

A Probabilistic Modelling Approach for Residential Load Profiles

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<p>Key-Words:</p> <ul style="list-style-type: none"> – Load profile generator – Residential loads – Distribution network – Electric vehicles – Heat pumps – Markov Chain Simulation – Time Use Survey 	<p>Abstract:</p> <p>In this paper, a model is presented that generates electricity load profiles for individual German households. It is assumed that the electricity consumption is mainly determined by the behavior of the residents and their appliances. Activity patterns for the residents living in the household are simulated by using a first-order Markov-chain, which has been calibrated by time use data from a German survey obtained in 2012/2013. The model is then validated by using the original sample to check whether daily routines are realistically reflected in the model. Furthermore, the electricity load profiles are validated by comparing the outcome of the model with real measured load profiles, synthetic load profiles but also statistical characteristics, which have been obtained through national surveys. Validation shows that the approach is suitable to simulate electricity demand that captures annual consumption, diurnal variation but also differences between individual households. The developed load profile generator can be used to analyze the impacts of the emersion and expansion of new technologies on residential load patterns and respective distribution network loads.</p>
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1 Introduction

1.1 Motivation

Global climate change requires a rethinking in all sectors in order to reduce CO₂ emissions. Especially the transportation as well as the space heating sector pose a great challenge in the German energy transition.¹ In this context, energy efficient technologies such as electric vehicles (EVs) and electric heat pumps can address this challenge, while also reducing the dependency on fossil fuels. Their expansion, however, will affect energy usage patterns, resulting in an additional demand for electricity that needs to be covered mainly on the residential distribution grid level. In 2016, the residential sector has accounted for about 26 % of the total energy consumption in Germany, and approximately 25 % globally.² The additional demand could not only further increase this share, but also change the shape of residential load profiles, which will impact decisions regarding grid extension measures. This predicament highlights the importance to fully understand the consumption characteristics of the domestic sector.

However, analyzing residential consumption patterns is far from trivial: On the one hand, real measured data is exemplary, and on the other hand scarce and comes in low quality.³ As representative surveys and studies are costly and laborious to obtain, they are not widely available.⁴ As a consequence, standard load profiles have been used for decades to roughly estimate the energy demand of residential customers. As the integration of new technologies and decentralized electricity generation will not distribute evenly across households, studies such as from Boßmann et al. (2013)⁵ underline that using historical load curves to calculate future electricity demand will lead to inaccurate results due to changes in electricity consumption patterns. Standard load profiles are therefore not suited any longer and methods are needed that model domestic electricity demand in more detail.⁶

1.2 Objective

In this paper, a model is developed that is capable of simulating high-resolution, appliance-specific electricity demand profiles for individual residential households. Highly resolved consumption profiles are simulated on a 10-min resolution that can be extrapolated for a number of dwellings in order to estimate the overall demand for a residential neighborhood, while considering versatility and coincident demand between individual customers. The total load profile for each household is generated by using a bottom-up modelling approach that simulates inhabitants' behavior, which is linked to the usage of appliances. Besides modelling electricity consumption of conventional appliances, the model is also capable of simulating additional demand caused by the presence of electric vehicles (EV), which is derived from synthetic mobility behavior of the residents and EV types.

The paper is organized as follows: In Chapter 2, existing literature on the estimation of residential electricity demand is reviewed. Advantages and disadvantages for each modelling approach have been identified. The model structure and input data will be described in Chapter 3. The electric vehicle module will be presented in a future paper. In Chapter 4, the model results are being validated by comparing the results to statistical parameters obtained from national surveys, in-sample data and real measured electricity load profiles. Finally, Chapter 5 summarizes the results and gives an outlook about future research opportunities.

¹ See Löschel et al. (2018), pp. 12.

² See German Environment Agency (2018); Pablo-Romero et al. (2017), p. 1.

³ See Seim et al. (2019), pp. 2.

⁴ See Kandler (2017), p. 15.

⁵ See Boßmann et al. (2013), p. 1209.

⁶ See Reinhold et al. (2018), p. 1; Zeilinger and Einfalt (2012), p. 1.

2 Overview of Relevant Energy Demand Modelling Techniques

Existing literature distinguishes between two categories to model the energy consumption of domestic households: top-down and bottom-up approaches.⁷ Top-down models provide beneficial results on a macro-level as they use aggregated data and consider the residential sector as an energy sink.⁸ Typically, consumption is traced back to variables such as characteristics of dwellings, historical energy consumption but also macro-economic factors, such as Gross Domestic Product (GDP) or population growth.⁹ As this data is widely available, top-down models are easy to develop. Unfortunately, as they use historical data and do not simulate energy consumption processes in great detail, top-down models lack the ability to estimate the potential impact of emerging or improving technologies.¹⁰

Bottom-up models take a more refined approach as they determine the relationship between electricity consumption and household characteristics by using high-resolution data, which has been obtained from individual households or appliances.¹¹ The results are then extrapolated in order to aggregate the total energy demand for a region or nation. Bottom-up approaches can be distinguished between statistical and engineering approaches.¹² Statistical methods strip down historical household load profiles and attribute the energy consumption to specific end-use appliances. Subsequently, these profiles are used to model the total electricity demand for individual households, based on the composition of appliances present in the dwelling. Engineering methods, on the other hand, use technical characteristics of the appliances (e.g. power ratings) and determine their usage frequency. A total electricity load profile for each appliance is then generated and finally aggregated to estimate the total energy demand for the dwelling. As these models do not rely on historical load data, engineering approaches are capable of considering new technologies in the simulation.

The high-resolution of bottom-up models is also one of the disadvantages, as complexity increases and thus, calibration requires more effort.¹³ Moreover, the required data might not be available on the desired resolution level. As a consequence, assumptions must be made in the model which might become arbitrary to some degree.¹⁴ A compromise must therefore be found to ensure a precise simulation and plausibility of the results while keeping the complexity in a manageable scope.

3 Electricity Demand Modelling for Residential Customers

The emersion of new technologies will not spread equally across households but will significantly alter residential consumption patterns when present. Thus, a model approach is needed that adequately considers these distinctions between households to simulate realistic and accurate electricity demand patterns.

The developed model is based on a bottom-up engineering approach that generates electricity load profiles in 10-min resolution for each day in 2018. The requirements this model needs to fulfill are the following:

1. The synthetic load profiles are realistic and representative for German households, individually and on an aggregated level
2. They have a high level of detail with regard to the underlying household appliances

⁷ See Gottwalt (2015), p. 33.

⁸ See Muratori et al. (2013b), pp. 465.

⁹ See Swan and Ugursal (2009), p. 1832.

¹⁰ See Fischer et al. (2015a), p. 1.

¹¹ See McLoughlin et al. (2012), p. 240.

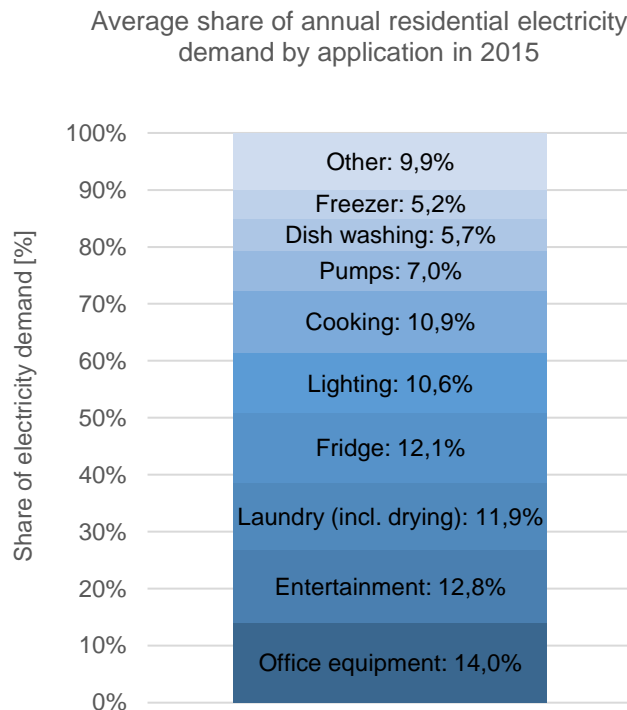
¹² See Hayn (2016), p. 136.

¹³ See Muratori et al. (2013a), p. 169.

¹⁴ See Gottwalt (2015), p. 34; Gao et al. (2018), p. 1.

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3. They represent a time horizon of one year, taking into account different seasons and weekdays
4. They have a high temporal resolution



In order to simulate electricity load profiles, it is important to know when and where electricity is consumed in the household. Figure 1 depicts the domestic electricity demand by consumer category in German households. As nine categories are accountable for over 90 % of the total electricity consumption, this allows for the identification and limitation of devices that should be considered in the model.

Figure 1: Average share of annual electricity demand by domestic category regardless of household size and without demand for electric water heating. Numbers taken from [Energy Agency North Rhine-Westphalia (2015), p. 12].

In a bottom-up model, it is assumed that electricity consumption is almost exclusively determined by the behavior of the household residents.¹⁵ For this purpose, a heterogeneous first-order Markov-chain is used, which is calibrated by time use survey (TOU) data collected by the German Statistical Office in 2012/2013. The stochastic approach enables the model to generate individual activity patterns and thus, synthetic electricity load profiles which differ for each simulation. Calibrating the model with TOU data allows for a variation of energy demand across time and populations, as socio-demographic characteristics for specific sub-populations as well as temporal aspects such as season and weekday can be considered.¹⁶

In the literature, two approaches are widely used to determine appliance usage. Firstly, by deriving usage probability, duration and frequency for the devices directly from the time use survey.¹⁷ Secondly, by generating activity profiles regarding daily routines of the residents, which are then linked to the usage of the appliances.

As the model pursues the aim to investigate the impact of new technologies, such as EVs and heat pumps, an approach is needed that models holistic daily routines of German inhabitants, including their mobility behavior. Therefore, the activity-profile approach is chosen. As a result, this paper extends the existing literature by providing a model, which generates residential load profiles for German households but also simulates the mobility behavior of its residents, which is essential in order to investigate the additional demand resulting from EVs.

To increase the accuracy of the model, socio-demographic and temporal factors as well as the diversity of household appliances are being considered. The latter is addressed by allocating devices based on national ownership statistics from the Federal Statistical Office.

¹⁵ See Hayn et al. (2014), p. 37; Swan and Ugursal (2009), p. 1820.

¹⁶ See Ramirez-Mendiola et al. (2017), p. 122; Fischer et al. (2015b), p. 170.

¹⁷ Examples can be found in Fischer et al. (2015b) and Reinhold et al. (2018).

In summary, the algorithm performs the following steps to simulate total residential electricity load profiles:

1. Define the set of simulated households. Households are characterized by number and socio-demographic factors such as level of employment and family status of the residents
2. Allocation of appliances and vehicle ownership based on national statistics
3. For each household, generation of synthetic activity profiles for each resident. Consideration of socio-demographic attributes, as well as temporal and seasonal factors
4. Determination of conventional electricity consumption of the dwelling by linking the residents' activities to the related appliances. Power characteristics are taken from real measured profiles, if available
5. Electricity demand for electric vehicle charging is based on the vehicle-usage pattern of the residents, the driven distance as well as power consumption characteristics of the electric vehicle. A realistic driving cycle is used to determine the consumption of the car for each trip
6. Aggregation of load profiles in order to estimate the total energy demand of the dwelling

The model outline can be illustrated as a modular approach which is subdivided into three components (Figure 2): the behavioral model, the residential power demand model and the transportation model.

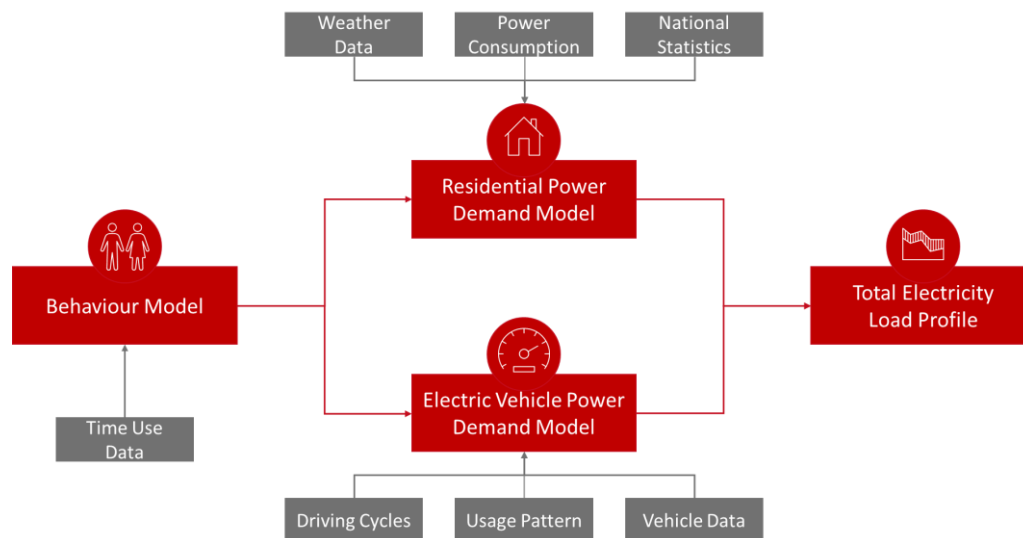


Figure 2: Outline of the developed bottom-up model. Own illustration based on Muratori (2018).

While the behavior and the residential power demand model will be presented and validated in this work, the electric vehicle power demand model is excluded but will be presented in a future work.

3.1 Residential Behavior Model

Simulating residential behavior patterns indicates what activity is performed by the residents and, thus, provides an insight into which electric appliances are potentially used. As the model needs to consider differences in daily routines due to socio-economic but also temporal and seasonal factors, modelling individuals' behavior is complex.¹⁸ The input data and the methodology used to generate synthetic behavioral patterns is described in more detail in the following.

3.1.1 Description and Preparation of Input Data

As input data for the behavioral model, the TOU data 2012/2013 for Germany, conducted by the Federal Statistical Office, is used.¹⁹ The survey provides dairies documented for about 12,000 persons aged

¹⁸ See Widen and Wäckelgard (2010), p. 1880; Muratori et al. (2013b), p. 469.

¹⁹ See RDC of the Federal Statistical Office and Statistical Offices of the Länder (2014).

ten years or older. As they reported daily routines on three days, the data set includes around 36,000 observations. The use of such a large database for the creation of activity profiles allows modelling the behavior of a specific type of person without losing variability, when picking a small sample for the simulation.²⁰ As the survey also provides relevant information regarding socio-demographic factors of the interviewees, the documented diaries have been clustered in order to account for differences in living conditions.

Definition of Household and Resident Types:

The annual electricity demand is mainly determined by the number of people living in the household, the status of employment of the residents and the electrical equipment present in the household.²¹ Other studies also consider further attributes such as age and income of the households.²² As a finer subdivision leads to a decrease in the amount of observations available for each class, a similar approach to FfE (2017)²³ was chosen. The approach ensures a sufficient amount of data per group but still adequately captures different subgroup behaviors. Table 1 outlines the types of households and resident types that can be simulated.

Household type	Resident type
Single household	Full-time employee Part-time employee Unemployed person (e.g. pensioner)
Two-person household	Two full-time employees Two unemployed persons One full-time and one part-time employee
Three-person household	Two full-time employees + one children One full-time and part-time employee + one children
Four-person household	Two full-time employees + two children One full-time and part-time employee + two children
Five-person household	Two full-time employees + three children One full-time and part-time employee + three children

Table 1: Defined synthetic household and resident types. Categorization derived from FfE (2017).

Differentiation by Temporal and Seasonal Factors:

In addition to household size and employment status, diaries are further separated by season and weekdays, as both factors influence the shape of the resulting electric load profiles.²⁴ While most models differentiate between working days, Saturdays and Sundays/holidays, Kandler (2017)²⁵ notes that differentiating between Mo-Thu and Friday within working days yields more accurate results when modelling the behavior of human beings. This approach is taken here too. Public holidays are determined by their fixed date in 2018. To account for seasonal variation, the months of winter (Nov-Mar), summer (Jun-Sep) and transition (April, May and October) are considered in the simulation separately.

Definition of Relevant Activities:

In order to improve the manageability of the model output, the initial 165 pre-defined activities reported in the diaries have been clustered. Essential activities related to the usage of appliances have been derived from Figure 1 and extended in order to simulate holistic daily routines. Sleeping, for example, is not related to electricity consumption, but takes about one-third of our daily time available.

²⁰ See Gruosso (2016), p. 2; Dickert and Schegner (2011), p. 2.
²¹ See Hayn et al. (2018), p. 8; Dickert and Schegner (2011), p. 2; Metz (2013), p. 61.
²² See Fischer et al. (2015b), p. 171.
²³ See FfE (2017), p. 165.
²⁴ See Li et al. (2018), p. 293.
²⁵ See Kandler (2017), pp. 56.

Additionally, for the transportation model, activities, which describe residents' mobility behavior as accurately as possible, were derived. As a result, residents can be involved in either one of the defined activities for each time step:

- Away (work)
- Away (leisure)
- Away (shopping)
- Sleeping
- Cooking
- Using dishwasher
- Doing laundry
- Watching TV
- Using PC
- Personal hygiene
- Ironing
- Listening to music
- Vacuuming
- Other (No-power activities, e.g. gardening)

3.1.2 Generation of Activity Patterns

Daily routines can be characterized as sequences of activities which vary by time, meaning that diurnal factors need to be considered.²⁶ For instance, going to sleep after brushing your teeth is more likely in the evening than in the morning. A dynamic modelling approach that adjusts the probabilities for each activity during the simulation is thus needed. Moreover, behavioral patterns do not always follow the same sequence but can be affected by randomness due to environmental factors such as weather, weekday or season but also by family internal factors.²⁷ The most obvious and simple method would be to determine the current activity in the sequence by the probability observed as the proportion from the whole sample. This approach, however, would not reflect individual behavior patterns and would only reproduce the overall and average distribution of the aggregated profiles.²⁸ To consider the factors stated above, a heterogeneous first-order Markov-chain is used to model activity patterns. Using a stochastic instead of a deterministic approach ensures that the outcome will vary for each simulation, hence considering different lifestyles of the synthetic households and residents.²⁹

In a first-order Markov-chain, it is assumed that the next state only depends on the present state and does not consider the past sequence of activities.³⁰ It is called heterogeneous, if the transition probabilities going from one state to another are adjusted for each time step. To match group-specific criteria of the person to be modelled, the clustered diaries are used to calculate the probabilities.

As interviewees also had the opportunity to document a second action, a side-activity pattern³¹ for each time step is generated, as these activities also affect total energy consumption of the household. Additionally, since usage of appliances is often shared by the residents in one household, a joint-activity factor is introduced that determines, whether residents share the usage of appliances when performing the same activity. It is derived once again from the TOU data, as interviewees also reported whether the activity was performed with someone else.

After the activity patterns have been generated, the related energy consumption of the appliances in the dwelling can be modelled. The residential power demand model is explained in the next section.

3.2 Residential Power Demand Model

As mentioned above, the set of appliances considered in the model has been mainly derived from Figure 1, but is extended by devices that have been considered in the existing literature. Since they

²⁶ See Widen et al. (2009), p. 1002.

²⁷ See Gao et al. (2018), p. 3.

²⁸ See Wilke (2013), p. 26.

²⁹ See Yao and Steemers (2005), p. 665.

³⁰ See Bruckner and Velik (2010), p. 3654.

³¹ For example, a person's main activity is cooking but is also listening to music.

differ by active usage dependency, they can be classified as illustrated in Figure 3 (electric vehicles will be discussed in a future paper).

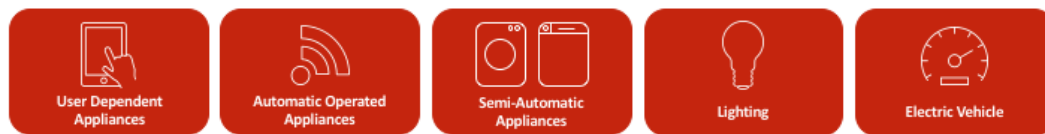


Figure 3: Classes of appliances considered in the model.

The set of appliances for each household is randomly allocated before the simulation. Probabilities regarding statistical ownership have been taken from national surveys, depending on the size of the household. As not all devices from Figure 1 have been reported in the diaries, assumptions were used to determine the presence of some appliances.

Beside the stock of appliances, different load profiles and power ratings for devices were considered to ensure a certain variability between individual households. Most power characteristics have been taken from the Tracebase data set, including real measured load profiles for appliances, conducted by the Technical University Darmstadt in 2012.³² Using this data set grants two essential aspects. Firstly, it ensures that the simulated appliances correspond to real household appliances, since they have been measured under real conditions. Secondly, apart from technological development since 2012, the data set can be considered approximately representative, as the campaign measured appliances that have been available in Germany during the time of conduct. If available, various device models have been implemented, in order to represent differences in consumption of these devices during stand-by and operation.³³ The original 1-sec resolution has been adjusted in order to match the 10-min resolution of the model. Unfortunately, it was not possible to obtain all the required power characteristics from this data set as not all appliances considered have been measured within the campaign. Some of the load profiles also appeared to be too high or low to reflect today's average appliances in German households or contained missing values. Further literature was therefore used to ensure the plausibility of the values and to complete the stock of appliances.

3.2.1 User Dependent Appliances

User dependent appliances are directly related to the activity patterns of the household residents and represent a high proportion of the total energy consumption.³⁴

If the residents perform a certain activity such as vacuuming, but the related appliance is not present in the household it is assumed, that the activity is performed without consumption of electricity, e. g. in this case with a broom. Cooking is a special case, as the activity is related to several devices and the total power consumption normally depends on the dish being cooked. While authors such as Widen and Wäckelgard (2010) and Torriti (2017) suggest a fixed power consumption during execution of the activity, the model considers power characteristics for a variety of kitchen appliances for variation in meal preparation. This is done for each time step when the activity is performed, resulting in a load profile that also varies during the temporal sequence of the activity. As not covered in existing literature, usage probabilities for the devices have been derived from assumptions and Garcia-Gonzalez et al. (2018)³⁵. Even if the latter surveys cooking behavior of people living in Spain, it is suggested that these results can also be partly deduced for German households. Validation of the load profiles shows

³² See Reinhardt et al. (2012), pp. 1.

³³ See Hauser (2013), p. 192.

³⁴ See Kandler (2017), p. 76.

³⁵ See Garcia-Gonzalez et al. (2018), p. 8.

that the assumptions made are in range with the expected annual electricity consumption of these appliances.

3.2.2 Automatic Appliances

Automatic devices are not dependent on the interaction of residents but determine the base load of residential load profiles.³⁶ In line with Muratori et al. (2013b)³⁷, in this paper devices such as refrigerators and freezers are modeled by a cyclic load, which consumes its nominal power rating when turned on. Load profiles are mainly selected from the Tracebase data set. The measured load profiles, however, are only used as time-use profiles. Power consumption per cycle has been scaled to match the annual electricity consumption reported for these devices according to Energy Agency North Rhine-Westphalia (2015)³⁸ depending on the number of inhabitants living in the dwelling.

3.2.3 Semi-Automatic Appliances

Semi-automatic appliances interact with the residents. The execution of the related activity, however, just determines the starting time during the day when the electricity consumption of the device occurs. If the device is present and the activity pattern includes one of the related activities, the time of occurrence over the simulation day of these activities is bundled. Stamminger (2008)³⁹ reveals that in Germany the washing machine is mostly turned on in the morning or in the evening. Therefore, the simulator considers the first-time step after the activity is performed to be the starting time of the load cycle. This approach is taken since the load cycle for a washing machine is normally longer than for a dishwasher, which has been observed by analyzing the real measured load profiles. Additionally, if a tumble dryer is present, which can only be used after the washing program has finished, the total load cycle for the activity is even longer. This approach should reduce the probability that the load profile overlaps with the respective activity in the next simulation day. If the load profile overlaps, the remaining load cycle is transferred in the following simulation day. For the dishwasher, the last occurrence of the day is determined as execution time. This assumption is in line with findings by EURECO (2002)⁴⁰. All the other activity states are considered to be loading and unloading of these devices. The appliances are characterized by multiple possible programs, which have a finite set of discrete operation states and vary due to different electricity consumption and load profiles.⁴¹ When the device is turned on, the appliance undergoes various steps of operations.⁴² A set of pre-defined load profiles for each device has been taken from the Tracebase data set and for each execution, a random number determines which program will be used. Probabilities for operation have been taken from existing literature or have been adjusted to match annual electricity consumption of these devices.

3.2.4 Lighting

Modelling the electricity demand for lighting poses a certain challenge as it is not related to a specific activity but, instead, depends on the occupancy pattern and solar irradiance of the location of the dwelling. Hence, the demand varies by seasonal and diurnal factors due to the fluctuation of daylight.⁴³

Occupancy of the dwelling is derived from the activity profiles by the aggregation of presence and active profiles of the residents. Solar irradiance data for Berlin Schönefeld in 2018 has been obtained from Germany's National Meteorological Service.⁴⁴

³⁶ See Metz (2013), p. 64; Nijhuis et al. (2015), p. 3; Dickert and Schegner (2011), p. 2.

³⁷ See Muratori et al. (2013b), p. 467.

³⁸ See Energy Agency North Rhine-Westphalia (2015), p. 12.

³⁹ See Stamminger (2008), p. 28.

⁴⁰ See EURECO (2002), pp. 86.

⁴¹ See Ji et al. (2018), p. 2; Metz (2013), p. 64.

⁴² For instance, for a washing machine: washing and spinning.

⁴³ See Widen et al. (2009), p. 1001.

⁴⁴ See DWD (2019).

Several approaches exist in the literature to estimate the electricity demand for artificial lighting. In this paper, the approach of Fischer et al. (2015b)⁴⁵ is being applied. Threshold values have been adjusted since validation of the annual electricity demand for lighting has shown that the consumption is too high and does not match with the average annual consumption recorded in national statistics. Lights are switched on if a person is at home and active, and if the global irradiation I_g is below a predefined value of 40 W/m². The model also considers the number of active persons at home n_{active} . The lower threshold $I_{g,min}$ is set to be (20 W/m²). The electricity consumption $P_{el,l}(t)$ for each time step t is calculated as:

$$P_{el,l}(t) = n_{active} * P_{el,l,pp}(t) * \frac{I_{g,max} - I_g(t)}{I_{g,max} - I_{g,min}}$$

$P_{el,l,pp}(t)$ is a constant value that differs depending on the size of the simulated household.

3.2.5 Stand-by Electricity Demand

Most of the appliances also consume electricity when they are not actively used. Stand-by consumption is estimated to be around 11 % of the annual electricity consumption and should be therefore considered when estimating the electricity demand of one dwelling.⁴⁶ Unfortunately, most of the devices measured within the Tracebase campaign are not characterized by a stand-by consumption. Further literature was therefore used in order to determine stand-by electricity consumption of the appliances.

4 Results

This chapter examines whether the developed model is capable of reproducing important statistical characteristics that can be obtained when comparing the results against in-sample data, real measured data as well as national surveys. The validation of the generated activity profiles in Chapter 4.1 is of particular importance since the electricity consumption and the mobility behavior of the household are mainly determined by the behavior of the inhabitants. A comparative analysis between the synthetic residential load profiles, real measured load profiles and empirical synthetic load profiles for German households is presented in Section 4.2.

4.1 Validation of the Behavioral Model

Analyzing the generated activity patterns provides insights about behavior characteristics generated by the model and aids in understanding the underlying data. Validation therefore aims at detecting possible distortions and outcomes that do not reflect human behavior in a realistic way.

The first step is to investigate whether the first-order Markov-chain is capable of reproducing activity patterns that coincide with the behavior documented in the national survey. While in rural areas, multi-family and single-family houses with several residents per household predominate, urban areas have a higher proportion of single households.⁴⁷ The present paper focuses on Berlin as a location for the dwellings, hence, activity patterns and load profiles for single-person households have been generated and will be validated. Moreover, according to Hauser (2013)⁴⁸ and Bottaccioli et al. (2019)⁴⁹, load profiles are characterized by a similar shape and differ mainly in the resulting annual consumption

⁴⁵ See Fischer et al. (2015b), p. 174.

⁴⁶ See Patrao et al. (2010b), p. 3; Liu (2018), p. 12.

⁴⁷ See Liu (2018), p. 13; FfE (2017), p. 165.

⁴⁸ See Hauser (2013), p. 206.

⁴⁹ See Bottaccioli et al. (2019), p. 11.

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and the extent of the occurring peak loads. Thus, the generated load profiles can be scaled and compared to areas of different household compositions.

For validation, synthetic activity profiles for full-time working and unemployed persons are generated. Both groups account for a large proportion of the total number of documented diaries in the survey.⁵⁰ It is also expected that the average behavior for these two groups differ mostly from each other.

As mentioned in Swan and Ugursal (2009)⁵¹, estimating occupant behavior is difficult since the behavior between individuals varies widely and in unpredictable ways. While individual patterns should deviate from the average behavior, the observations obtained from a sample of synthetic activity patterns should be consistent with the characteristics derived from the reported diaries.⁵² Hence, it is necessary to obtain information about how the model behaves for a large number of simulations.⁵³ For both resident types, a sample of 4000 activity patterns for each day type is simulated. The aggregated results are compared to the properties in the TOU survey. Structural differences of the aggregated patterns are analyzed with regards to diurnal and seasonal factors and employment status. The synthetic and the original TOU distribution for a full-time working household for weekdays during winter are presented in Figure 4. Complementing figures of other workdays, seasons and households can be found in the appendix A.

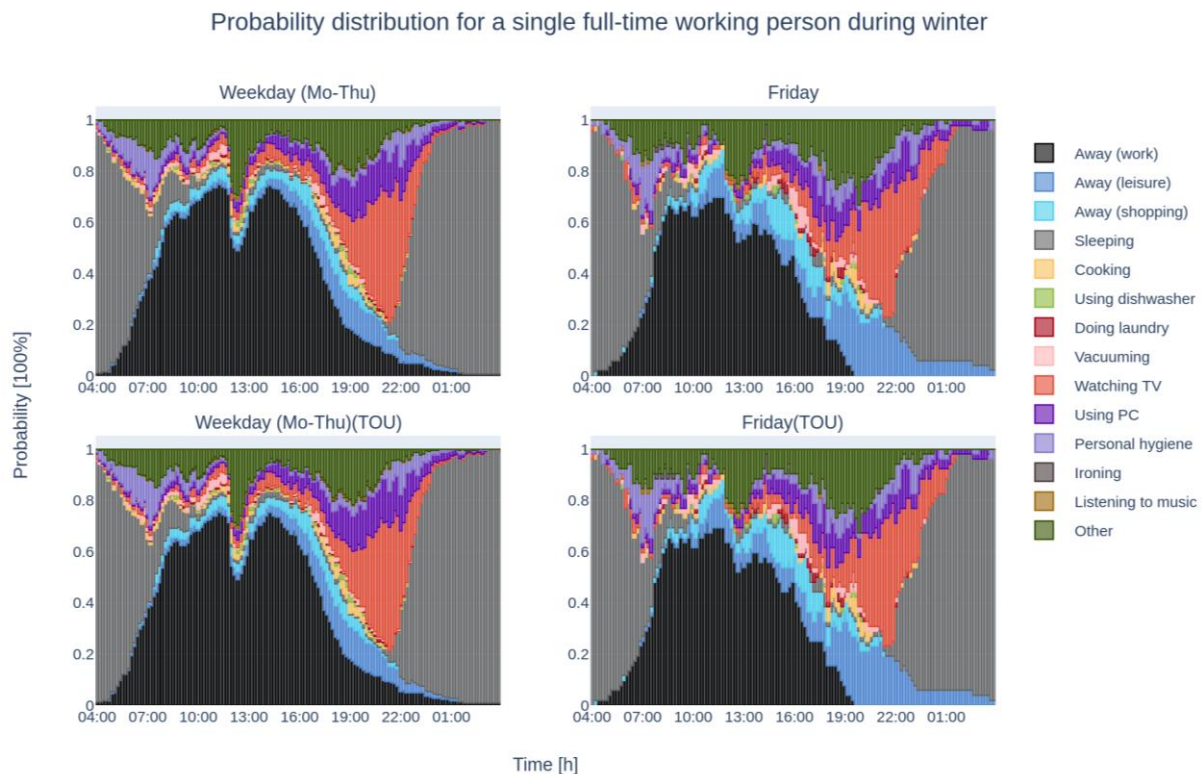


Figure 4: The figure shows the cumulative probability for each activity as a function of time for a single full-time working person. 4000 activity profiles for a weekday (Mo-Thu) and Friday during winter have been generated. The lower figures show the probability distribution obtained from the original TOU data set.

The figures indicate that the heterogeneous first-order Markov-chain approach is well capable of reproducing the overall distribution from the original data set.

⁵⁰ As shown in Table 2, 1128 diaries for full-time employees and 1266 diaries for unemployed persons have been reported. Only 317 diaries, however, have been reported for part-time employees.

⁵¹ See Swan and Ugursal (2009), p. 1823.

⁵² See Flett and Kelly (2016), p. 222.

⁵³ See Widen et al. (2009), p. 1003.

The results underline that the separation between working days is essential, as daily routines on Fridays for full-time employees differ, compared to other working days. Further activity profiles have been generated for validation but are not presented due to space restrictions (See appendix A). The results emphasize that behavioral patterns vary between resident type, day and season.

The results, however, should be treated with caution, as some of the observations cast doubt whether they are representative on a national level. For example, the activity patterns for a full-time working person on a Friday show a clear tendency to finish work earlier at the end of the week. While it is expected, that this tendency can be observed regardless of season, both, synthetic and original data show higher probabilities for this trend during winter than summer. While in summer, the probability for the activity *Away (work)* stays around 10 % for each time step, it decreases to 0 % in winter around 8 p.m. However, it is expected that in reality the probability for the activity *Away (work)* will not decrease to 0 % at any time for a full-time employee. These observations indicate that the survey participants' behavior might deviate to some extent from a national average. This concern is also shared by Swan and Ugursal (2009)⁵⁴, suggesting that national surveys always fail to replicate nationwide characteristics on national levels since they are difficult to conduct and costly.

As mentioned by Flett and Kelly (2016)⁵⁵, the number of total observations should be at least 200 in order to guarantee robust statistical assumptions when describing behavior patterns. The total number of submitted diaries in the TOU survey for each one-person resident type with regards to day type and season is displayed in Table 2. It indicates that for Fridays, Saturdays and Sundays and for each day type during transition months, the total number of observations does not satisfy this condition. If seasons are neglected, the total number of observations for each day increases. However, some numbers still deviate significantly from the recommended threshold. Moreover, findings by Torriti (2017)⁵⁶ indicate that daily routines are influenced by seasonal variation and thus, cannot be neglected. The table supports the conclusion that the number of documented diaries for one-person households in the national study might be too small in order to derive reliable results as a basis to make assumptions regarding behavior patterns on a national level.

Day type	Winter			Summer			Transition			Total		
	FT	UE	PT	FT	UE	PT	FT	UE	PT	FT	UE	PT
Mo-Thu	226	263	64	206	257	60	154	144	36	586	664	160
Friday	52	66	21	53	55	14	29	41	8	134	162	43
Saturday	79	90	23	68	84	21	39	53	9	186	227	53
Sunday	85	83	26	72	73	15	65	57	20	222	213	61

Table 2: Reported diaries for each resident type by day type and season. FT= full-time working, UE= unemployed and PT= part-time working.

For a more in-depth analysis, the method by Muratori et al. (2013b)⁵⁷ is used to check whether the mean value for each activity during each time step in the original survey is within the 95 % confidence interval of the synthetic probability distribution. The analysis focuses on a simulation of 4000 weekdays (Mo-Thu) for a full-time working person in winter. The synthetic confidence interval is compared to the mean value calculated from the 226 diaries in the time use survey. The complete results for all activities are shown in the appendix B.

⁵⁴ See Swan and Ugursal (2009), p. 1821.

⁵⁵ See Flett and Kelly (2016), p. 223.

⁵⁶ See Torriti (2017), p. 43.

⁵⁷ See Muratori et al. (2013b), p. 471.

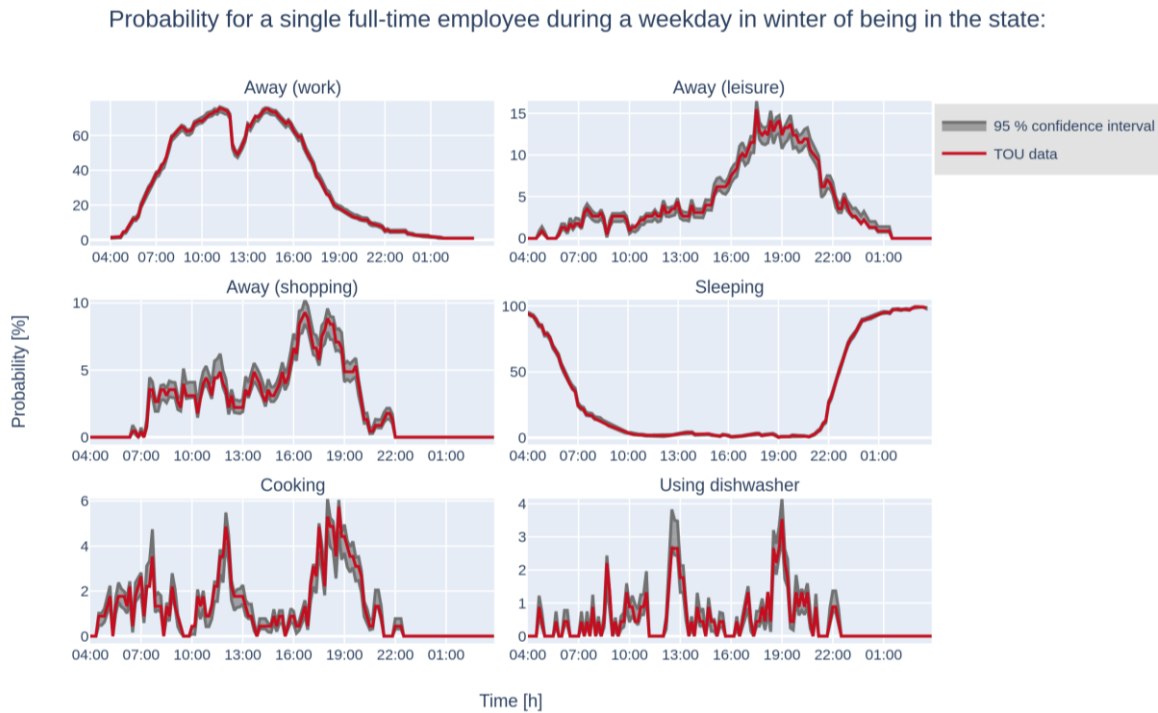


Figure 5: 95 % confidence interval for exemplary activities as a function of time [h] from the simulated activity profiles and the mean value calculated from the original time use survey data. The complete set of activities can be found in appendix B.

Figure 5 shows that the chosen first-order Markov-chain approach is able to correctly reproduce the characteristics that can be observed in the time use survey. While this holds true for an aggregation of activities across a number of households (also shown in Figure 4), the Markov-chain approach exhibits shortcomings to reproduce behavioral patterns for *individual* households: residential activity patterns normally follow a regular routine, recurring in time and space. This is one of the main reasons why electricity demand peaks normally occur during the same time for the same day type.⁵⁸ Due to its stochastic approach, the model is well capable to generate reliable and plausible load profiles for *a number of* households but lacks the ability to reproduce realistic characteristics of an *individual* household, which is in line with findings by Flett and Kelly (2016), Bottaccioli et al. (2019) and Wilke (2013).

Recent efforts are therefore focusing on the improvement of the accuracy of social behavior modelling by developing semi Markov-chains⁵⁹. However, the advantages of using these techniques are less conclusive and are also not capable of capturing repetitive behavioral patterns that characterize human behavior.

To summarize, there is still no established model in the literature as best practice for modelling human behavior. Each model has its strengths and weaknesses. According to Flett and Kelly (2016)⁶⁰, variations about the mean within limits can be accepted as long as the model is capable of reproducing the broad occupancy characteristics.

4.2 Validation of the load profile generator

In this section, the outcome of the residential power demand model is compared against measured load profiles and synthetic historical profiles by exploiting two data sets. First, aggregated load profiles have been provided by Stromnetz Berlin GmbH (SNB) and second, the available data set published by

⁵⁸ See Torriti (2017), pp. 37.

⁵⁹ For example, see Bottaccioli et al. (2019).

⁶⁰ See Flett and Kelly (2016), p. 222.

the University of Applied Science for Engineering and Economics Berlin (HTW)⁶¹ is used. While the first data set provides aggregated consumption patterns for 121 households in 15-min resolution for each day in 2018, the latter one includes individual synthetic historical load profiles in 1-sec resolution for 74 German households, covering an electricity demand for a one-year period in 2010. Due to the limited number of benchmark profiles, the following validation chapters are of indicative rather than exhaustive character.

A widely applied and utilized approach for validating results is to check whether the simulated aggregated electricity demand depicts statistical characteristics of the benchmark profile.⁶² Since the energy demand between individual households varies widely, error bars showing the minimum and maximum value for each time step are presented in order to assess the dispersion around the mean value.

Both data sets do not provide any information regarding socio-demographic factors of the measured households. As a consequence, the aggregated SNB data set can only be used for validation, after load profiles have been normalized for comparison. From the HTW data set, two synthetic load profiles have been chosen as they might belong to one-person households based on their annual electricity consumption⁶³.

To enable comparison, an average load profile is generated for a sample of single-person households, which accounts for an average weighting of employment derived from Microcensus Germany in 2018. The simulated weighted profile is then compared to both, the SNB and HTW profiles. Additionally, a sample of 121 full-time working households has been generated and is compared against the HTW data set, as the benchmark profiles appear to correspond to full-time working households. Due to space limitations, the illustrations for comparison with the HTW data set can be found in appendix C.

4.2.1 Annual and Average Monthly Electricity Demand

Table 3 demonstrates that the average annual electricity consumption for the simulated households is on a par with the average demand observed in the HTW profiles. Minimum and maximum value, however, scatter more widely around the mean value.

	HTW profiles	Weighted profiles	Full-time profiles
Avg. demand [kWh/y]	1622	1711	1468
Min. demand [kWh/y]	1398	1216	1060
Max. demand [kWh/y]	1847	2637	1857

Table 3: Comparison of average annual electricity demand between the simulated and synthetic HTW households.

Figure 6 shows the mean daily load per month. Both, the SNB and HTW benchmark profiles, clearly show a seasonal trend in demand as consumption increases during winter and decreases again over summertime. Seasonal differences can also be observed in the simulated load profiles but differences in consumption are less pronounced. This tendency, however, is compensated over the months, which is reflected in the similar annual electricity consumption.

4.2.2 Average Daily Electricity Demand

One aspect that often determines the integrity of a model is its capability to reproduce the peak load that can be observed in the benchmark profile.⁶⁴

Figure 7 (and Figure 15 in the appendix C) indicate that the model is capable of well reproducing the overall shape that characterizes the diurnal development in the benchmark profiles.

⁶¹ See Tjaden et al. (2015), pp. 1.

⁶² See Ramirez-Mendiola et al. (2017), p. 122; Hauser (2013), p. 192.

⁶³ See Energy Agency North Rhine-Westphalia (2015), p. 6.

⁶⁴ See Nijhuis et al. (2015), p. 4.

Average daily electricity demand per month in 2018

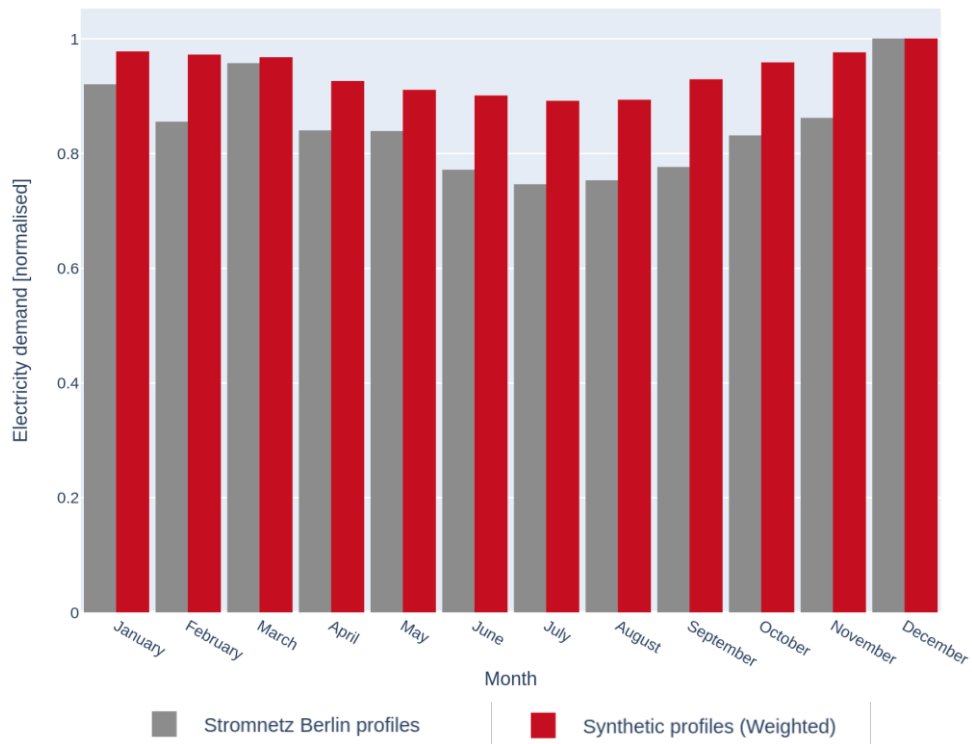


Figure 6: Comparison of daily average demand per month for the synthetic households and the SNB data set.

Synthetic and Stromnetz Berlin load profiles for each day type during winter in 2018

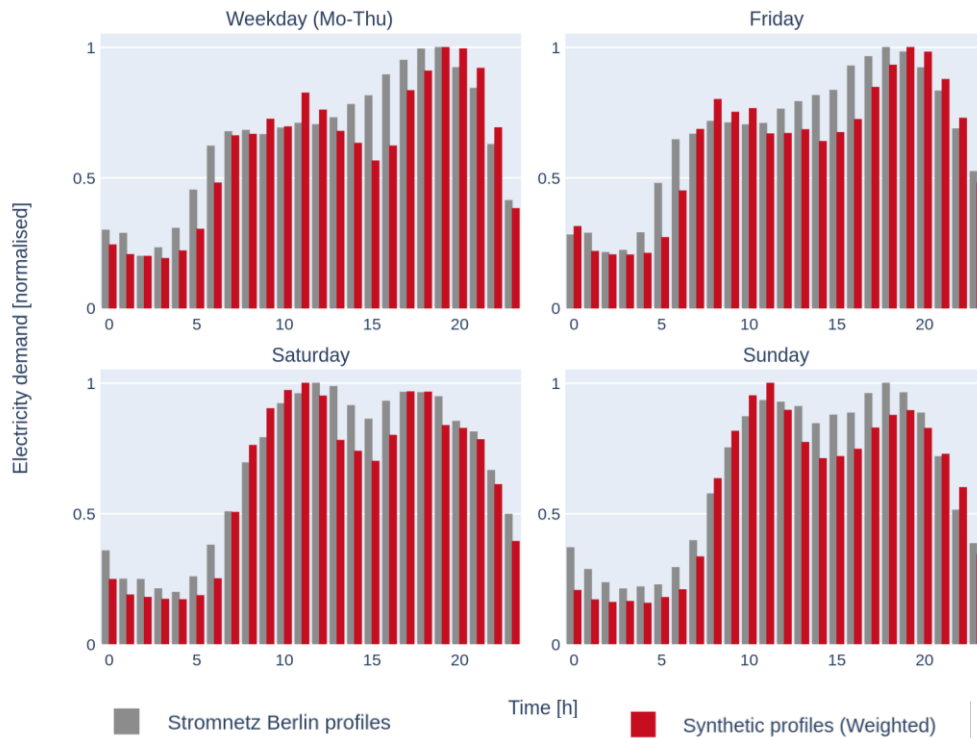


Figure 7: The figure shows the synthetic and SNB load profiles for each day type during winter. Weighted load profiles have been generated for comparison.

Regardless of socio-demographic attributes of the households, during night, consumption is mainly determined by the base load of the stock appliances. While for full-time working households, consumption increases during morning hours but decreases as soon as the resident leaves to go to work, DOI: 10.5281/zenodo.3689339

consumption within the weighted sample further increases and reaches its first peak around noon. The rise in consumption can mainly be attributed to the use of kitchen appliances, which has been further analyzed by breaking up the aggregated profile into the individual demand profile of the appliances. All profiles show increased consumption patterns during the evening hours as people return home and start preparing food or watch television. The consumption of full-time employed households in the evening is lower than the consumption for the weighted sample, which is in line with Bottaccioli et al. (2019)⁶⁵ who mention that full-time employed residents sleep most of the time, when being at home. Regardless of resident type, consumption decreases in the late evening hours since people start going to bed and thus, stop using appliances.

Consumption patterns on Friday increase earlier during the afternoon and peaks during the evening are higher compared to other working days. These observations endorse the decision to distinct between different working days. For Saturdays and Sundays, average demand over the day is higher compared to working days, which is in line with findings from Chuan and Ukil (2015)⁶⁶ and Paatero and Lund (2006)⁶⁷. Comparing working with weekend days also shows that the increase in demand during morning on Saturday and Sunday is shifted backwards, indicating that people sleep longer on weekends.

While the model reproduces the timing of higher consumption that can be observed in the benchmark profiles, it fails to reproduce the height of the peak load. During winter, the model appears to underestimate the morning and evening peak load compared to the HTW profiles. During summer, only the morning peak is underestimated. Due to normalization of the load profiles from SNB, only the daily course can be compared but not the actual demand. Even if the maximum load time is identical to the compared profile, the actual consumption can still vary considerably. The comparison suggests, that the base load and the morning peak are slightly underestimated by the model.

4.2.3 Total Annual Demand for Individual Appliances

Next, the share of electricity demand of the stock of appliances is evaluated and presented in Table 4. For comparison, the values listed in EA-NRW from Energy Agency North Rhine-Westphalia (2015)⁶⁸ are used. For a visualization of appliance-specific load profiles, see appendix D, Figure 16.

Category	Average EA-NRW [%]	Weighted profiles [%]	Full-time profiles [%]
Office equipment	17.95	12.67	13.37
Entertainment	14.68	10.96	12.17
Laundry (incl. drying)	6.53	9.31	9.87
Fridge	17.78	17.17	20.26
Lighting	10.74	16.10	15.97
Cooking	11.07	15.8	12.11
Pumps	5.80	5.44	5.97
Dish washing	2.81	5.3	3.79
Freezer	3.06	1.17	1.36
Other	9.58	6.08	5.20

Table 4: Average share of domestic electricity demand by category for a one-person household, without hot water preparation. Numbers taken from EA-NRW Energy Agency North Rhine-Westphalia (2015).

As the comparison suggests, annual energy demand for almost all devices is in range with the statistical data. Some categories, such as *Office equipment*, however, clearly deviate from the values reported in the survey. This can be explained by the fact, that only demand for PCs and routers but no other

⁶⁵ See Bottaccioli et al. (2019), p. 11.

⁶⁶ See Chuan and Ukil (2015), p. 4.

⁶⁷ See Paatero and Lund (2006), p. 275.

⁶⁸ See Energy Agency North Rhine-Westphalia (2015), p. 12.

devices such as printers and smart phones have been considered. Further adjustment of the lighting model is necessary to match with the statistical characteristics reported from German households. Stand-by electricity consumption of all appliances is 24.53 W on average, which is in line with Fischer et al. (2015b)⁶⁹ and corresponds to an annual share of around 12 %. Hence, the model captures stand-by consumption quite well.

4.2.4 Final Discussion of the Residential Power Demand Model

Validation has shown that the model is capable of reproducing annual electricity demand, the patterns of daily load profiles and the timing of peak loads. As mentioned above, robust patterns can only be reproduced if the number of simulated households is sufficient.

While the individual load profiles in the HTW portfolio show a regular occurring pattern of energy demand, meaning that peak loads always occur around the same time during the day, the synthetic load profiles generated for individual households are likely to deviate. This can be traced back to the stochastic Markov-chain approach. Using a semi-Markov-chain might help to mitigate this issue. However, as long as the number of simulated households is sufficient, the stochastic first-order Markov-chain is well able to generate reliable synthetic load profiles.

Besides the characteristics mentioned above, the model also generates mean daily load profiles that reflect seasonal variation in demand. However, the differences between summer and winter months could be more pronounced. Li et al. (2018) compare the results for a monitored data set for residential customers to the synthetic load profiles that have been generated by the model of Richardson et al. (2010) and come to the conclusion, that this trend is also underestimated in the synthetic load profiles generated by the model. It is therefore suggested that the property of underestimating seasonal trends can be attributed to the chosen modelling method, as the electricity consumption is almost exclusively determined by the behavior of the residents.

Hence, seasonal variation in electricity consumption can only be traced back to differences in activity patterns. According to Klingler et al. (2016)⁷⁰ the evening consumption in wintertime is higher compared to summer. This seems valid due to short daylight hours and presumably more indoor activities. The HTW profiles emphasize this tendency. For the simulated load profiles, however, the increase barely exists. Investigating the activity patterns shows that they do not significantly differ between seasons. The only seasonal effect that is reflected is an increased energy demand due to lighting, which depends on the solar irradiance outside the dwelling. However, results by Li et al. (2018)⁷¹ suggest that lighting is not a key driver that influences seasonal variation. Thus, beside the modelling approach, the use of the TOU survey data 2012/2013 might be accountable to some degree.

As behavioral patterns are characterized by daily routines regardless of season and as indicated in the benchmark profiles, it is suggested that seasonal differences in demand are not caused by changes in general daily routines, but rather by extraordinary events. This assumption is supported by findings of Li et al. (2018), who show that lower demand in summer coincides with the holiday season, leaving many houses vacated during this period. McQueen et al. (2004)⁷² also note that holiday periods must be considered when modelling energy demand of residential households. Diaries obtained within national surveys, however, do not include these extraordinary events since they aim to describe daily routines of the interviewees. Furthermore, national events such as Christmas or weather fluctuations

⁶⁹ See Fischer et al. (2015b), p. 175.

⁷⁰ See Klingler et al. (2016), p. 6.

⁷¹ See Li et al. (2018), p. 299.

⁷² See McQueen et al. (2004), p. 1689.

can both alter social behavior dramatically but are also not fully captured within these surveys.⁷³

Due to intra-group variation, a comparison between households with the same number of inhabitants and the same level of employment is only possible to a limited extent.⁷⁴ It is therefore argued that social behavior is likely to be influenced by further factors. According to Liu (2018)⁷⁵, household income in particular has a strong influence on energy demand, as a higher income allows the purchase of more electrical appliances as well as a more generous and modern housing situation. Considering these attributes when calculating the transition probabilities in the Markov-chain could, however, be associated with a further decrease of available observations for each sub-class. This increases the potential of non-realistic activity patterns and has already been discussed in Section 4.1.

Compared to both profiles, the model tends to underestimate the resulting morning and evening peak loads. It is suggested that the deviations can partly be explained due to the absence of additional office or cooking devices that might be used simultaneously in reality. Since bottom-up approaches require exhaustive amounts of data, the probability of missing appliances is likely.⁷⁶ The morning peak might result due to an increased usage of kitchen appliances, but also electric hot water preparation. The lower demand during evening hours in winter could stem from the absence of electric heating. Another reason could be that residents tend to spend less time outside during evening hours in winter time compared to summer evenings as suggested by the TOU data and therefore, use their electric devices, e.g. for cooking more intensively. In addition to missing appliances, Ji et al. (2018)⁷⁷ mention that underestimation of the mean load profile can also be partly explained by the restriction of available appliances per type, which, in the simulation, is either one or zero. This restriction cannot be observed in reality, especially in multi-family houses. According to Fischer et al. (2015b)⁷⁸, deviations also result from different power consumption values of the individual devices. Even if variability between households, due to a selection of different device models (such as TVs), has been considered, differences can hardly be projected holistically within one model.

To summarize, for further implementations, extraordinary activities such as holiday seasons need to be considered in order to model seasonal variation more precisely. Moreover, electric hot water preparation and space heating should be implemented in the model. General conclusions based on the observations from both data sets should be treated with caution, since, both data sets do not provide information regarding socio-demographic properties and stock of appliances of the households.

The results in this chapter, however, indicate that the bottom-up approach yields plausible results and thus can be used in order to model electricity demand profiles for the residential sector.

5 Conclusion and Outlook

5.1 Conclusion

In this work, a bottom-up model has been developed, that simulates holistic electricity load profiles for individual residential buildings in Germany based on the behavior of the residents. Since human behavior is not deterministic, a stochastic modelling approach is chosen and synthetic activity patterns are generated, by using a heterogeneous first-order Markov-chain. The model has been calibrated with TOU survey data for Germany, obtained by the Federal Statistical Office in 2012/2013⁷⁹. The model

⁷³ See Paatero and Lund (2006), pp. 275.

⁷⁴ See Pflugradt and Muntwyler (2017), p. 4; Bottacciolo et al. (2019), p. 2.

⁷⁵ See Liu (2018), p. 11.

⁷⁶ See Labeeuw and Deconinck(2013), p. 1561.

⁷⁷ See Ji et al. (2018), p. 298.

⁷⁸ See Fischer et al. (2015b), p. 178.

⁷⁹ See RDC of the Federal Statistical Office and Statistical Offices of the Länder (2014).

takes into account variation in behavior of the residents due to socio-demographic characteristics such as household size and occupation. Temporal resolution is addressed in the model by generating activity sequences for different weekdays and seasons. Different technical parameters of appliances are implemented to allow for variability between the simulated households. Real data obtained during measuring campaigns or taken from national statistics are used in order to simulate the characteristics of average German households.

To assess the validity of the developed model, an in-sample validation was conducted by comparing the synthetic activity patterns to the behavior observed in the time use survey. The generated activity patterns prove the capability of the model to reproduce the underlying behavior that is observed in the original data. The results indicate that socio-demographic factors such as household size, occupation of the residents as well as the day of the week are all key factors that influence social behavior. Seasonal variations can also be observed but have a rather small impact.

Furthermore, the generated synthetic load profiles have been validated by comparing the outcome with real measured electricity consumption, historical synthetic load profiles and national statistics. The model succeeds to generate realistic electricity load profiles which reproduce statistical average annual consumption, seasonal and diurnal variation, overall patterns of daily consumption as well as timing of peak loads which characterize residential energy consumption. While the first-order Markov-chain methodology is not capable of reproducing reoccurring behavioral patterns for *individual* households, the results demonstrate that the methodology is well capable of reproducing *aggregated* activity patterns observed in national surveys and related energy consumption. Concerning the underlying activity profiles of the German time use survey, the model results indicate that survey representativeness could be affected due to the comparably small sample sizes. In view of the forthcoming new edition of the time use survey in Germany 2021/2022, the authors recommend to cover a larger population and incorporate spatial information, i.e. where and in which locality certain activities have been performed. This has been part of previous studies and will particularly be helpful with regard to the transportation model, which will be further introduced in a future study.

5.2 Outlook

The comprehensive investigations carried out within this work have obtained several conclusions, but also envisioned recommendations for the further methodological development of the model, which have been indicated in Chapter 4. In addition to the aforementioned model improvements, the developed bottom-up approach can easily be adapted to analyze the integration and the potential impact of emerging technologies. Examples range from the expansion of distributed technologies, such as electric vehicles, photovoltaic systems or heat pumps. In addition to that, future research could include potential impacts of demographic changes and efficiency gains on the grid infrastructure.

Moreover, modelling residential behavior not only allows for simulating the associated demand of energy, but also conveys implications for the demand of *energy services* (e.g. a fully charged electric vehicle or clean laundry at a specific point in time). This information can be of particular use for investigating the demand side management potential in the residential sector, further enhancing the energy system's capability to integrate fluctuating renewable energy sources. This includes conventional potentially flexible appliances, such as washing machines or dishwashers, but also charging stations for electric vehicles, potentially incorporating electrical storage capacities of a vehicle-2-grid technology. Furthermore, the inclusion of elasticity of energy demand data allows for a more detailed quantification of demand side management potential in relation to flexible load tariffs.

Given a further model extension, the above analyses can potentially be conducted for every region in Germany, as long as sufficient regional parameters are available.

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A. Appendix: Comparison of Activity Profiles

Probability distribution for a single full-time working person during winter

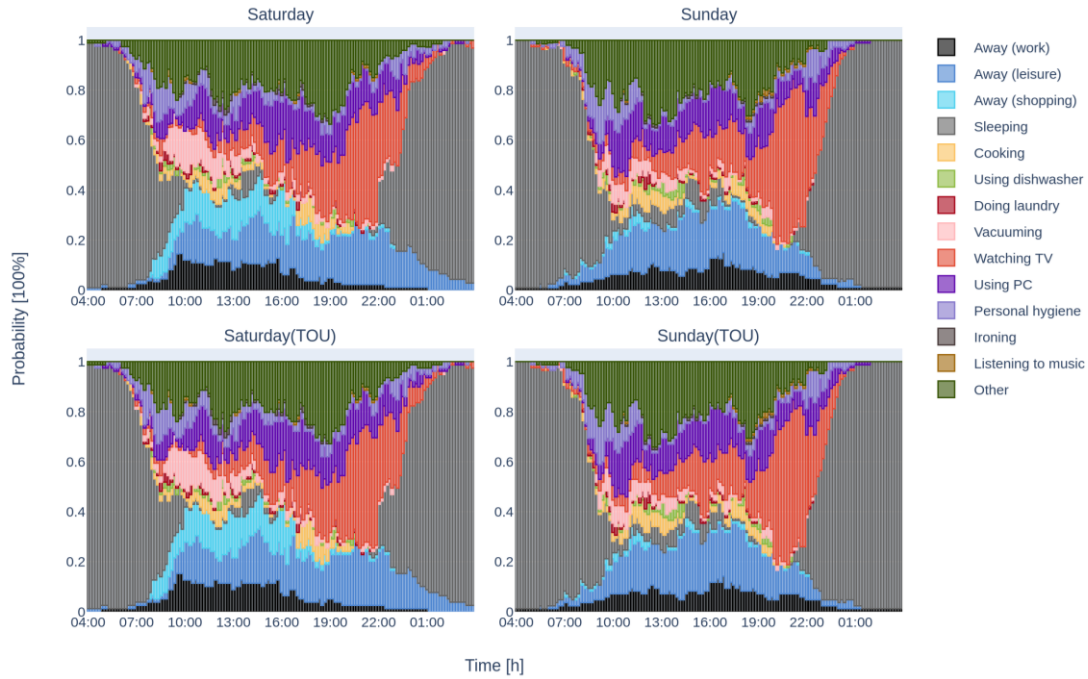


Figure 8: The figure shows the cumulative probability for each activity as a function of time for a single full-time working person. 4000 activity profiles for a Saturday and Sunday during winter have been generated. The lower figures show the probability distribution obtained from the original TOU data set.

Probability distribution for a single full-time working person during summer



Figure 9: The figure shows the cumulative probability for each activity as a function of time for a single full-time working person. 4000 activity profiles for a weekday (Mo-Thu) and Friday during summer have been generated. The lower figures show the probability distribution obtained from the original TOU data set.

A Probabilistic Modelling Approach for Residential Load Profiles

Probability distribution for single full-time working person during summer

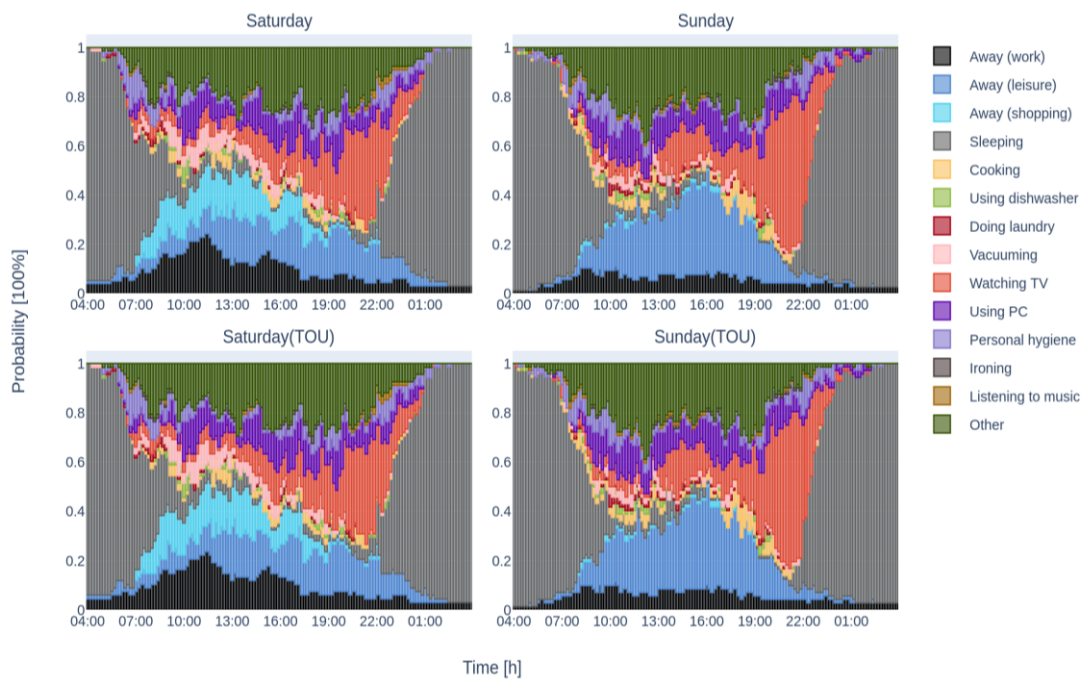


Figure 10: The figure shows the cumulative probability for each activity as a function of time for a single full-time working person. 4000 activity profiles for a Saturday and Sunday during summer have been generated. The lower figures show the probability distribution obtained from the original TOU data set.

Probability distribution for an unemployed person during summer

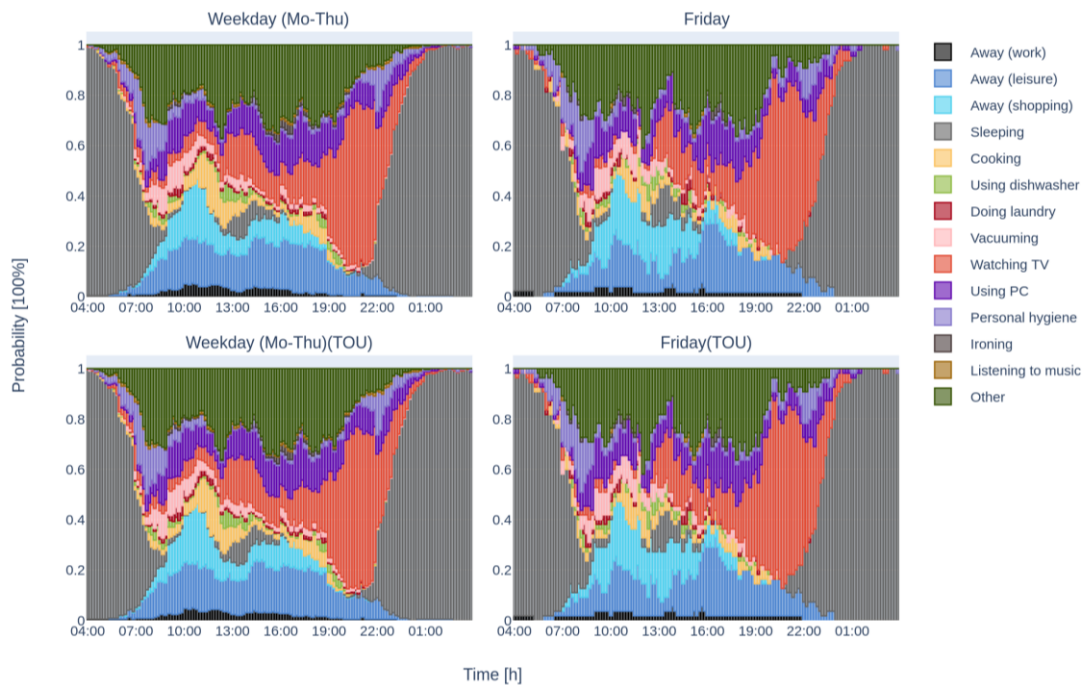


Figure 11: The figure shows the cumulative probability for each activity as a function of time for a single unemployed person. 4000 activity profiles for a weekday (Mo-Thu) and Friday during summer have been generated. The lower figures show the probability distribution obtained from the original TOU data set.

A Probabilistic Modelling Approach for Residential Load Profiles

Probability distribution for an unemployed person during summer

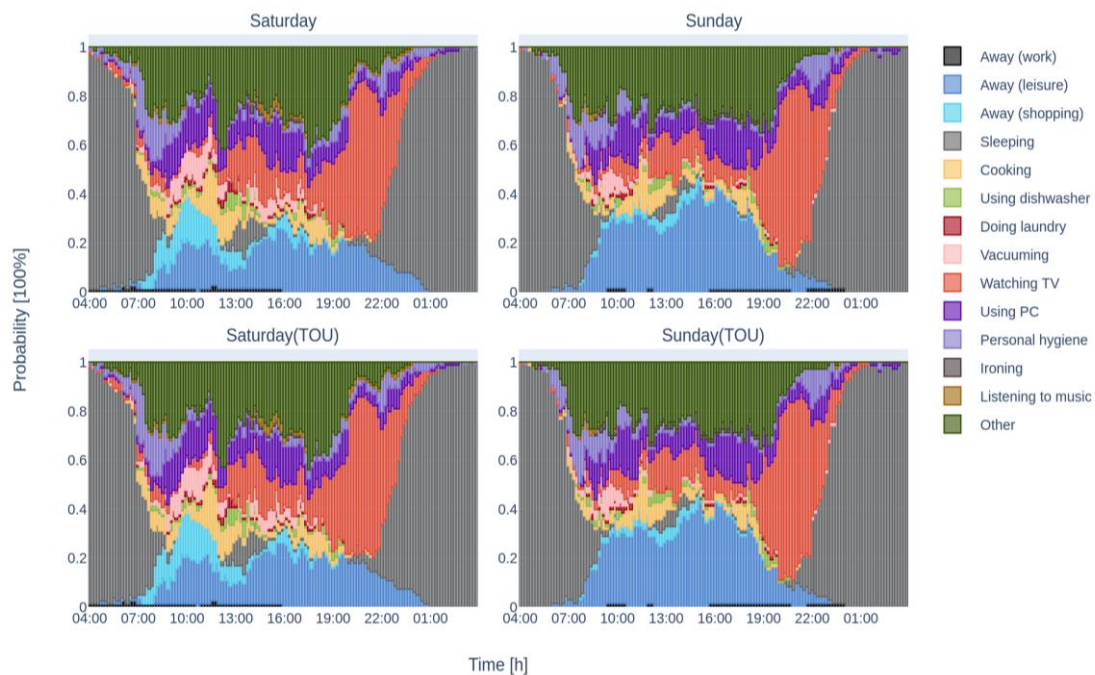


Figure 12: The figure shows the cumulative probability for each activity as a function of time for a single unemployed person. 4000 activity profiles for a Saturday and Sunday during summer have been generated. The lower figures show the probability distribution obtained from the original TOU data set.

B. Appendix: Results for the 95 % Confidence Interval of the Synthetic Activity Profiles

Probability for a single full-time employee during a weekday in winter of being in the state:

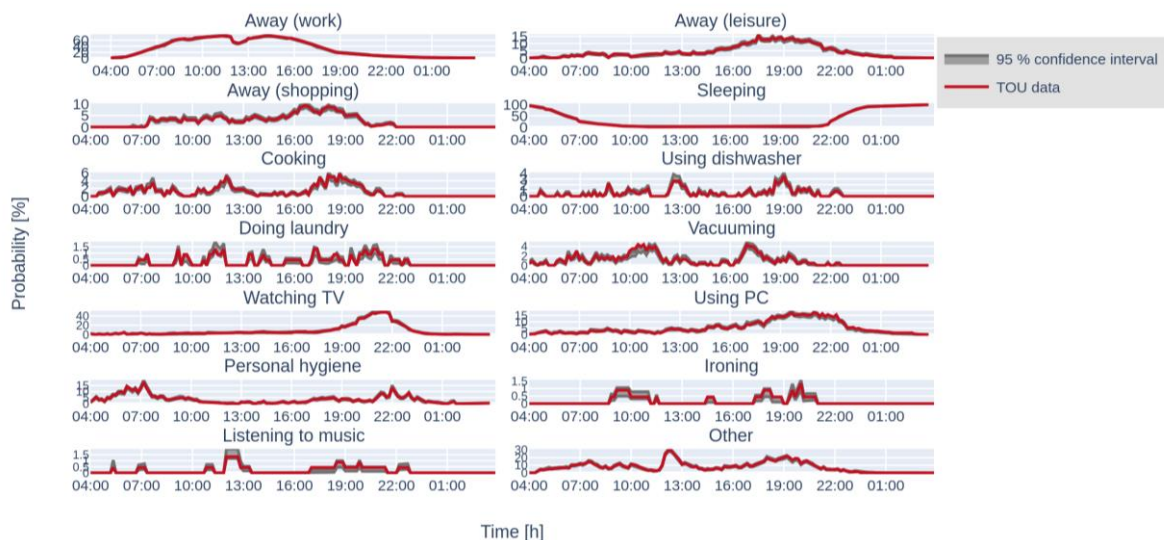


Figure 13: Mean value for each activity as a function of time. The red line shows the average value obtained from the TOU survey data, while the grey area is the 95 % confidence interval calculated from the synthetic profiles. Example is shown for synthetic activity patterns for a single full-time working person during a weekday in winter.

C. Appendix: Results for the Residential Power Demand Model

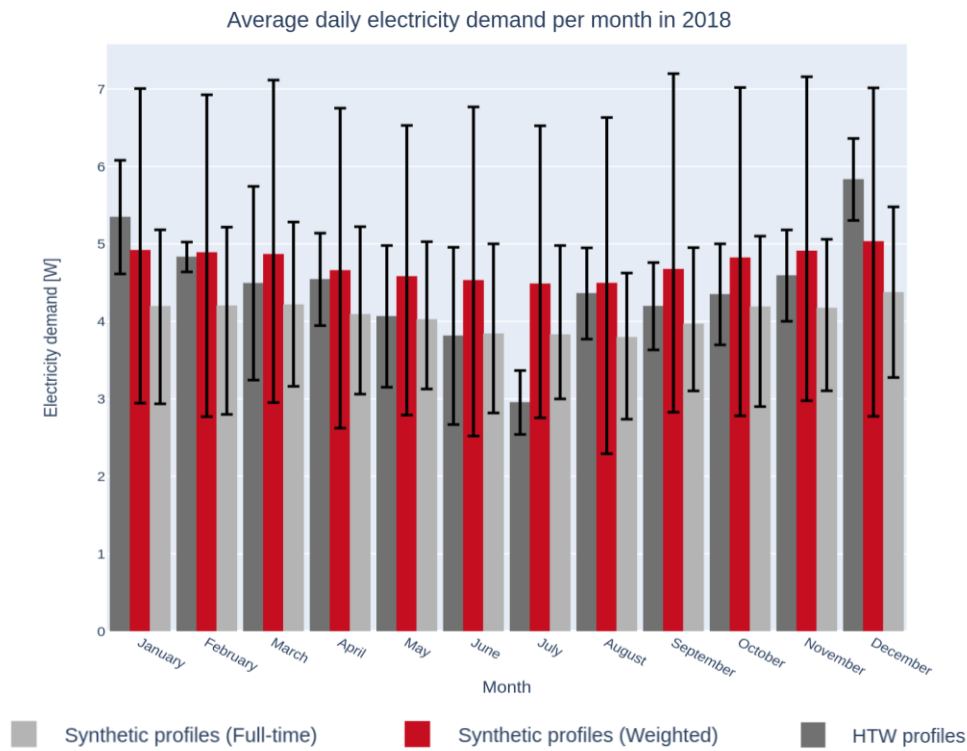


Figure 14: Comparison of daily average demand per month for the synthetic households and the HTW data set.

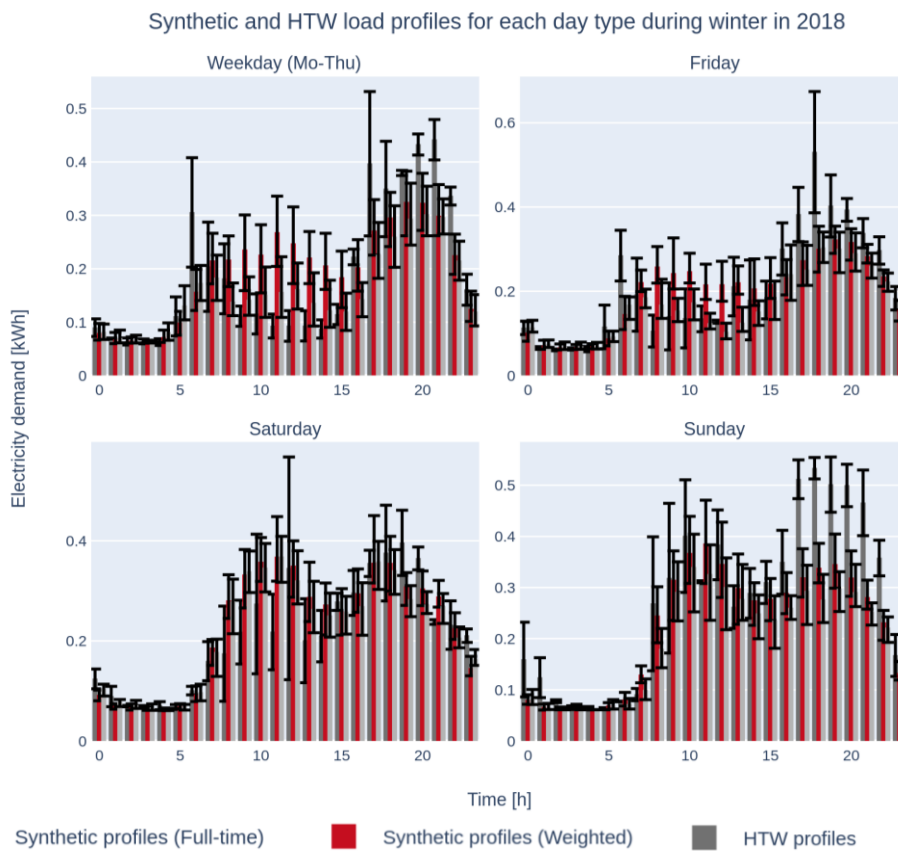


Figure 15: The figure shows the synthetic and HTW load profiles for each day type during winter. Weighted and full-time household load profiles have been generated for comparison.

D. Appendix: Synthetic Load Profile by Appliance Type

Full-time synthetic load profiles during winter with individual appliance demand

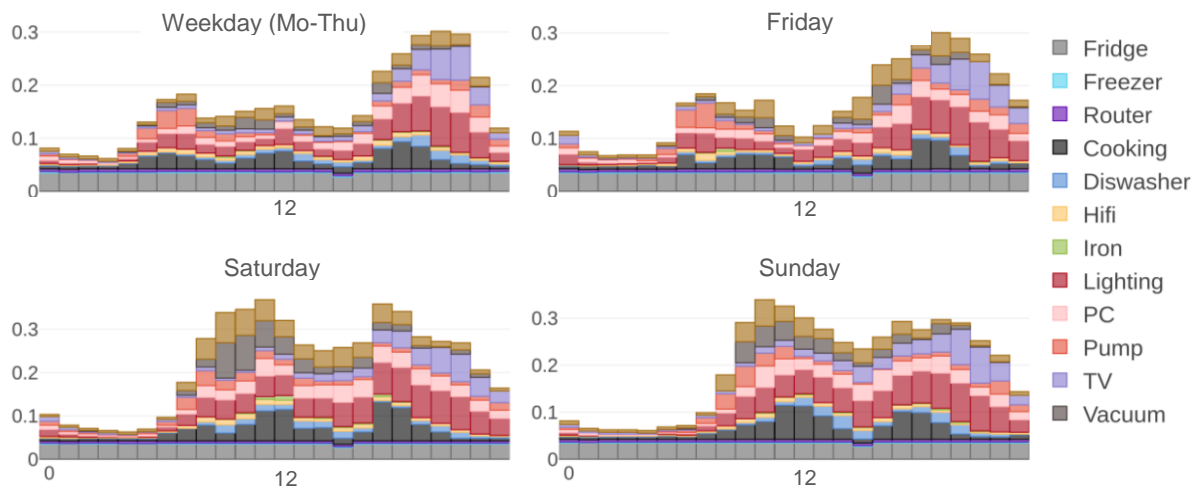


Figure 16: Average electricity consumption for the full-time working load profiles (normalized) by appliance share during winter