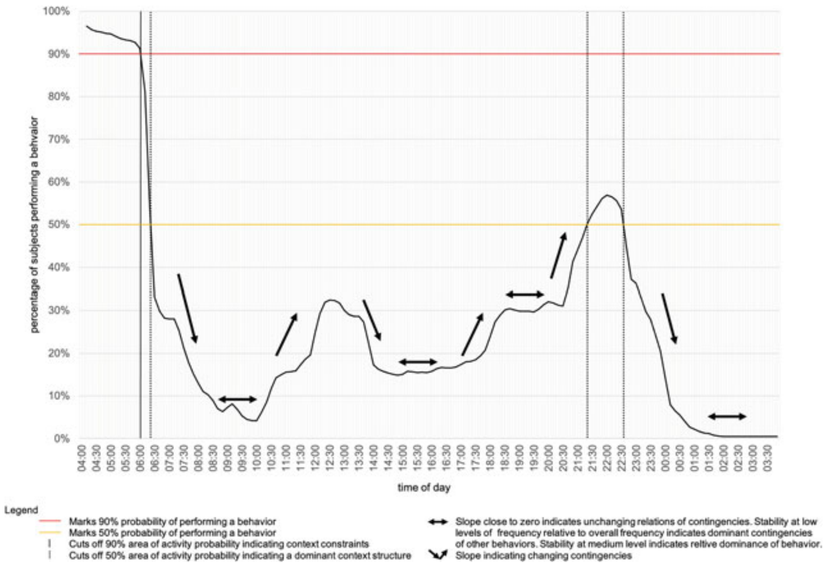

Figure 4.8 Illustration linking behavioral variability and TUD activity curves

It can be seen that this hypothetical activity curve has large differences in frequency throughout the day ranging from above 90% probability of individuals performing a behavior (marked off by a solid vertical line and horizontal red line) to close to zero frequency indicating changing contingencies probably due to restricting constraints. Time periods with medium to high activity frequencies (marked off by dotted vertical and orange horizontal line) are indicative of a dominant context structure because still for most individuals behavior is selected for this time period. In the time periods with low to medium activity frequencies close to zero slopes indicate unchanging contingencies. Few positive and negative slopes and longer time periods with slopes close to zero indicate few restrictions by other behaviors in those time periods a behavior can distribute freely, while many changes in slopes indicate more changes in relative contingencies between behaviors such as in the illustration above.

The cluster algorithm helped order weekend and weekday data in a way that the differences between clusters lie in different distributions of high frequencies of certain activities over the course of a day. Identifying communalities in activity sequences is thus an important step in the analysis of behavioral variability because it highlights common distributions of activities over the course of a day. From the argument above on how one can describe behavioral variability in TUD activity curves it follows that all those activities which mark the major differences between clusters are candidates for being restricted in their timely distribution by constraints or dominant context structures and are thus candidates for having low degrees of freedom in terms of distributing behavior freely over a day. For now, other behaviors are candidates for having high degrees of freedom of where to distribute behavior and analyzing these activities as suggested can help describe in what ways the activities distribute approximately evenly within a cluster and in what ways their distribution in time appears to be characterized by changing contingencies due to restrictions by other behaviors. Something that can be described by looking at the distribution of the same activities between clusters and by comparing this variability between clusters to how the activities distribute within a cluster. To evaluate these questions exemplary for the focus of this study on appliance using behavior, the variability of the following behaviors will be analyzed (view *Figure 4.9*): sleeping and watching TV in all clusters because they differentiate between the clusters but are relatively homogeneous in curve shape; occupational activities in weekday cluster 1 and weekend cluster 6, educational activities in weekday cluster 2, hobbies in weekend cluster 2, and social activities in weekend cluster 3 and 4 because they differentiate between the clusters; physiological recreation, preparing meals, doing laundry, listening to radio and music and using computer or smartphone in all weekday and weekend clusters because they are less frequent, appear to be more heterogeneous and are coupled with electrical consumption of appliances in the building model. So, for these behaviors there is a special interest in identifying in how far they distribute freely throughout the day. As theoretically for main consequences of those behaviors almost constant contingencies in terms of regularities in context structure can be assumed (doing laundry will always result in clean and dry laundry, physiological recreation will always result in energy and fluid intake or a clean body, preparing meals and cleaning will result in processed food ready for eating or clean dishes etc.) they are listed as candidates for having high degrees of freedom.

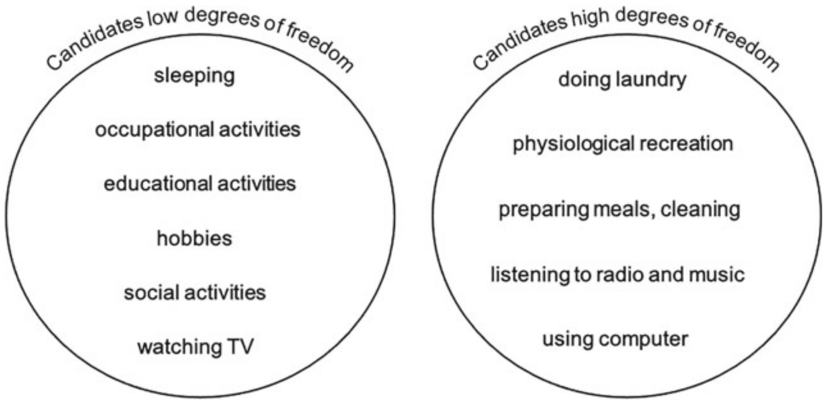

Figure 4.9 Candidates for low and high degrees of freedom in behavioral variability (own diagram)

The description of the timely distribution of the sleeping curve already showed it to be a very homogeneous behavior across all weekday and weekend clusters. Looking at variability in sleeping activity in weekday data (*Figure 4.10*) and weekend data (*Figure 4.11*) one can see two steep slopes, one in the morning hours and one in the evening hours indicating many individuals changing behavior in a relatively short time span. This time period thus seems to be a period in which individuals adapt their behavior to changing contingencies and the fact that it occurs so fast and for so many people (large differences in frequency from above 90% to below 10%) can be taken to mean that the context structure which provides the pattern of contingencies is also homogeneous. The large differences in frequency indicate restricting constraints. Thus, for the sleeping activity on weekdays and weekend days one can assume limits in distributing behavior: For the weekday clusters more that 90% are sleeping between 00:50 and 04:40 and for weekend cluster between 03:00 and 04:50 making other behavior very unlikely due to contextual constraints.

During the day between approximately 10:00 and 20:30 for all weekday clusters and 12:00 and 21:00 for weekend clusters there are relatively unchanging contingencies for sleeping, except for a slight increase in frequency between 12:30 and 15:00 especially for the weekend clusters and weekday cluster 3. This again is an observation that points out a difference between weekday cluster 1 and 2 against weekday cluster 3 in terms of where the sleeping activity is distributed to: The morning slope of weekday cluster 1 and 2 are much closer together than

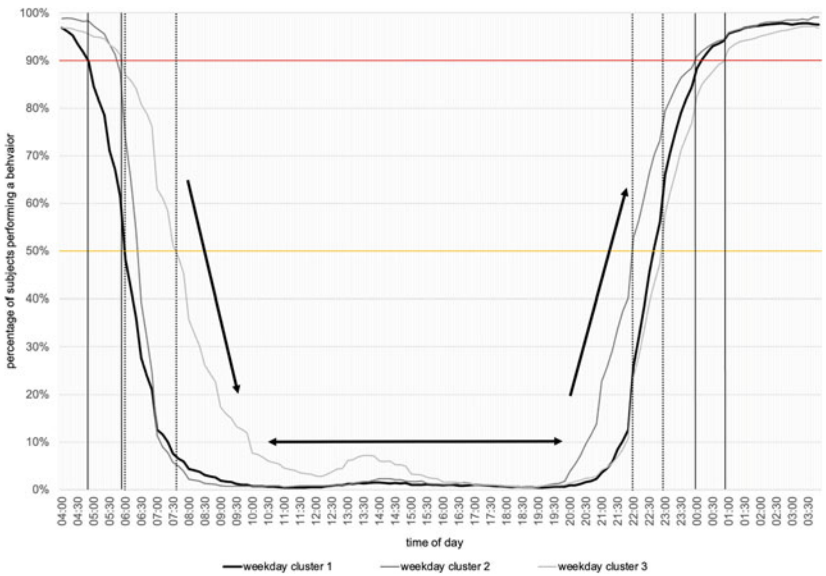

Figure 4.10 Variability in sleeping activity between all weekday clusters. (FDZ der Statistischen Ämter des Bundes und der Länder, n.d., own calculations)

the slope from cluster 3. When looking at the other activities as to which might correspond to the differences in variability between the positions of the sleeping slopes in the morning, one can find a correspondence to the most frequent behaviors in those clusters. It appears that changing contingencies for educational (Figure 4.12) and occupational activities (Figure 4.13) are so homogeneous that they dominate the distribution of sleeping behavior in the morning, but not in the evening.

In weekend cluster 6 (Figure 4.14), where the high frequency of occupational activity is also a difference to the other weekend clusters, but at no time throughout the day, more than 50% of people in the cluster perform such an activity, the rising and falling slopes are much less steep than during weekday occupational cluster indicating less homogeneity in changing contingencies for working on weekends. This greater variability between individuals in this cluster in terms of changing working contingencies as indicated by less steep slopes in the morning as well as in the evening corresponds to a less steep sleeping curve in the morning. It seems that the less "decisive" the restrictions for an activity are, the less it determines where other activities can be distributed to in time.

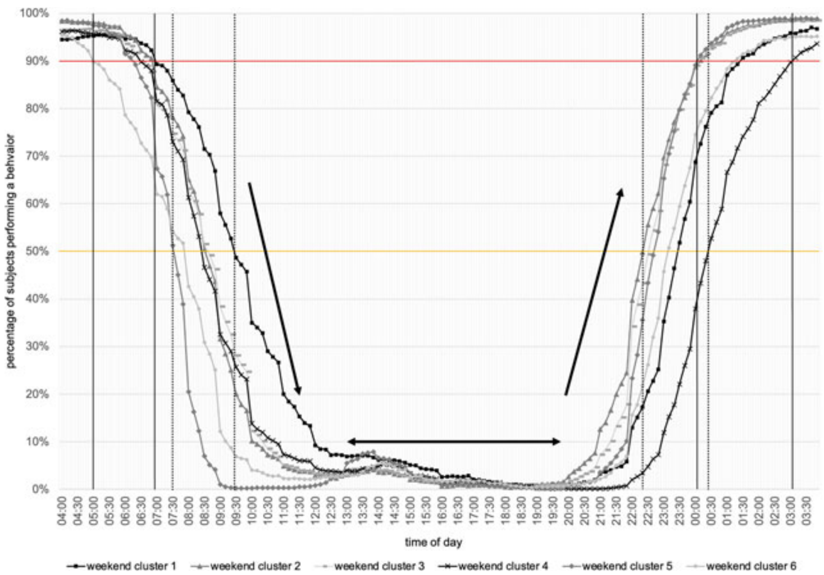

Figure 4.11 Variability in sleeping activity between all weekend day clusters. (FDZ der Statistischen Ämter des Bundes und der Länder, n.d., own calculations)

Similarly, physiological recreation in weekend cluster 5 (Figure 4.15) and social activities in weekend cluster 4 (Appendix D *Figure D.1*) seem to correspond to a shift in the weekend sleeping curve in the morning hours and in the evening hours, respectively. Physiological recreation was categorized before as candidate for high degrees of freedom in distributing behavior because it is not one of the major characteristics differentiating the different clusters and not as frequent as sleeping activity to give enough weight to timely shifts in this activity when ordering behavioral frequencies according to similarities. But as one can see in closer inspection it seems that it is an important characteristic in cluster 5 which potentially influences the variability of the sleeping curve in the morning in comparison to the other weekend sleeping curves, making it for individuals in this cluster a dominant context structure. Thus, depending on the main behavioral activities, the 22 activities can be categorized differently in terms of their degrees of freedom and in what ways they dominate the distribution of other behaviors in a cluster. In comparison, physiological recreation is less restricting in the morning hours in the other weekend clusters but the distribution of slopes is again

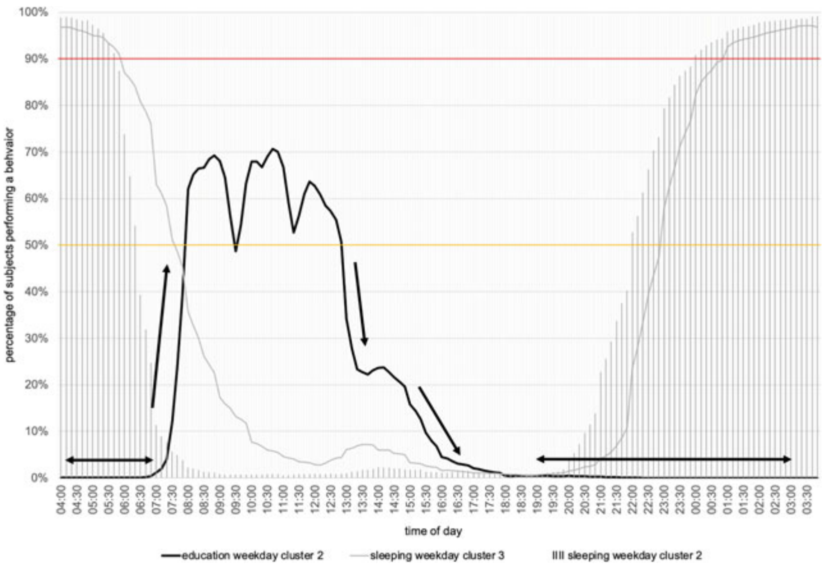

Figure 4.12 Correspondence between educational activities in cluster 2 and its morning sleeping slope in comparison to sleeping slope of weekday cluster 3. (FDZ der Statistischen Ämter des Bundes und der Länder, n.d., own calculations)

very homogeneously distributed between the clusters (Figure 4.16). As there are many slopes, although rather small in frequency differences in comparison to sleeping, occupational and educational activities, the variability in distribution of this activity is also structured and slopes during the day are fairly steep indicating less variability in structuring contingencies, except for the slope close to zero between approximately 15:00 and 16:30 for all weekend clusters (also differing in absolute frequency) and very small slopes in weekend cluster 1 and weekend cluster 3 between 09:00 and 13:20 for which other dominating activities start later (watching TV weekend cluster 1 and midday social activities weekend cluster 3). Variability between weekday clusters is also relatively small and similar to the distribution of slopes as in the weekend clusters with steeper slopes in the morning for the occupational and educational cluster than in weekday cluster 3 without dominant context structure (Appendix E *Figure E.1*). This points again towards the possible restrictions occupation and education schedules put on the variability of other activities. Overall, apart from the different steepness in the morning curves, the variability between clusters is very small throughout the day

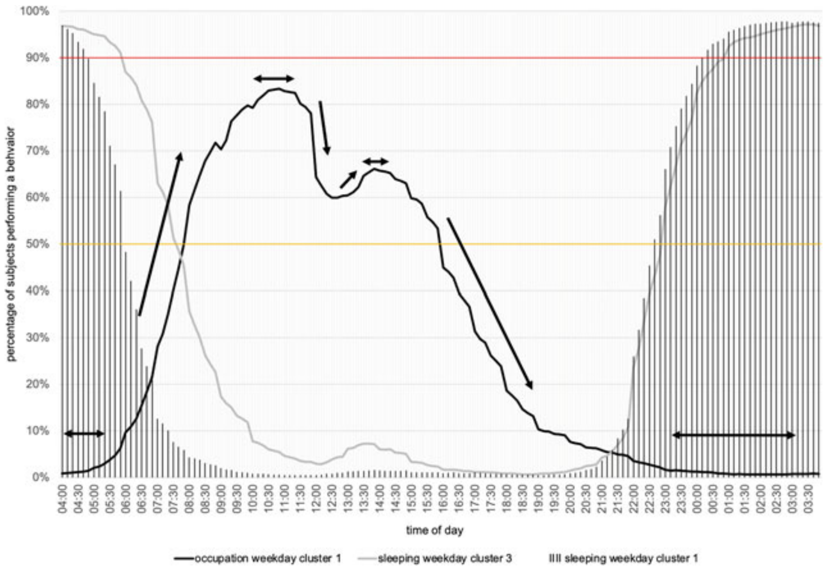

Figure 4.13 Correspondence between occupational activities in cluster 1 and its morning sleeping slope in comparison to sleeping slope of weekday cluster 3. (FDZ der Statistischen Ämter des Bundes und der Länder, n.d., own calculations)

indicating rather low than high degrees of freedom in distributing physiological recreation activities. Just as with sleeping where other behaviors and regularities in context could influence the timely distribution, it is also thinkable that the homogeneity in positioning of peaks throughout the day indicates regularities in context other than other behaviors.

The remaining candidates for low degrees of freedom such as social activities in weekend cluster 3 and hobbies in weekend cluster 2 start to rise in frequency between 9:50 and 15:00 (social activities) and 9:50 and 11:10 (hobbies) and fall between 16:50 and 19:50 (social activities) and 17:00 and 19:00 (hobbies), thus, too late in the morning and too early in the evening to restrict the variability in the sleeping curve (Appendix D *Figure D.2* and *Figure D.3*). Nonetheless, they potentially influence the distribution of other behaviors which are candidates for having high degrees of freedom. Another behavior which is high in frequency during very specific times for most clusters is watching TV. It thus is another possible context structure which influences the variability of other activities and in turn is performed at specific times because contingencies are strongly selective. Weekday cluster 3 and weekend clusters 1, 5, 3 and 6 have frequencies above 50% within the time periods of 20:20 and 21:40 (weekday) and 19:40 and

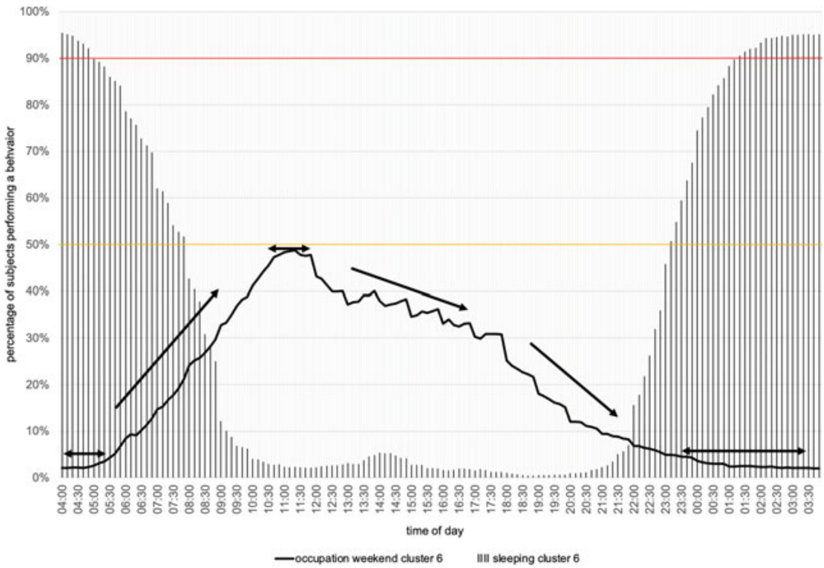

Figure 4.14 Correspondence between occupational activities in weekend cluster 6 and its sleeping slope. (FDZ der Statistischen Ämter des Bundes und der Länder, n.d., own calculations)

22:50 (weekend) (view *Figure 4.17* and *Figure 4.18*). Due to this large homogeneity it is plausible to assume a regularity in context structure which selects behavior for this time period and limits the degrees of freedom in distributing it outside of those limits. An exception is observable in weekend cluster 4 with a dominant context structure during late evening: social activities. For all weekday and weekend clusters between 02:00 and 18:00 watching TV has approximately a slope near zero indicating unchanging contingencies and a very low frequency near zero indicating unselective contingencies, except for in weekend cluster 1, in which watching TV is a differentiating activity between clusters and a slow rise in frequency begins between 08:30 and 16:30 before the evening peak.

So far, one could see that the very frequent activities (above 50%) correspond in timely position and steepness of curve to the sleeping curve in the morning hours or evening hours. Steep slopes, thus shorter time periods in which many people switch between activities indicate common and homogeneous contingencies in comparison to flatter slopes which indicate more variability (less homogeneity) in changing contingencies. Thus, breadth of slopes relates to possibilities to shifting a certain activity in those time ranges. For an individual the contingencies might be non-variable as for example when the occupational

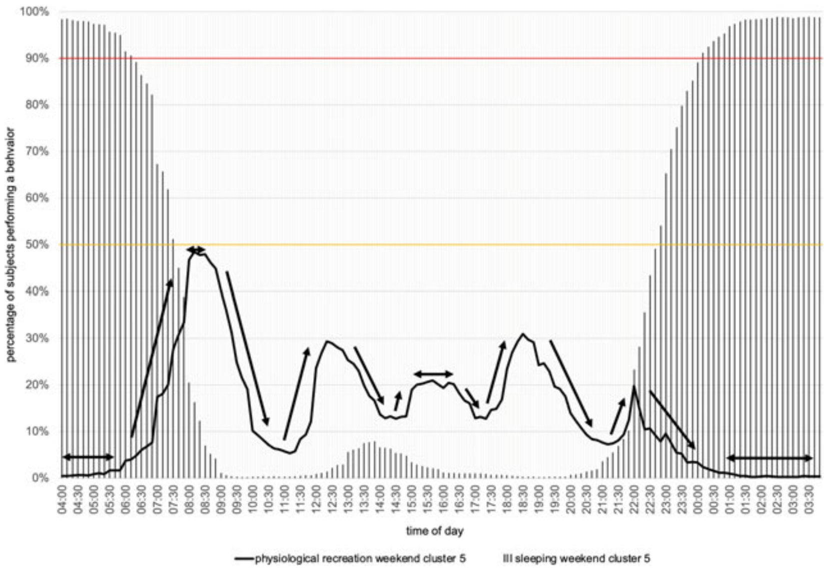

Figure 4.15 Correspondence between physiological recreation activities in weekend cluster 5 and its sleeping slope. (FDZ der Statistischen Ämter des Bundes und der Länder, n.d., own calculations)

activity is fixed for certain times but if aggregated, the flatter the slope the more variable is presumably the context structure leaving options for shifting behavior in time. Also, some activities less frequent (below 50%) but still differentiating between clusters such as hobbies in weekend cluster 2, social activities in weekend cluster 3, physiological recreation in weekend cluster 5 and occupational activities in weekend cluster 6 appear to have a dominant context structuring effect for some other behaviors. In how far these activities, the other activities described as constraints, or even other regular occurring context contingencies might structure activities which are assumed to be associated with appliance using behavior and hence electricity consumption and were previously described as having high degrees of freedom is analyzed next. While for the very frequent activities with large frequency differences over the day a strong influence of regular context patterns is assumed, for the activities low in frequency it is assumed that the other behaviors low in degrees of freedom due to context constraints possibly have a role in dominating the distribution of such behaviors throughout the day.

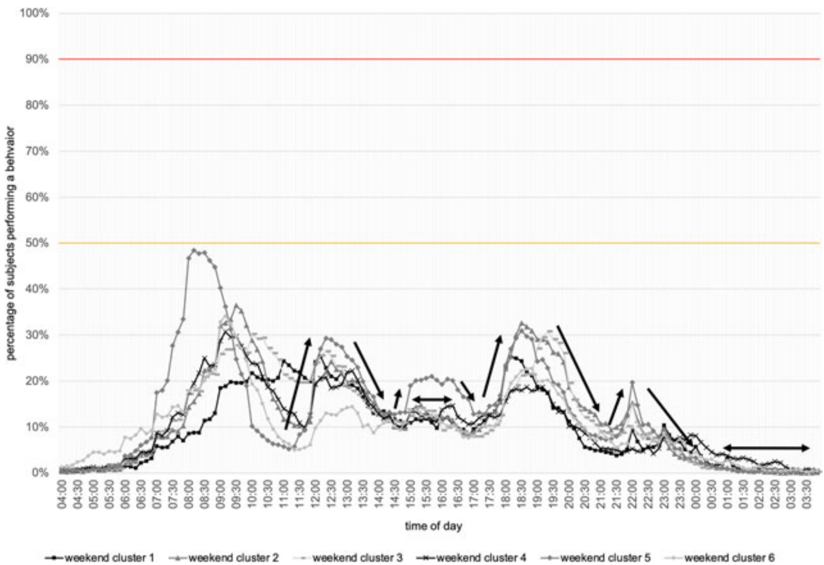

Figure 4.16 Variability in physiological recreation activities between all weekend clusters. (FDZ der Statistischen Ämter des Bundes und der Länder, n.d., own calculations)

Similar to physiological recreation in distribution over the day but less frequent (scaling of y-axis changed in figures for this and following activities with low overall frequencies) is the activity preparing meals and cleaning as can be seen for the weekday clusters in Figure 4.19[12]. There is a time period between approximately 22:30 and 04:30 with very low frequency of behavior and slopes close to zero and during the day there are three peaks in all three clusters at similar times: In the morning the peak is most pronounced for the occupational weekday cluster and begins sloping upwards about an hour earlier than in cluster 2 and 3. While in cluster 3, without a dominant context structure, the slope then levels out indicating unchanging contingencies in the early morning hours, the contingencies appear to change in clusters 1 and 2, presumably due to restrictions of education and working schedules. The peak at about 11:50 in cluster 3

[12] For weekend data preparing meals is homogeneous between all clusters except for weekend cluster 5, which in correspondence to its high peak in physiological recreation in the morning also has a steeper rise in the morning for preparing meals and cleaning and a very high frequency in the midday peak: 23% maximum compared to 8% maximum (weekend cluster 3); view Appendix E *Figure E.2*.

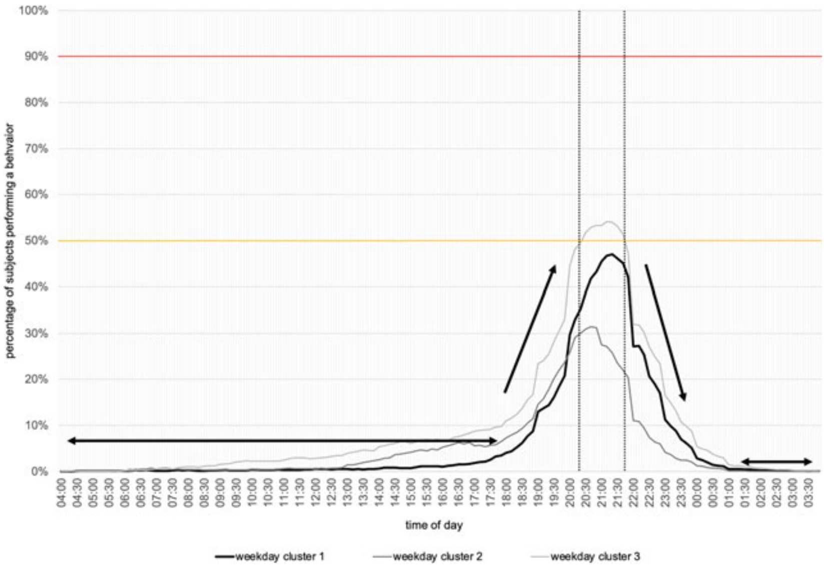

Figure 4.17 Variability in watching TV activity between all weekday clusters. (FDZ der Statistischen Ämter des Bundes und der Länder, n.d., own calculations)

is much higher and about half an hour earlier than in clusters 1 and 2 which have very similar preparing meals and cleaning up afterwards curve around midday. The evening peak occurs for all clusters between 17:30 and 19:30 and is of similar high frequency in cluster 1 and 3. The variability in where over the day behavior is distributed to is again similar between the weekday clusters but especially so between weekday cluster 1 and 2 which have both a dominant context structure restricting distribution of behavior during morning and afternoon hours. Additionally, there also appears to be a timely sequence in which the rising slope of preparing meals and cleaning precedes the peak of physiological recreation for the midday and evening peak. In comparison to physiological recreation activity there is no late evening peak observable in preparing meals and cleaning.

If looking at the doing laundry activity for weekday clusters in Figure 4.20 (for weekend data view Appendix E *Figure E.3*) a homogeneity is again that it rarely takes places in time periods during which more than 90% of subjects in all weekday clusters are sleeping (indicated by solid vertical black line). Although doing laundry mainly distributes within those limits, it does so differently depending on

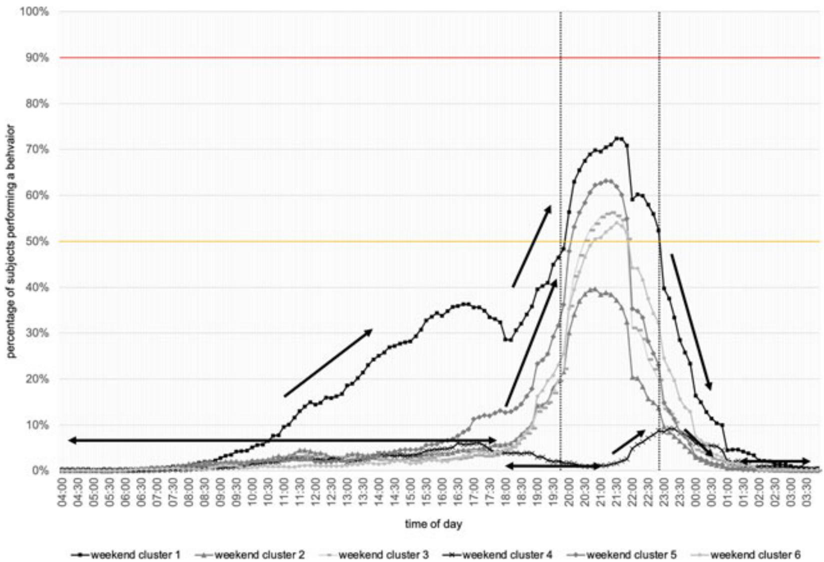

Figure 4.18 Variability in watching TV activity between all weekend clusters. (FDZ der Statistischen Ämter des Bundes und der Länder, n.d., own calculations)

the assumed dominant context structure for a cluster[13]: In comparison to weekday cluster 3 which can be described by two peaks with steeper slopes between 09:00 and 12:00 during forenoon, the slopes are smaller for weekday cluster 1 and 2 beginning a little earlier at around 07:00 but also having a relative low point at 12:00. While the increase in doing laundry is then again steep for cluster 3 and starts declining at about 17:00, the rise in cluster 1 is shifted towards later hours lying mostly outside the hours in which more than 50% in that cluster perform occupational activities (dotted vertical lines). Cluster 2 with educational activities has from noon on a very low frequency with a slope approximately zero indicating unchanging contingencies in this cluster. During the late afternoon hours such a period of stable contingencies but at higher frequencies are observable for weekday cluster 1 between about 17:00 and 20:30. So, an activity such as doing laundry for which the outcome of performing a behavior is very

[13] The overall frequencies of the doing laundry activity in terms of mean values and standard deviations are not meaningfully different between clusters: weekday cluster 1 ($M = 0.66$, $SD = 1.69$); weekday cluster 2 ($M = 0.31$, $SD = 1.42$); weekday cluster 3 ($M = 1.22$, $SD = 2.74$).

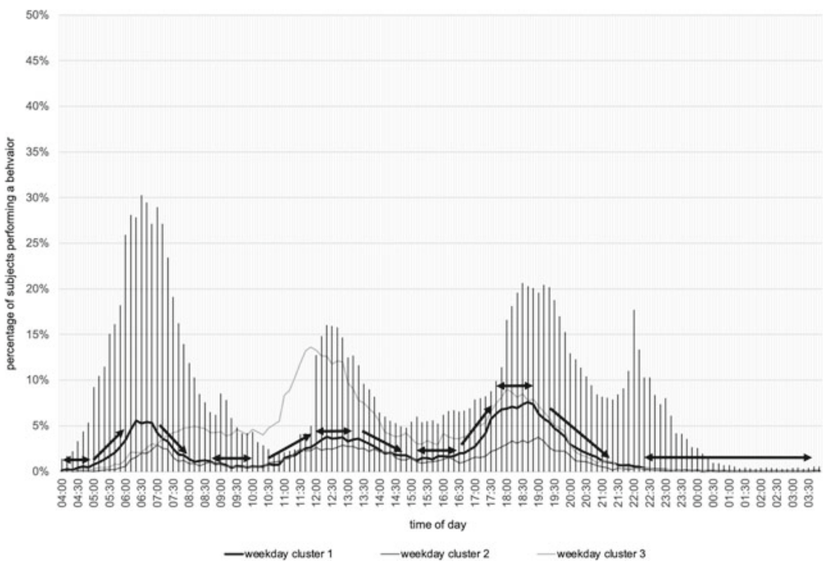

Figure 4.19 Variability in preparing meals and cleaning activity in all weekday clusters with physiological recreation activity curve from weekday cluster 1. (FDZ der Statistischen Ämter des Bundes und der Länder, n.d., own calculations)

similar throughout the day in terms of the important consequence of getting clean and dry laundry thus should be high in degrees of freedom, can be seen to distribute differently between clusters. Since major differences between clusters are the dominant activities in those clusters, it seems justified to argue for them having an influence on the variability in distribution of behavior between clusters. If one were to ignore restrictions by other behaviors, one could easily assume too high degrees of freedom for certain behaviors associated with appliance using behavior.

Two further examples for candidates for high degrees of freedom are the activities listening to radio and music and using the computer or smartphone. As can be seen for weekday data displayed in Figure 4.21 (weekend data in weekend data in Appendix E *Figure E.4* and *Figure E.5*) listening to music or the radio has a morning peak in all clusters beginning after the sleeping restriction (solid vertical line) and declining towards 08:10 in cluster 2 (dotted vertical line indicating more than 50% of subjects in cluster 2 performing educational activities) and about 07:20 in cluster 1. In clusters 1 and 2 very low stable frequencies

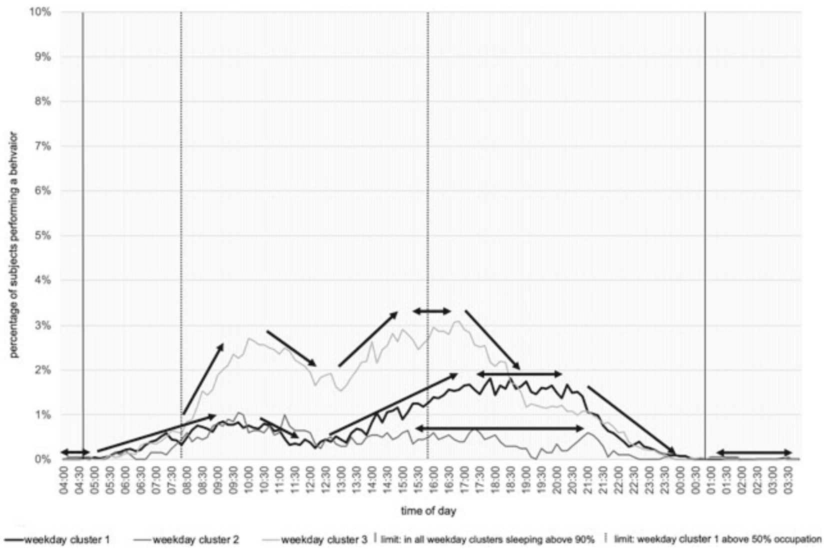

Figure 4.20 Variability in doing laundry activity in weekday clusters with sleeping activity limits from all weekday clusters and limits from occupational activity in weekday cluster 1. (FDZ der Statistischen Ämter des Bundes und der Länder, n.d., own calculations)

are then observable before a steeper rise of listening to music outside the 50% education activity bound for cluster 2 and a flatter and about two hour later rise in cluster 1. In difference to this similarity in variability of listening to music or radio behavior in clusters 1 and 2, which have a dominant context structure in the forenoon hours of a weekday, the slope in weekday cluster 3 is approximately zero throughout the day indicating unchanging contingencies and more degrees of freedom for this behavior in this cluster.

The activity using the computer is again relatively homogeneous between weekday clusters 1 and 2 (view *Figure 4.22*; weekend data is in Appendix E *Figure E.6* and *Figure E.7*). There is one small rise in frequency of using the computer around 05:10 followed by an approximately zero slope from 07:50 until 15:50 for cluster 1 (dotted vertical lines indicating 50% or more subjects performing dominant context structure occupational activity) and until about 13:00 for cluster 2. As can be seen in Figure this corresponds to the dotted line for 50% or more performing activity education in weekday cluster 2 linking the rising late afternoon slopes of using the computer in cluster 1 and 2 to their respective

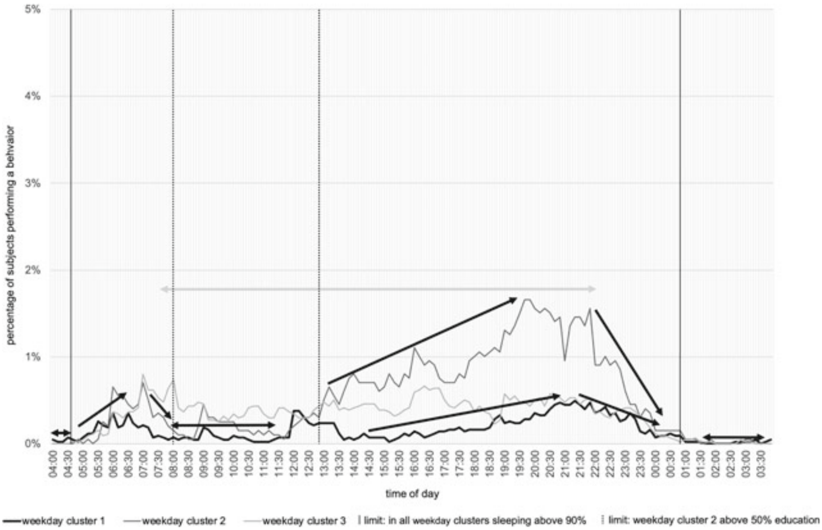

Figure 4.21 Variability in listening to music, radio activity in weekday clusters with sleeping activity limits from all weekday clusters and limits from educational activity in weekday cluster 2. (FDZ der Statistischen Ämter des Bundes und der Länder, n.d., own calculations)

dominant context structures. In cluster 3, similarly as for the activity listening to music or radio, a slope of approximately zero can be observed throughout the day between 11:30 and about 20:20 (time after which the activity watching TV in this cluster falls below 50%). Thus, also the appliance using activity using the computer or smartphone, even though very infrequent and theoretically with constant contingencies throughout the day, can be linked in its variability between clusters to restrictions from other behaviors.

For several of the investigated activities one can see similarities in variability between clusters. For example, there are weekday clusters such as the occupation and education cluster and weekend cluster 5 which have steep slopes and similar timings for physiological recreation in comparison to weekday cluster 3 and other weekend clusters. Or, there are weekday and weekend clusters which differ in timing of sleeping activity. So, one could suppose that the similarities and differences observable between weekday and weekend clusters might be mainly attributable to individuals moving from similar behavioral patterns during weekday to similar behavior patterns during weekends. But this does not seem to be the case for the overall movement between clusters as can be seen by the

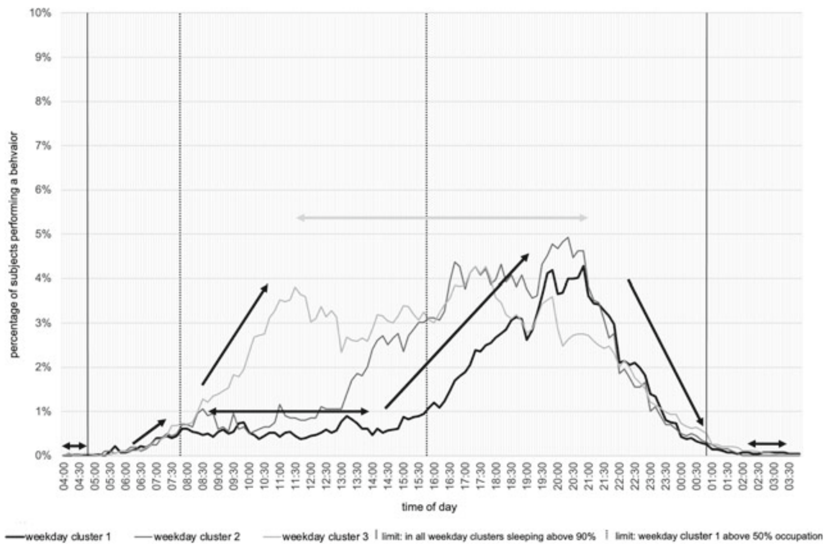

Figure 4.22 Variability in using computer activity in weekday clusters with sleeping activity limits from all weekday clusters and limits from occupational activity in weekday cluster 1. (FDZ der Statistischen Ämter des Bundes und der Länder, n.d., own calculations)

relatively even distribution of cluster belongingness from moving from weekday clusters to weekend clusters in Figure 4.23. This again is an argument for analyzing behavior as being selected by contingencies in context structure and not as something ascribable to something within individuals causing variability.

The main summary point of the variability analysis of behavior is that behavior is not free in its distribution across a day. There are behaviors which are so frequent and homogeneous either between all weekday and weekend subjects or within the clusters that they can be assumed to be restricted in their timely distribution. For those behaviors such as sleeping, working, going to school, watching TV and late-night social activities it can be well argued that they are restricted by regularly occurring patterns in context structure. These activities can still be accurately categorized as having low degrees of freedom. Furthermore, they appear to be dominant context structures for other activities by influencing the variability of distributing these behaviors across the day. Thus, even behaviors with presumably high degrees of freedom due to theoretically almost unchanging patterns of context regularities throughout a day are restricted in their timely distribution.

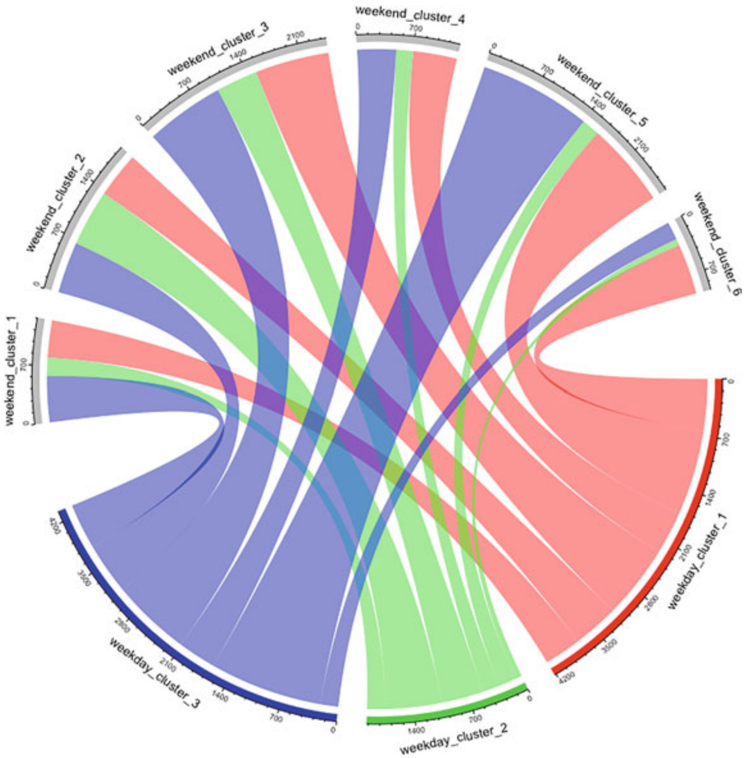

Figure 4.23 Flow of subjects from weekday clusters to weekend clusters. (FDZ der Statistischen Ämter des Bundes und der Länder, n.d., own calculations)

This was more so for physiological recreation and preparing meals in most clusters than for doing laundry, listening to music and using computer or smartphone. Also, for those last three activities with really low frequencies and consequently seemingly insignificant variability between clusters, variability can be linked to restricting dominant context structures. Hence, there is still a structure in behavioral sequences and 'people do not just do what they want' or distribute their behavior completely free. It is not the case as suggested by some TUD research that behavior is so complex since it varies immensely between each individual. Instead of predicting and dividing behavioral variability into some characteristics attached to individuals which presumably capture behavioral variability because they are correlated with people operating in certain context structures, it seems more promising to try to identify relevant context structures and in what ways they determine behavioral variability. In this way, what is theoretically relevant is not obscured by attempts to fit an a-theoretically used statistical model. This distinction might seem unimportant as long as the model predicts energy demand accurately but as soon as one wants to think about changing behavior to make it usable for DSM purposes, one has to have a model of behavior which actually reflects relevant characteristics of behavior.

It is suggested that when selecting activities from TUD to analyze some specific activities such as those associated with electricity consumption, one should take other behaviors into account as they seem to be relevant for their timely distribution. Some behaviors such as sleeping or working appear to correspond to specific homogeneities in behavioral variability of other behaviors such as listening to music and are thus part of their context structure. Considering context structure for distribution of behavior can inform the degrees of freedom in behavioral variability and is thus important for describing the potential to change behaviors to other time points. Neglecting the context structure for analysis of shifting potential of appliance using behavior means also neglecting the potential which lies in changing context structure.

On this basis a categorization of activities according to their degrees of freedom in distributing behavior throughout the day is proposed which considers relevant context structure. As became clear in the analysis of behavioral variability, it depends on the dominant context structure in a cluster in how far other activities are more or less free in their distribution across a day. So, an activity cannot be categorized into a certain degrees of freedom category per se, but only in consideration of its context structure. Thus, the following exemplary categorization in Table 4.4 is specifically based on the analyzed cases in the clusters.

The results are in line with previous discussions which pointed in the direction of more invariability in activity sequences. For example, Aerts et al. (2014) looked at transition probabilities between the three states being at home, sleeping and being absent. They found that sequence of occupancy states is relatively fixed, while the starting times and durations may vary which fits this analysis's description of the sleeping curve in all clusters, the corresponding rise in physiological recreation in the morning (being at home) and then for most weekdays (cluster 1 and 2) relatively steep but timely shifted slopes into an absent state. In the late afternoon and early evening varying durations for the state absence could correspond to the difference between working and schooling schedules and then further to different working schedules because as one can see, the afternoon occupational slope is flatter than the educational activity slope. Paying more attention

Table 4.4 Categorization of Selected Activities in Terms of their Degrees of Freedom

Degrees of freedom	Description	Activities
very low	Homogeneous context structure of an activity is substantially different over the course of a day, so that the pattern of contingencies (the regularities in context structure) restricts the timing of an activity.	sleeping in all weekday and weekend clusters
low	Different homogeneous context structures of an activity are substantially different over the course of a day, so that the pattern of contingencies restrict the timing of an activity.	occupational activity in weekday cluster 1, educational activity in weekday cluster 2, watching TV in all weekday and weekend clusters, late-night social activity in weekend cluster 4
medium	Heterogeneous context structure (context structure is more diverse because it depends on different discriminative stimuli such as elapsed time, other behaviors and behavior of others, but those discriminative stimuli might share timing communalities) of an activity is substantially different over the course of a day.	occupational activity in weekend cluster 6, hobby activity in weekend cluster 2, physiological recreation in all weekday and weekend clusters, preparing meals and cleaning in all weekday and weekend clusters, doing laundry in weekday cluster 1 and 2, social activity in weekend cluster 3
high	Constant context structure of an activity and substantial common differences in relative changes in contingencies between behaviors.	doing laundry in weekday cluster 3, listening to music or radio in weekday cluster 1 and 2, doing laundry in weekend cluster 5, using the computer or smartphone in weekday cluster 1 and 2, listening to music or radio in weekend clusters 2,3,4,5,6

(continued)

Table 4.4 (continued)

Degrees of freedom	Description	Activities
very high	Constant context structure and no substantial common differences in relative changes in contingencies between behaviors.	using the computer in weekday cluster 3 and all weekend clusters, social activity in weekday cluster 3, doing laundry in weekend clusters 1,2,3,4,6 listening to music or radio in weekday cluster 3 and weekend cluster 1

to analyzing behavioral variability and looking at more than three activity states can be an asset to better understand the relevant influences for appliance using behavior. Another author analyzing TUD who also discusses high homogeneity in behavioral variability and hypothesizes about the importance of occupational activity patterns and family commitments as causal influences on timely distribution of appliance using behavior is Torriti (2014; 2017). Those ideas are supported by the current analysis. Although the data itself cannot be used do conclude causal influences of context structure such as sleeping, schooling or working schedules on variability of other behaviors, the analysis of variability between the clusters and the variability of how behavior distributes within a cluster as indicated by steepness of slopes and timely sequences of behavior show a relationship between different behaviors which applying behavior theoretical principles can be interpreted in such a way.

4.4.3.3 Restrictions of Appliance Using Behavior Given the Chosen Cluster Solution

As Morris (1993) stated, context-as-place, or context-as-structure as I think it more helpful to think about it, may be most usefully employed if restricted to either a formal meaning, as an initial or boundary condition or a functional meaning, as conditions that alter functional relations within the three-term-contingency. For this analysis, both meanings are useful. The latter, formal meaning being a good starting point because as was shown in the analysis of variability, the identified differentiating activities between clusters (i.e., work and educational activities and sleeping for weekday clusters; work and social activities, hobbies, watching TV and sleeping for weekend clusters) restrict and structure possible times of appliance using behavior.

Activities, when associated with absence from home, which is true in most cases for occupational and educational activities and often true for hobbies and social activities, do so by rendering the behavior of *using* an electrical appliance at home impossible and the *use* of an electrical appliance at home more unlikely because it necessitates the use of a programmable timing function or an internet-based application. One might say that modelling occupancy of a home, for example by using points of arrival and departure is then sufficient for modelling energy behavior. While this is effective for the sake of estimating energy demand (e.g., Diao, Sun, Chen, & Chen, 2017), it is insufficient for identifying context structure of appliance using behavior because the necessary information is not included in occupancy information. The first argument for interpreting the above stated differentiating activities as context structure is that showing one of those behaviors excludes the possibility of showing a behavior at home and thus limits the possible hours within the day where a home-associated appliance using behavior can be shown. This limitation of times per day where a behavior can be shown is a restriction. This seems sufficient to fulfil the formal meaning of a context structure according to Morris (1993). But what with the cases, where hobbies or social activities take place at home or with the other differentiating activities sleeping and watching TV for weekend days. In how far can they be theoretically interpreted as context structure?

One can answer this question by arguing for or against the fulfilment of the restricting variability condition, like it was done above for behaviors which do not take place at home, or by giving a theory informed explanation how a certain hypothesized context structure selects behavior and through this arrangement might restrict the variability of behavior. Doing this for the described dominant context structures differentiating between weekday and weekend clusters can link them to restrictions by regularities and by other behaviors.

The relative frequency distribution of an activity in comparison to other activities would be assumed to distribute approximately according to the relative contingencies of reinforcement of those behaviors (as stated by the Matching Law). For this argument, linkages between certain activities and use of an electrical appliance are assumed. If a hobby or social activity is performed at home for a certain time one can say, that it is performed instead of other alternative behaviors at that time like for example doing laundry and watching TV. One could then interpret all identified activities as structuring context in a sense because choosing one activity over another alters the timely distribution of other behaviors and the condition of restricting the variability of behavior would be fulfilled. But this condition would hold for all cases of choice behavior and thus would not be sufficient in defining a meaningful category of context-as-structure.

Fortunately, performing a behavior is also associated with a specific timepoint which is determined by differential consequence outcomes when operating on the context at that point of time versus another point in time. In case of the activity watching TV for example, one can observe a clear rise and peak in frequency in all clusters for around 8 p.m. which corresponds with the time when national news come on and fifteen minutes later the evening program in German free TV starts. This is a different consequence outcome compared to performing the behavior of turning on the electrical appliance TV at 7 a.m. with mainly morning shows in the program. Context structure thus also needs to encompass what determines the different consequence outcome for operation on the context at different time points. Applying this theoretical background to the employed level of data aggregation, it seems useful to interpret behavioral activities as restricting context for other behaviors if they influence the variability of other behaviors AND if they correspond to *regular* occurring changes in the available consequences for a significant amount of people or a specific group of interest depending on the aggregation level.

In this case, the differentiating activities between clusters seem to correspond to regularities determined by day-and-night rhythm in case of sleeping, occupational and educational activity, hobbies and social activities and by societal structures in case of working and schooling hours, TV program, sleeping, hobbies and social activities. If regularities in the environment are observable, which are associated with similar changes in consequences when operated upon by a large number of individuals or relevant subgroups (depending on the level of analysis), one can categorize those as context structures. The types of regularities associated with the timing of operant behavior might be a good starting point to evaluate possibilities for intervention, especially in cases where the problem is not one of net energy demand but one of supply and demand at certain time points because the aim is to change the pattern of regularly occurring points of simultaneously high energy usage.

For weekdays and weekend days one context structure is sleeping and change would in principle have to address regularities of the environmental signals, predominantly light, with which the circadian rhythm is synchronized to ensure that behavioral rhythms are timed appropriately with daily changes in the environment (Czeisler & Gooley, 2007). Changing regularities in natural light is unreasonable, but evidence points to artificial light, being introduced commonly in the twentieth century, shifting circadian rhythms (Emens, 2017) and depending on the extent of circadian misalignment health consequences are discussed (Czeisler & Gooley, 2007; Emens, 2017). Even though lightning technology is also employed in resetting circadian rhythms of night shift workers (Czeisler & Gooley, 2007), due to potential health consequences, changing the regularities influencing the circadian rhythm does not seem helpful. Instead one could focus on lifting restrictions set by other context structures which influence sleep and wake patterns and also further a circadian misalignment. Wittmann, Dinich, Merrow and Roenneberg (2006) describe large differences in humans' timing of sleep and activity, often referred to categorically as different "chronotypes" and the role of social schedules, importantly school and work schedules, which interfere for the majority of individuals with their sleep "preferences". Apart from their discussion on influences on wellbeing when social schedules induce a misalignment with circadian rhythm, the benefit in terms of intervention when lifting the context restriction of work and school and maybe other "social schedules" would be a greater variability in timing of sleeping hours due to the large natural variability in chronotypes. This could then entail an increase in timely variability of using electrical appliances, especially in the morning hours where there appears to be high similarity in timing of activities such as physiological recreation.

The two context structures of most importance are occupational and educational activities. They determine the structure of most days of the week and for a small number of people even the weekend, even though the variability in working schedules seems more diverse in the working weekend cluster (as the morning and afternoon increasing and decreasing slopes are flatter) than in weekday cluster 1. Additionally, they also seem to influence sleeping activity. Occupational and educational activities are highly structured and predefined in their timing by society, which makes them, in contrast to sleeping, in principle accessible for intervention.

If one assumes the operant *being at a work place at certain times* produces as central consequence money (which is simplified, but in approximation sufficient for this argument), the regularities that need changing, are the times in which money can be produced. Leading to an intervention which in its extremes would allow individuals to produce money at a work place at any time point. Lifting the restriction of only being able to produce the central consequence of being at work at certain time points, would thus increase the possibilities for distributing behavior more freely. Studies on working hour arrangements in Germany estimate fixed working arrangements to make up between 60% (data from Statistisches Bundesamt, Mikrozensus 2010) and 63% (Zapf & Weber, 2017; SOEP data 2011) of working hours' arrangements, meaning the employer fixes daily working hours including beginning and ending. Flexible working hours' arrangements like flextime arrangements or working hours set by the employee make up between 37% (SOEP) and 38% (Mikrozensus 2010). Those numbers show potential for increasing behavior variability in use of electrical appliances at home by lifting restrictions set by fixed times where being at work results in the consequence of producing money. One needs to keep in mind though, that while called flexible working hours' arrangements this flexibility might not only be used by employees, but also by employers. Employers and characteristics of the job itself may play an important role in influencing the distribution of working hours instead of characteristics of the employee's freer behavior distribution, which is an aspect also highlighted by Zapf and Weber (2017).

Educational activities mainly include going to school, to vocational training institutions and to higher education institutions like universities. Each of them differs in detail concerning their strictness of structure, but analogous to occupational activities, the regularities which need changing are those determining the time points when as consequence of being present the fulfilment of certain requirements can be produced. Concepts increasing the possible timepoints of producing the relevant consequences could be developed, maybe even building on the idea of different schooling hours' arrangements with more flexibility through diverse arrangements could be a possibility. Current discussions on delaying school starting points mainly focus on health and performance consequences (Marx et al., 2017) but if thought not only in terms of a fixed delayed starting point, but in terms of flextime, also in school, an increase in behavioral variability seems possible. Changing only one of the two regularities, work or schooling would probably limit the achievable increase in behavior variability because living together in one household the restriction of for example a schooling schedule of a child would also influence sleeping activity, preparing meals etc. of the parent. Some support for this argument can be drawn from a research project in Australia. Employing a social practice conceptual approach by in short viewing "electricity consumption as an outcome of participating in shared social practices which are routinely carried out." (Nicholls & Strengers, 2015, p. iii), they focused in one part of their project on conducting a national survey with households with children ($N = 547$) to better understand "how (in)flexible their household energy practices are at different times of the day" (p. iii). Based on analyzing respondents' statements, the authors conclude that many activities are routinised during the mornings and late afternoon/early evening periods. Many activities are said to "bundle together" like homework, cleaning, washing, food preparation and bathing. This, in the authors opinions reflects "parent's need to respond to external activities (e.g. work and school), create positive bedtime routine for their children, and/or achieve their aim of creating some 'downtime' later in the evening." (Nicholls & Strengers, 2015, p. iv). Although based on verbal statements to survey questions, if assuming some validity of individuals recognizing daily aspects influencing their timing of behavior, one can evaluate the conclusion as pointing in the same direction as the argument of restrictions on child behavior also restricting parent's behavior.

Differentiating factors on the weekend are more diverse, with social activities even differing in the pattern of timely distribution (weekend cluster 3 "midday social activities" vs. weekend cluster 4 "late evening social activities") probably due to different functions of the behavior categorized as "social activity". This highlights an important problem when trying to identify regularities of hobbies and social activities: They themselves are not constructible as one operant class, making it impossible to identify relevant regularities at this level of analysis. Watching TV is also less straight forward in its interpretation. It is a distinguishing factor for weekend clusters, but the similarity in the shape of this activity clearly shows for all clusters a relatively high frequency in the evening hours between 8 p.m. and midnight. Interpreting watching TV as a context structure differs from the other structuring contexts in the way, that the regularity determining the available consequences is the schedule of the TV program, while the influenced activity is the activity watching TV itself. Furthermore, it is not a restriction like occupational or educational activities and is also influenced by those. What can change the consequence outcomes of watching TV is the program type and what function the behavior watching TV has at a certain time, for example in connection with whom a program is watched. This again makes it a problem of unclear operant. Nonetheless, from the variability description of watching TV, in which it was categorized as having low degrees of freedom due to homogeneity between clusters and relatively steep slopes in the late afternoon and evenings indicating homogeneity in changing contingencies between individuals, an effect of introducing flexibility in the available TV program for example through streaming services and online media libraries, though in principle correct because it changes one consequence produced when switching on the TV, will probably have only small effects in terms of an increase in timely distribution of watching TV. For families with children, Nicholls and Strengers (2015) come to the same conclusion: "These findings also highlight the importance of the *timing* of TV (ICT)[14] usage, which is oriented around the family peak period (2–9 pm) and the later evening period of 'downtime'. The findings suggest that the emergence of 'on-demand' television is unlikely to have a significant impact on the times at which television is watched in family homes" (p. 38). While here the estimation of low flexibility in watching TV, even when the program options are always available (constant contingencies of program type if ignoring functions

[14] ICT is used by the authors as an abbreviation for 'information and communications technologies' (Nicholls & Strengers, 2015).

resulting from other individuals being present or not), is rooted in the context restrictions imposed by children, at least for individuals in cluster 1 and cluster 2 occupational and educational schedules as well as sleeping probably play an important role as restricting other behaviors as well.

What becomes evident through applying behavioral principles to an analysis of variability of TUD activities is, that if one wants to specify a behavior theoretical model of appliance using behavior, one needs to consider context structure of appliance using behavior. This might seem like a trivial point to make but it is important for two reasons. First, it offers explanations for the observation of homogeneities in behavior variability, which are important because under the assumption of association of certain behaviors and electricity consumption, homogeneities in behavior variability leads to events in the energy system like peak loads. Second, common context structures between individuals determine distribution of behavior, setting limits to distribute it freely across the day which does imply observable homogeneities but additionally highlights the limits of shifting behavior arbitrarily in time. This implies thirdly, that any intervention aiming at changing behavior which ignores context structure misses to specify the limits of this intervention and misses an opportunity to broaden the effectiveness of an intervention by changing context structure. In order to evaluate the possibilities for shifting user behavior and its potential in mitigating the challenge of discrepancies between energy supply and demand, estimations of energy using flexibility should consider these context restrictions.

4.5 Relevance for the Energy System: Load Profiles for Household Appliances

Behavior does not distribute freely throughout the day. There are different degrees of freedom in distributing behavior. Once ordered for similarity of behavioral sequences it can be argued that very frequent behaviors which can be described as common context structures for a large amount of people restrict the timely distribution of other behaviors. They themselves are so homogeneously (similarly) distributed that this fact is attributed to regularities in context structure. Furthermore, behaviors which from a first impression after clustering seemed to have high degrees of freedom in terms of where behavior can be distributed to and for which interpretative considerations pointed towards unchanging contingencies are shown to not distribute freely. Thus, it is argued that behaviors with low degrees of freedom restrict the distribution of behaviors with higher degrees of freedom, which in term of context regularities have high degrees of freedom, but are restricted in their variability by other behaviors. Taking those results into account for analyzing consequences of appliance using behavior for the energy system means two things: For one thing, depending on electrical consumption of appliances, times with high consumption or peaks will become apparent because they lie in times with higher frequencies of an appliance using behavior. This was already describable with previous building models[15] combining TUD with electrical consumption of appliances. The addition is that the groupings of individuals into the identified clusters seems to be theoretically relevant in terms of context structure. And second, high consumption is connected to appliance using behavior as restricted by context structure. As the different weekday and weekend clusters seem to capture important differences in main activities which are on the one hand structured by context regularities and on the other hand structure the context of other behaviors such as appliance using behavior, a building model considering these determinants of variability of behavior can be used to further explore potentials for shifting appliance using behavior.

The connection between information on behavior variability and energy demand in buildings is necessary to provide information at different levels of the energy system on when certain electrical loads are to be expected and look at what possibilities exist for DSM options and make effects or consequences from behavioral variability visible for the energy demand of households. Torriti (2014; p. 265) frames the importance of this link between energy using behavior in TUD and electricity demand in the following way:

> "Time use is becoming increasingly relevant for peak electricity demand issues. At what time residential end-users switch lights, heating and appliances on, for how long, and at what time they switch them off determines the individual electricity consumption profile in the household. The sum of individual profiles in a neighbourhood or district determines the time-related electricity consumption of a specific section of the distribution network. Peak loads in the transmission grid occur when on aggregate a vast amount of residential end-users is using electricity at the same time. When this happens, typically in the late afternoon of a winter day, the costs and negative environmental impacts of meeting this extraordinarily high demand are higher than normal. This is because energy suppliers have to activate carbon intensive power plants to compensate for such increase in demand."

[15] Even though the general term building model is used which can include many different components, here it is only regarded in reference to shifting energy using behavior in time, i.e., without considering other components such as thermal components or transmission losses which would be relevant for a complete description of a building model.

In addition to the peak load problem, which is going to become more relevant with larger residential end-users such as heating pumps and electric vehicles, one can also address the problem of shifting using behavior to times of energy availability from VRE, which is the focus of this analysis. A prerequisite for doing so is to describe the consequences of modelling appliance using behavior in terms of context structure groupings in a building model on the household level. For this end, the proposed cluster solution was integrated into an engineering physics-based building model as part of an interdisciplinary project (NEDS – Nachhaltige Energieversorgung Niedersachsen[16]). This differs from approaches employing socio-demographic or – economic categorizations because they are often used as categorizations without theoretical argument for why they are relevant structuring factors for the phenomenon under investigation; an aspect which was described in detail above for the summary of behavioral variation in stochastic building models, but which is common to a lot of models or explanations of energy using behavior and which has been criticized early on (e.g., Lutzenhiser & Gossard, 2000).

The coupling of appliance using activities in the different clusters and electrical consumption from appliances was done in the MATLAB-based modular simulation environment eSE – elenia Simulation Environment (Reinhold & Engel, 2017) which is developed by the project partner elenia (Technische Universität Braunschweig – Institute for High Voltage Technology and Electrical Power Systems). A main simulator (a MATLAB class) connects to all modules (e.g., thermal systems, control systems, grid calculation etc.) and handles their data management and information flows between models (Reinhold, 2019). In this way, different aspects of a building model can be investigated. For the current analysis a 'User' module was developed and coupled with an 'Appliance' module in eSE as part of the user-appliance intersection. Other modules like 'Forecasting Methods', 'Control Systems' and 'Economic Analysis' were also used to run the building simulation in the NEDS project (Reinhold, 2019).

As did other building models using TUD, a bottom-up approach is followed. The appliance model in eSE is based on functional descriptions of appliance characteristics which can be freely parameterized (Reinhold, 2019). The user model describes appliance using behavior based on TUD and behavioral activity patterns from the cluster solution from which three descriptive parameters are derived: duration of use, frequency of use and time-related probability of use. Together

[16] Supported by the Lower Saxony Ministry of Science and Culture through the 'Niedersächsiches Vorab' grant program (grant ZN3043). Final Project report in Blaufuß et al. (2019).

with assumptions on appliance coupling (what types of activities are coupled with what types of appliances) and simulation properties (start time (04:00), end time (03:50), simulation step size (10 min) individual activity profiles, appliance activity profiles and appearance profiles can be generated (Reinhold, 2019). Two procedures for generating profiles were implemented: an empirical and a synthetic method, which are first described in Reinhold, Wille, Engel and Eggert (2018). Here, the synthetic method of profile generation is used as it is independent of original TUD in comparison to the empirical method.

As a result of the cluster analysis, different behavioral activity patterns were described in 0. For some of the activities an interaction with an electrical appliance can be assumed and thus a description of electrical power profiles of appliances in households can be generated. For the appliances listed in Table 4.5 a direct user interaction is assumed with the listed upper categories of activities (a list with lower level category TUD codes is in Appendix F). The stated linkages between activities and use of an electrical appliance is comparable to other electrical consumption and activity coupling approaches (e.g., Diao et al., 2017; Torriti, 2017).

For example, the categories 'preparing meals, cleaning' and 'preparing food, washing dishes' are coupled with the same appliance types, except that instead of an electrical stove, Torriti (2017) uses a hob and that in the user model a coffee machine is additionally assumed. Very similar are also the categories 'doing laundry' and 'washing clothes' and 'using computer or smartphone' and 'using computer', as the appliance smartphone is not available for coupling in the Appliance module in eSE. Small differences are also that the category 'watching TV and listening to radio' is split up in the user model into 'watching TV, DVD etc.' and 'listening to music, radio' but again the coupled appliances are similar. Alike is also the summary of the category 'physiological recreation' and 'washing' but what is different is the focus on appliance type. While the appliance model only has information on a coffee machine and focuses on the drinking and eating aspect, Torriti (2017) coupled an electric shower and heating pump focusing on the washing aspect. Clear differences are that the appliance model does not supply information on electrical consumption of a vacuum cleaner.

Modelling energy consumption or demand, other appliances causing electrical loads such as a refrigerator need to be considered as well. But for the case of modelling appliance using behavior and its resulting electrical load profile in a household, only those appliances are considered, which have a user interaction to produce consumption. As a refrigerator is continuously running, the timing of its electrical power profile does not primarily depend on user interaction. Sometimes appliances with a direct user interaction are also referred to as discrete appliances

Table 4.5 Coupling of Activities and Electrical Appliances with Average Electrical Consumption in Comparison to Torriti's (2017) Coupling

Activity		Appliance		Average electrical consumption in Watt	
User model	Torriti (2017)	User model	Torriti (2017)	User model[1]	Torriti (2017)
physiological recreation	washing	coffee machine		900	
			electric shower		9000
			central heating pump		600
preparing meals, cleaning	preparing food, washing dishes	electric stove	hob	3800	2400
		oven	oven	3300	2130
		dishwasher	dishwasher	2900	1130
		microwave	microwave	750	1250
			kettle		2000
		coffee machine		900	
chores at home	cleaning		vacuum		2000
doing laundry	washing clothes	washing machine	washing machine	2000	410
		tumble dryer	tumble dryer	2900	2500
			iron		1000
watching TV, DVD etc	watching TV and listening to radio	television	TV	60	120
			TV receiver box		30
			radio		not available
listening to radio and music		hifi system		180	

(continued)

Table 4.5 (continued)

Activity		Appliance		Average electrical consumption in Watt	
User model	Torriti (2017)	User model	Torriti (2017)	User model[1]	Torriti (2017)
using computer or smartphone	using computer	computer	computer/console	200	140
other activities[2]		none			

Note [1] electrical consumption for appliances are assumptions from project partner elenia based on internet research.
[2] travel and commute activities; occupational activities; education in school, college; other education like homework; childcare at home; social activities; hobbies; reading; sleeping; gardening and animal care; handicraft activities; care of adult household members; other housekeeping activities; volunteer work; shopping, use of services

(Weber & Perrels, 2000). Since the displayed results will only include appliances with user interaction the electrical power profiles are comparable to unregistered power profile measurements in households with the difference that user behavior is estimated at this point to determine electrical power instead of measuring loads of appliances in households. Integrating a user model within a building model can help improve statements about appliance power profiles and allow for evaluations of DSM, which cannot be done, if user information is not integrated.

On the basis of the behavioral activity patterns in the different clusters and the coupling assumptions, synthetic power profiles are generated by determining the three descriptive parameters duration of use, frequency of use and time-related probability of use for each appliance and each activity. Time-related probability of use determines the absolute and relative frequencies of activities for each time point for a selected day type and cluster (this is what was displayed in *Figure 4.3*, *Figure 4.4*, *Figure 4.5*, *Figure 4.6* and *Figure 4.7* in Section 4.4.3.1 for all activities) and then the activity / appliance coupling information is used to specify time-related probability of use for each appliance (Reinhold et al., 2018). Duration of use indicates how long an appliance using activity is performed continuously and is determined by selecting day type, cluster and activity and calculating the duration of each activity from TUD. By use of the coupling information, duration of use for each appliance is calculated for each start point. Activity and appliance duration data are described by an automatic MATLAB fitting algorithm. The same procedure is followed for frequency of use. Fitted distribution functions with parameters and exemplary mean values and standard deviations of appliance use durations and frequency are reported in Reinhold et al. (2018). The synthetic method for generating power profiles uses as input variables the simulation properties (start time, end time, simulation step size), user properties (day type, cluster) and coupled appliances. For each step the time-related information is determined, an activity is stochastically selected from time-related probability of use distribution and coupled with the appliance type. Then activity duration is queried from a database and activity and appliance activity are added to an existing time series which are assigned to the user model after all simulation steps have been completed (Reinhold et al., 2018).

To exemplify the resulting electrical power profiles from coupling appliance using behavior and electrical consumption, simulation outputs are presented for some single-person households individually. The effects of different behavioral variabilities between weekday and weekend clusters on electrical consumption on the household level are presented by aggregating (summing) the electrical loads from simulating 100 single-person households within each cluster[17] for the year 2020. The following main assumptions are made for the building simulation of electrical appliances with user interaction: start time 04:00 one day, end time 03:50 next day, step size 10 min and distribution of appliances in households in Table 4.6 is assumed to be the same in every household.

Table 4.6 Assumptions for Equipment Inventory (from project partner elenia)

appliance type	number of appliances in single-person households
television	2
computer	2
hifi system	1
electric stove	1
oven	1
coffee machine	1
microwave	1
washing machine	1
tumble dryer	1
dishwasher	1

[17] In addition to the assumptions from TUD, driving schedules are implemented into the model (Reinhold, 2019). In this simulation for 60% of the people in each cluster, further influencing the presence times at home.

An example of resulting active power profiles from coupling activities with electrical behavior of appliances is shown in *Figure 4.24* for weekday cluster 1 and in *Figure 4.25* for weekend cluster 1. As can be seen, active power curves from different appliances can occur simultaneously such as using an oven and hifi-system beginning at 06:20 a.m. in the morning in weekday cluster 1 or using an oven and computer beginning at 08:10 a.m. on a weekend. Durations of electrical consumption for the same appliance can differ within a day. The duration of using the computer is for example longer in the evening of weekend cluster 1 than in the morning. Also, not all appliances are used every day, so that in addition to the aforementioned appliances only stove, coffee machine, microwave, television and dishwasher are included in this example simulation output of weekday cluster 1 and coffee machine, television and microwave in weekend cluster 1.

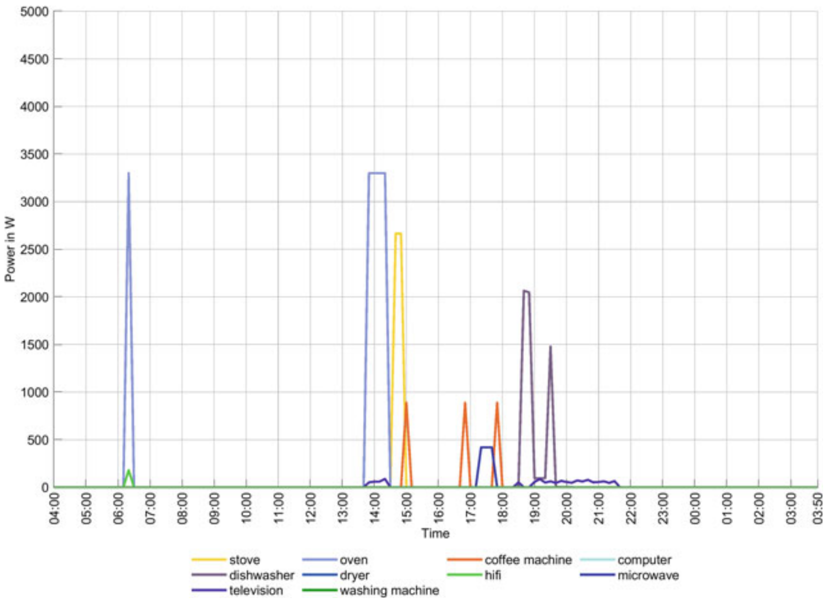

Figure 4.24 Example of a generated active power profile for a single-person household in weekday cluster 1. (provided by Christian Reinhold according to author's specifications)

Simulating 100 of these single-person household buildings and summing their electrical power profiles within each activity cluster gives an overview of the resulting load patterns and their timely distribution and variability in turn as they would be relevant for shifting energy demand. Even though behavioral patterns

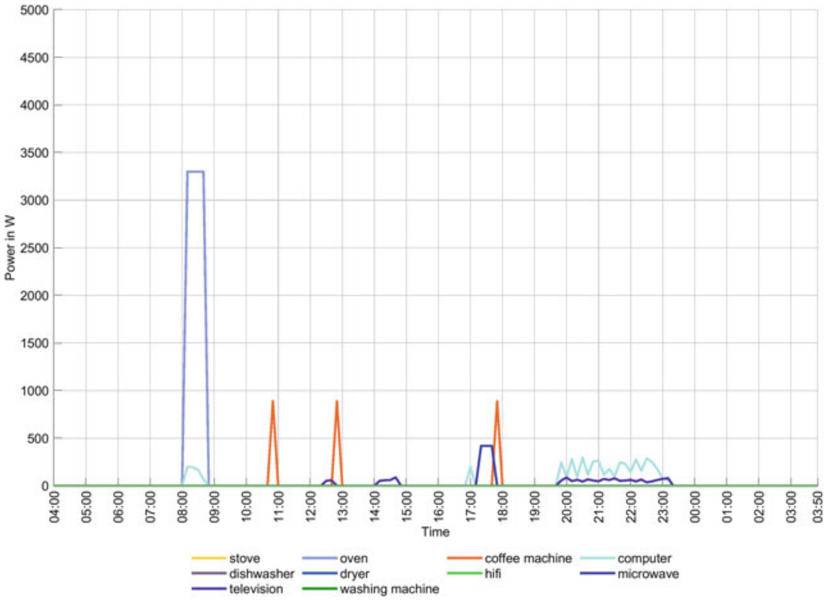

Figure 4.25 Example of a generated active power profile for a single-person household in weekend cluster 1. (provided by Christian Reinhold according to author's specifications)

and load patterns are closely linked in this type of building simulation, the power denoted on the y-axis of the figures is now not only a result of the frequency of simultaneously occurring behaviors, but also a result of the characteristic active power profile patterns of individual appliances as they were shown in *Figure 4.24* and *Figure 4.25*. Keeping this in mind, the simulated load patterns seem able to reflect some of the differences between the weekday and weekend clusters. In *Figure 4.26* and *Figure 4.27* examples of aggregated load patterns are shown for weekday cluster 1 (occupational activity cluster) and weekend cluster 1 (TV activity cluster with small midday peak around 16 p.m. and large peak at 22 p.m.). The load patterns for the other clusters are in Appendix G. The total aggregated load of all appliance types is displayed in the upper left-hand corner of a figure and then three displays follow with appliances grouped to a "cooking" (oven, stove, microwave, coffee machine), a "chore" (dishwasher, washing machine, dryer) and an "entertainment" (television, computer, hifi-system) category in the upper right, lower left and lower right-hand corner, respectively. Also note that the y-axis has either a maximum of 40 kilowatt or 14 kilowatt.

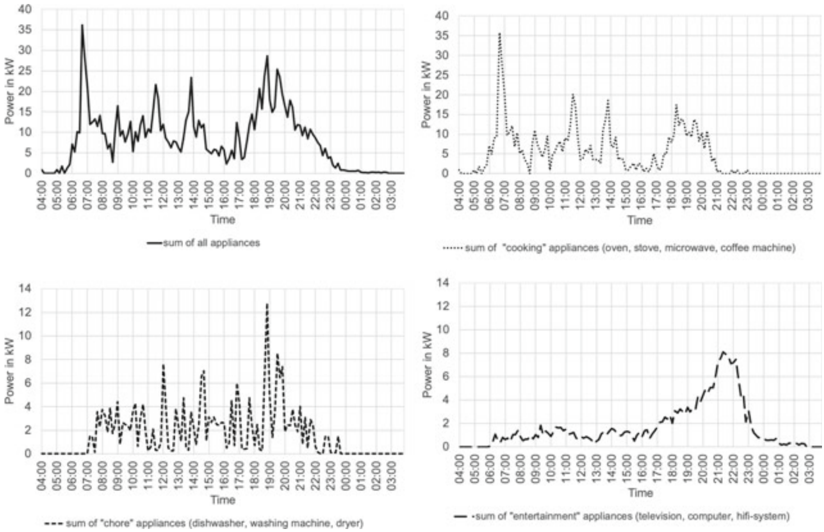

Figure 4.26 Example of aggregated load profile for 100 simulated single-person households in weekday cluster 1. Total sum (upper left) and grouped for appliance categories cooking (upper right), chore (lower left) and entertainment (lower right) (based on simulation data from Christian Reinhold)

Results of the simulations seem to recover the working and education restriction in the morning between weekday clusters (1 and 2) and weekend clusters. For example, the total aggregated load pattern in weekday cluster 1 starts about an hour earlier than for weekend cluster 1, which is mainly associated with the timing of the cooking load. The cooking load pattern resembles the total aggregated load pattern most closely in all clusters as it is associated with the largest loads. A noticeable difference is a more pronounced load distribution in chore appliances in the evening hours in weekday cluster 1 and to a lesser extent in weekday cluster 3 in comparison to weekend clusters, which have load patterns with higher power in the mornings and early afternoon as can be seen for example in *Figure 4.27* (lower left corner) for weekend cluster 1. Also, the entertainment appliances are again characteristically distributed with a peak in the evening in all weekday and weekend clusters but on the weekends, there is an early afternoon

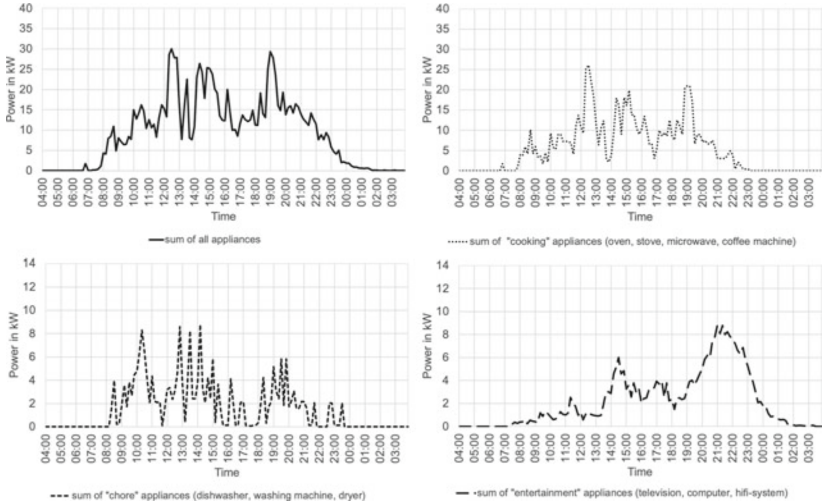

Figure 4.27 Example of aggregated load profile for 100 simulated single-person households in weekend cluster 1. Total sum (upper left) and grouped for appliance categories cooking (upper right), chore (lower left) and entertainment (lower right) (based on simulation data from Christian Reinhold)

peak as well. Accordingly, even though the differences in load pattern between weekday cluster 1 and weekend cluster 1 seem small, the overall load pattern for weekend cluster 1 appears to distribute more evenly throughout the day. This is what would be theoretically expected if fewer context structure restrictions exist for energy using behaviors and corresponds to less variability in load patterns. Smaller differences between maximum and minimum loads mean a relative larger amount of baseload, which could be covered by non-variable renewable baseload supply units. This would decrease the relative amount of VRE that the energy system would have to accommodate and thereby mitigate the mismatch problem through increasing energy using flexibility by increasing the possibilities for behavioral variability, i.e., increasing the degrees of freedom in distributing energy using behavior. Without making the connection between behavioral and appliance load patterns exploring such consequences of energy using behavior for the energy system and exploring explanations and points of intervention for affecting load patterns in suitable ways to provide services for the energy system would not be possible.