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Electricity load profiles in Europe: The importance of household segmentation

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ABSTRACT

In the current market design, the increasing use of renewable energy sources for electricity generation leads to new challenges in balancing supply and demand. While households are responsible for 29% of total electricity demand in Europe, a good understanding of their consumption and load profiles is missing. Similar to existing clustering methodologies from marketing science, this paper proposes an approach for the segmentation of households. The approach particularly focusses on the impact of socio-demographic factors and the equipment with electric appliances as well as new technologies for electricity and heat supply on residential load profiles. In addition to these three factors themselves, the dependencies between them are identified as crucial. Therefore, in order to adequately assess the future development of residential load profiles, on the one hand, a qualitative analysis of socio-demographic factors is carried out and, on the other hand, the influence of selected technologies is quantitatively modeled. Beyond the mere impact on households' annual energy demand, in focus of most existing research in the field, particular emphasis will be given to the peak load development, which is considered increasingly relevant for balancing supply and demand and maintaining security of supply.

1. Introduction

Many European energy systems are undergoing significant changes. The increasing share of renewable energy sources (RES) leads to more distributed and fluctuating power generation. From systems with a limited number of large players with conventional power plants being responsible for power generation, they move to systems where many small players participate in the market. Even households, formerly classic electricity consumers, nowadays take part in power generation through photovoltaic (PV) and micro-CHP (combined heat and power). Responsible for 29% of total electricity demand in Europe (cf. Fig. 1 [1]), households play an important role in future electricity systems as they provide an increasing share of power generation capacity and are at the same time an important electricity consumer. Nowadays, neither their generation nor their consumption are well controllable for external parties but they strongly influence the electricity system, especially in low voltage grids, to which they are attached. To enable electricity markets to cope with these upcoming challenges on a macro-, e.g., security of supply, and micro-economic level, e.g., capacity pricing, households' load profiles need to be better understood. Especially in Germany these effects can be observed due to the so called "Energiewende" (energy transition mainly based on RES). Additionally, the German government decided the nuclear phase-out until 2022 resulting in even less predictable power generation capacity [2]. Hence, potential solutions developed for Germany might become a role model for other countries and are in special interest of research.

Overall, electricity markets strive to a cost structure similar to today's ICT (information and communication technology) markets. In ICT markets, the single bite or phone call create only negligible variable costs while the investment in the required infrastructure, e.g., fiber optic cables and mobile transmission towers, are the key cost drivers. Consequently, most existing internet tariffs consist of a fix price component based on the chosen transmission capacity whereas the data volume is often for free, i.e., so called flat-rate tariffs. Obviously, in electricity markets flat-rate tariffs are undesirable due to environmental reasons. Moreover, the variable costs constitute a significant cost component in markets dominated by fossil power generation. Nevertheless, the variable costs of electricity generation constantly decrease in electricity markets driven by RES. Contrariwise, the investments in market

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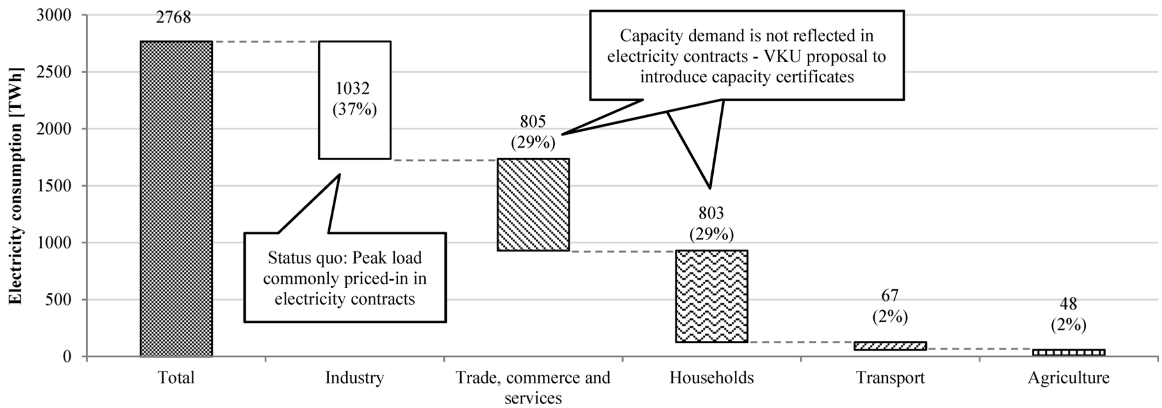

Fig. 1. European electricity consumption by sector, 2011 [1].

infrastructure, e.g., grid technologies, increase in order to ensure the required transport capacity from the many distributed generation sites to the consumers. In the existing "energy-only" market design in Germany's electricity market the pure availability of generation capacity is not rewarded, except from the share of flexible capacity traded at the balancing markets. With decreasing wholesale electricity prices and less operating hours of conventional power plants due to RES feed-in, covering the fix costs of conventional plants becomes more challenging. The profitability of those plants is at risk leading to the ongoing discussion on capacity mechanisms in Germany [3]. Besides capacity mechanisms, also means to increase demand flexibility are in focus of research, especially demand response[1] (DR), in order to decrease the peak load of the entire system aiming at a reduced need in conventional generation capacity [5]. For households, responsible for around 29% of Europe's electricity demand (cf. Fig. 1), currently discussed DR measures are, for instance, based on electricity tariffs with dynamic electricity prices (per kWh) with the purpose to shift or reduce load in times of high prices and increase demand in times of low prices. The technical load reduction potential of these measures in Germany's residential sector is estimated at around 6.7 GW on average [5]. If this technically available load reduction potential coincides with the peak load of a country, less installed conventional power plant capacity would be required to fulfill demand. Even if only one-tenth of the technical potential could be realized during peak load times, it may still substitute some smaller gas power plants. The use of new technologies for electricity and heat supply in households in the course of technological change and innovation may further alter the DR potential. Additionally, other forms of residential electricity tariffs, for instance, tariffs with variable capacity prices[2] (in kW) similar to industrial tariffs, can reveal further opportunities for load reduction. These tariffs can also help to increase overall system stability if households' demand can be reduced in critical peak times. To analyze the effect of those DR measures a better understanding of households' electricity consumption over time, i.e., their load profiles[3], especially in conjunction with the increasing penetration of new technologies, such as PV, micro-CHP and heat pumps, is required.

A recently published study of the German VKU (Verband kommunaler Unternehmen e.V.) proposes a new market design introducing a decentralized capacity market with capacity certificates. In this model, electricity contract providers are requested to purchase enough certificates to ensure the security of supply for their customers [6]. In industry tariffs, it is already common to include a price component for capacity. The VKU now suggests to extend this model to trade, commerce and services as well as to the residential sector in order to better predict the required market capacity (cf. Fig. 1). Therefore, electricity tariffs with variable capacity prices can be an adequate means to capture the individual level of desired supply security. A similar concept is discussed by Oren [7] who suggests electricity tariffs with different prices depending on the level of contracted service reliability. Based on such tariffs load reduction potentials can be realized in case of generation shortages as every customer can be restricted to its contracted level of supply security. This would increase the market's ability to balance electricity demand and supply. To enable households or intermediaries offering such kind of contracts to define the appropriate height of required capacity ensuring the desired level of supply security, households' load profiles need to be better understood. Besides the analysis of new tariffs as described above, a better understanding of household's electricity consumption is also required to evaluate the impact of changing consumer behavior or technological trends on low voltage grids or residential load management potentials [8].

In energy systems modeling, households are often represented with a standard load profile (SLP), e.g., the H0 profile of the BDEW (German Association of Energy and Water Industries), or based on guideline VDI 4655. As these profiles are based on historical data and do not reflect the ongoing changes they are only of limited usability for modeling and predicting load profiles of small samples or technological trends. However, the ongoing changes in electricity systems require to analyze more distributed and consequently smaller systems. Also new technologies like PV, e-cars or heat pumps will alter the electricity consumption of households (cf. Section 5). Hence, even in large samples the existing standard load profiles might not be appropriate anymore. A more detailed segmentation of residential electricity consumption enables a better reflection of future energy systems and allows for a wide range of related analyses, e.g., the need for grid expansion or load prediction for electricity markets, and might even be used for new load profiles [9]. Creating household segments based on replicable characteristics with comparable load profiles would help to better model households' electricity consumption. The development of these segments through the analysis of the influence of different

[1] Definition according to the U.S. Department of Energy [4]: "Changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized."

[2] The term "variable capacity prices" is used in this paper to describe the occurrence of different prices for different levels of secured capacity in households' electricity tariffs.

[3] A load profile represents the electricity use of a unit in watt, e.g., a household, a device or a plant, over time, e.g., in minutes, hours or days.

factors on residential electricity consumption and load profiles is the objective of this paper.

Market segmentation is a central element in marketing in order to identify consumers with similar needs and behaviors [10]. The idea of market segmentation goes back to Smith [11] who stated in 1956 that it is critical for companies to better understand their customers in order to cope with the diversity on the demand side. As shown above, this diversity is neglected in electricity markets when using SLPs to represent households' electricity consumption. Important determinants with regard to market segmentation are general characteristics such as socio-demographics and lifestyles but also situation specific characteristics such as product usage patterns and responses to new products [12]. Therefore, this paper analyses the effect of lifestyles, socio-demographic factors, electric appliances and new technologies for electricity and heat supply on households' electricity consumption and load profiles.

In doing so, we intend to contribute to several topics of interest in the context of energy research and social science [13]. The chosen approach considers the human dimension of energy use (human-centered research, social psychology and behavior) as well as the impact of new, evolving technologies for residential electricity and heat supply (R&D and innovation). The results of this paper can be used to derive appropriate means and mechanisms supporting the integration of RES and consequently belongs to the topic of politics and political economy.

Since the penetration of new technologies in households strongly depends on their socio-demographic characteristics, household segmentation and impact assessment of new technologies cannot be treated independently. Therefore, the analysis done for this paper combines these two parts. On the one hand, an extensive literature review was performed to identify key drivers influencing households' electricity consumption. On the other hand, the impact of new technologies for electricity and heat supply was modeled as there is little evidence in literature covering their impact on load profiles. The results will help to better understand and model energy systems even in small samples and could allow to create customer specific incentive schemes for households to change their consumption patterns influencing both, electricity consumption (kWh) and capacity demand (kW).

The focus of most studies reviewed for this paper lays only on households' total electricity consumption. Nevertheless, these insights are also valuable with regard to load profiles as total consumption is the result of the accumulated load profiles of households. Even though concrete conclusions on load profiles cannot necessarily be drawn, it is very likely that factors influencing total consumption also influence load profiles at some point. However, related literature is considered whenever possible and complemented with own thoughts.

In Section 2, the impact of lifestyles on households' electricity consumption and load profiles is reviewed, followed by the impact of socio-demographic factors (Section 3) and the equipment with electric appliances (Section 4). To illustrate possible effects of new technologies such as PV, micro-CHP and battery storage on households' load profiles, a model-based analysis is shown for a single family house (SFH) in Section 5. The modeling approach was chosen as hardly any literature was found covering this topic. The paper concludes with a proposal on adequate segmentation factors for households and an outlook on further research (Section 6).

2. Segmentation based on lifestyles

The idea of lifestyle segmentation is prominently used in the field of marketing communication and combines the two concepts of lifestyle patterns and market segmentation. First, lifestyle patterns are identified and then used to perform an in-depth market segmentation. A very common approach to identify lifestyle patterns is based on AIO surveys (activities, interests and opinions) [14].

Several studies already analyzed the interdependencies between lifestyles and electricity consumption [15–17]. They all have in common that they develop a certain household segmentation based on lifestyle clusters. Nevertheless, as every author analyses data collected with a different method, the resulting lifestyle clusters differ as well. In Otte [18] common shortfalls in lifestyle research are criticized based on a meta-analysis of various studies. To overcome these shortfalls Otte [18] developed a conceptual typology with nine lifestyle clusters but without a special focus on the impact of these clusters on electricity consumption.

Besides, the term lifestyle is used differently in various studies as no common definition of this term exists [19]. Consequently the concept of lifestyle segmentation is broadly discussed and regularly adopted to specific needs of research projects [20–22].

In all reviewed studies clear lifestyle clusters are identified by the authors, but still the impact of lifestyles on electricity consumptions remains vague [19]. The Austrian Energy Agency [23] even states that there is no significant difference of the annual electricity consumption per household or per person in the identified lifestyle clusters. Hauser et al. [24] refer in their study to Otte's lifestyle typology mentioned before [18]. Focus of their analysis is not the impact of lifestyles on total electricity consumption but on residential load profiles. The published findings conclude that different lifestyles do influence the load profile of the respective households. Nevertheless, in their explanation of the differences they rather refer to socio-demographic criteria like the age of the persons and the equipment with electric appliances in those lifestyle clusters. A proper distinction of the impact of lifestyles and underlying socio-demographic factors is not feasible.

Also other reviewed studies can only explain a very little part of the variance between households' electricity consumption by the use of lifestyle segmentation, attitudes and behaviors [19,25–27]. More often, only the impact of socio-demographic factors like number of persons per household and net income on households' electricity consumption occurs evident. Also the equipment with electric appliances seems to be more important as Sanquist et al. [17] identify usage patterns of television, air condition, laundry, PC, etc. as main drivers for electricity consumption in American households.

3. Segmentation based on socio-demographic factors

As already mentioned above, the impact of households' socio-demographic factors on their electricity consumption is described in various studies [23,26–29]. Almost all reviewed studies analyze only the impact on the electricity consumption in total and not possible effects on the load profile of a household. Only Yohanis et al. [30] directly measured the impact on load profiles; McLoughlin et al. [31] at least observed the impact of different socio-demographic factors on households' maximum load[4] and Kavousian et al. [32] analyzed the impact on selected features of the consumption data, e.g., daily average, minimum and maximum demand.

Table 1 shortly summarizes the incidence of different socio-demographic factors in the reviewed studies. The shown factors are not necessarily independent from each other but a separated consideration can make sense as they might add further insights

[4] The maximum load is the largest value of electricity demand in a specific period of time [31].

Table 1
Incidence of socio-demographic factors in reviewed studies and their impact on energy demand.

Research focus	Source	Criteria								
		Household size	Dwelling size	Income	Age of reference person	Employment status/occupancy	Education	Rural vs. urban housing	Ownership structure/Dwelling type	Other
Electricity, measured	Kavousian et al. [32]	+	+	-	+	+		+ Zip code	-	– Building age
	McLoughlin et al. [31]	+	+ No. of bedrooms	+ Social class	+	+ Social class[a]	–		+	+ Household composition
	STATISTIK AUSTRIA [28]	+	+		+	+	–	+	–	+ Year of construction
	Yohanis et al. [30]	+	+	+	+	+		+	+	+ No. of bedrooms
Electricity, survey	Austrian Energy Agency [23]	+	+	+	+		–	+		
	Gram-Hanssen [33]	+	+	+	–		–			
Electricity and heat, measured	Brandon and Lewis [26]	+		+	+				+	
Electricity and heat, survey	Abrahamse and Steg [29]	+		+	–					– Gender
	Gatersleben et al. [27]	+		+	–		–			
Electricity and heat, meta-analysis	Schipper et al. [15]	+	+	+	+	+			–	+ Family composition

+ = significant impact on energy demand; – = low to no significant impact on energy demand; Empty field = not analyzed.
[a] Employment status not evaluated individually due to high correlation to social class.

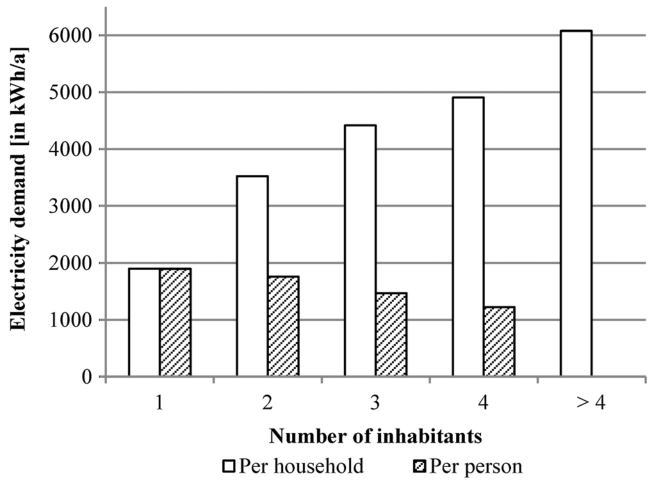

Fig. 2. Average electricity demand per household and per person for different household sizes in Germany, 2010 (cf. [36]).

to those studies. For instance, household size and dwelling size strongly correlate as bigger households normally occupy more rooms but the differentiation can be important for heat related energy consumption [23]. In some studies, different factors were used as substitutes as the preferred ones were not available from the data; McLoughlin et al. [31] for example use social class as an indicator for income because concrete data on income was not collected in the underlying survey. The evaluation of the shown criteria is mainly based on qualitative statements in those studies. A detailed overview of the statements can be found in the analysis report in appendix A.

The biggest impact observed in these studies is the size of a household, i.e., the number of persons living in a household, and the net income. Household size is the underlying scaling criteria in guideline VDI 4655, often used as a SLP, as well [34]. In the following, the findings from the literature review of the most significant socio-demographic factors will be presented.

3.1. Factor 1: household size

The most evident socio-demographic factor influencing household's electricity demand is the number of persons living in a household. All reviewed studies come to the conclusion that the size of a household is positively correlated with its total electricity consumption [15,23,26–33]. The number of people living in a household also has an impact on the number of available electric appliances, e.g., computers, TVs and fridges [35]. On the contrary, the specific electricity consumption per person, i.e., the total electricity consumption of a household divided by its size, decreases in bigger households (cf. Fig. 2). A single household uses more electricity per person than a four person household. This phenomenon can be explained by the fact that bigger households make use of home appliances like refrigerators, dish washers and washing machines more efficiently and that the electricity consumption for lighting, for instance, does not scale one-to-one with the number of persons [28,30,33].

Even though hardly any analyses on the impact of household size on the timing of consumption could be found, some hypotheses can be made. For instance, the load profiles of two and three person households look pretty similar, but the morning (7.00–9.00 a.m.) and evening peak (4.00–10.00 p.m.) become more pronounced with an increasing size [30]. Also the maximum load increases with the number of persons living in a household [31]. Additionally, the usage patterns of electric appliances should differ as washing machines, dish washers and TVs are used more frequently in bigger households, and the light is switched on in more rooms at the same time. These two effects should clearly increase the magnitude of the load profile which will in the long term result in higher electricity consumption as highlighted in the abovementioned studies.

3.2. Factor 2: net income

The second socio-demographic factor similarly evaluated amongst almost all studies is the monthly net income of households. With increasing net income, the consumption of electricity increases [29]. The Austrian Energy Agency [23] indicates that there is a positive correlation between net income and electricity consumption but with two limitations. First, the correlation exists only on a household level and not on the specific consumption per person and second, there seems to be saturation in electricity consumption above a certain level of net income.

Abrahamse and Steg [29] point out that household size and net income are positively correlated. In general, bigger households have a higher net income. According to their analyses, the main socio-demographic factor influencing electricity consumption in households is their size.

McLoughlin et al. [31] support a possible income effect on electricity demand stating that households with higher incomes – in their case represented by the social class – tend to have more electric appliances and consequently consume more electricity. This relation is also underlined by Kavousian et al. [32]; albeit no significant correlation between income and electricity consumption was found in the analyzed, from an income point of view rather homogeneous household sample, it is stated that higher incomes often come along with an increasing stock of electric appliances which results in higher electricity consumption.

From our point of view net income can have two opposite effects on total electricity consumption; higher available income allows to buy more electric appliances but also to buy more efficient appliances. Hence, the number of appliances increases the electricity demand but more efficient devices can reduce it.

A higher net income is often related to some other socio-demographic factors as well. For instance, the income often increases with the age – at least to a certain level – and is often influenced by the level of education [30,31]. A higher net income might go along with a fulltime employment which directly influences the load profile as the occupancy times are shifted toward the evening [30]. According to Yohanis et al. [30] the evening consumption of households with larger incomes is 2.5 times higher than average. This should be especially true for small households with high incomes while bigger households might still have peaks during daytime as children or other occupants might be at home.

A comparison of load profiles of households with different incomes points out that lower incomes come along with a rather constant consumption during daytime with only one peak at dinner time, while higher incomes show a clear morning and evening peak [30].

3.3. Factor 3: age of reference person

Another socio-demographic factor analyzed in several studies is the age of a household's reference person. The results regarding this factor differ amongst the reviewed studies. While most studies find a correlation between age and electricity consumption [23,26,28,30–32], some others do not confirm this [27,29,33].

According to the Austrian Energy Agency [23] and STATISTIK AUSTRIA [28], the specific electricity consumption of elderly people (youngest person in household above 60 years) is higher than the rest. Comparing the consumption on a household level, middle-aged households (reference person between 35 and 60 years) use most electricity. Reasons for these results can be derived from the family lifecycle. Elderly people, in general, spend more time at home as they do not have to leave for work or studies [28]. Consequently, they use more electricity for lighting and consumer electronics. Additionally, elderly people more often live in single households so the specific consumption per person is higher (cf. Section 3.1) [28]. Besides, younger households tend to have more modern and energy efficient household appliances, which lower electricity consumption. The highest consumption of middle-aged households on a household level can be explained by the fact that middle-aged households have the biggest share in non-single households. Hence, the higher electricity consumption follows from their size (cf. Section 3.1) [28]. Additionally middle aged households often have children living at home which also results in higher electricity use [31].

Even though Gram-Hanssen [33], Abrahamse and Steg [29] and Gatersleben et al. [27] do not observe similar effects in their studies, the rationale described by STATISTIK AUSTRIA [28] is plausible. Differences in the observations of the studies can have various reasons like size and characteristics of the sample.

The impact on the load profile is difficult to predict but is probably rather related to the family lifecycle than to the age itself. For instance, McLoughlin et al. [31] prove that the maximum load is influenced by household's composition which also depends on the age of the inhabitants – a family has a higher maximum load than an adult single household. Yohanis et al. [30] and Kavousian et al. [32] explain the differences in load profiles for different ages with reference to the occupancy times of households that often base on the employment status.

3.4. Factor 4: employment status

The electricity use of households differs considerably depending on their occupants' employment status. Households without an employment, i.e., retired persons, students and unemployed persons, have the highest electricity consumption in the reviewed studies, followed by households of self-employed persons [28]. Salaried employees and public servants have roughly the same electricity consumption while workers have the lowest [28].

As the employment status directly influences the net income of a household, one reason for differences in electricity consumption can be derived from this. Households with better paid employments have a higher net income and thus use more electricity (cf. Section 3.2) [31].

Additionally, the time spend at home varies significantly between different employment status. Household members without an employment spend more time at home and consequently use more electricity for lighting and consumer electronics. According to STATISTIK AUSTRIA [28] households without an employment have the biggest share in single households which is another reason for higher electricity consumption (cf. Section 3.1).

A possible reason for the higher consumption of self-employed persons might be that self-employed persons work at home more often than others. Hence, they spend more time at home using electricity and might even have more office equipment like printers, servers or copying machines at home. Of course this is not valid for all self-employed persons as they might have dedicated business or office space outside their residential buildings.

The different occupancy times depending on the employment status also impact the load profile of a household. Households with all occupants at work or at school show a high peak in the morning and in the evening [30]. The typical lunch peak in standard load profiles should not occur in most households with fulltime employees as lunch is normally taken at work. Having that said, a load shifting toward the evening is observable as washing machines and dish washers are used more often after work [30]. The morning peak can be explained through showers using electricity to produce warm water and the preparation of breakfast [30].

3.5. Other socio-demographic factors

Besides the beforehand described factors, several others were analyzed by different authors. For instance, in [23,27,28,31,33] the impact of the educational level of the surveyed reference person on the household's electricity consumption was analyzed but none of the studies identified a significant correlation between these two variables.

Some authors additionally looked into the effect of the location where the household lives [23,28,30]. STATISTIK AUSTRIA [28] distinguishes between rural and urban areas based on the population density of Austrian provinces. The Austrian Energy Agency [23] makes a more detailed distinction based on the population size of Austrian cities. Both see a slight decline of electricity consumption in households in more urbanized areas. This thesis is supported by Yohanis et al. [30], stating that homes in the countryside have a much higher daytime demand – a possible explanation according to their studies is the existence of farms with higher occupancy times during the day and an active business.

Albeit dwelling size and type was analyzed separately in some studies, they will not be reviewed in detail here. The dwelling size is strongly correlated to the household size [23] so its effect is already covered. Additionally, larger households in general inhabit larger dwellings which also affects the dwelling type at some point. The bigger the dwelling or respectively the household size, the more likely it is that the dwelling is a house and not an apartment. Also other variables like number of bedrooms – used by Yohanis et al. [30] and McLoughlin et al. [31] – are, in our opinion, less suitable than household size. The number of bedrooms strongly correlates to the number of persons living in a household [31] and thus household size is the determining factor.

Some studies refer to some more socio-demographic factors, e.g., year of construction or ownership structure of residential buildings [28,30], but as those factors have only a minor impact on the electricity consumption of households – or are also reflected by other mentioned factors – they are excluded from a detailed description in this paper.

3.6. Summary on socio-demographic factors

The review of several studies shows that there exist socio-demographic factors influencing households' electricity consumption. The studies are able to explain about one third of the variance in electricity consumption between different households [27,29,33]. Consequently, two third of the variance cannot be explained. Nevertheless, socio-demographic factors prove to be better qualified then lifestyles to predict households' electricity demand [23]. The impact on households' load profiles was hardly analyzed in former research.

Summing up the findings on socio-demographic factors, the most important ones seem to be household size, net income and employment status. We do not suggest considering age in a segmentation approach due to the reasons stated before (cf. Section 3.3).

As some factors influence the characteristics of others and vice versa, e.g., the relation between net income, age, level of education and employment status, it might make sense to construct family cycles as seen in [15]. The author distinguishes between singles, singles with children, couples, etc. These segments can be described by the mentioned socio-demographic factors and should show

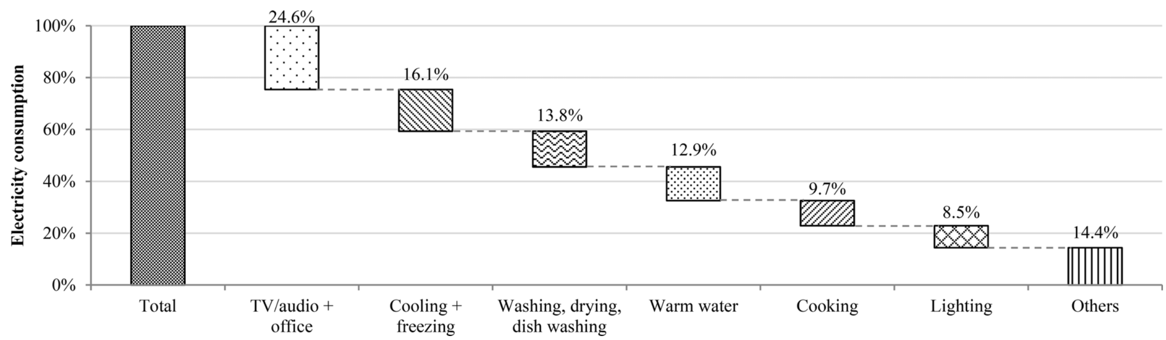

Fig. 3. Electricity consumption in German households by application type, 2012 [44].

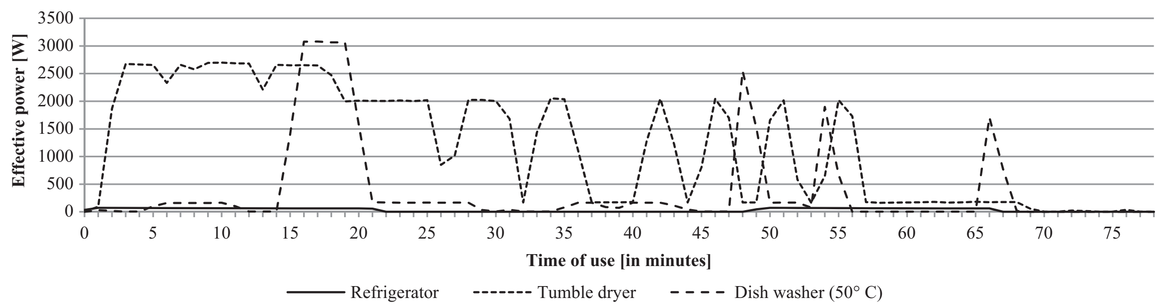

Fig. 4. Measured load profiles of an illustrative refrigerator (No-name, max. 90 W, year 2007), tumble dryer (Miele, max. 2850 W, year 2007) and dish washer (Miele, max. 2400 W, year 2007) – own measurements.

different load profiles as they should be characterized by different times of electricity use based on their work and family life. Additionally, the data required for such segments, e.g., household size and employment status, is widely available from public sources like federal statistical offices which facilitates a broader use.

4. Segmentation based on the equipment with electric appliances

Lifestyle and socio-demographic characteristics can partially explain the differences between households' electricity consumption, but the existence and use of electric appliances in households is the core of the resulting load profiles. This finding is underlined by the fact that bottom-up models for synthetic load profiles, which base their simulation on the use of appliances, provide very satisfying results. According to Gobmaier [37], his developed bottom-up load model achieved an R^2 value of 96.9% compared to measured load profiles. Therefore, appliances as a segmentation criterion will be reviewed in this chapter.

In general the use of electricity is not driven by the will to use electricity but to consume a service provided by using the related electric appliance, e.g., watching TV, washing clothes, or cooking dinner [38]. Hence, the number of electric appliances and their use correlates strongly with households' electricity consumption [31,33]. Consequentially, households' electricity consumption can be described through the type and number of electric appliances and their specific time of use [39].

As the pure existence of electric appliances does not necessarily imply electricity consumption, the user practices, sometimes called routines, are an important factor affecting households' electricity consumption. Unfortunately, these routines are only to some part determined by objective characteristics like socio-demographic factors of households. Gram-Hanssen [33] shows that the number of electric appliances and their type, e.g., their efficiency and size, is related to the net income of a household. Households with higher incomes are less reluctant to spend money on additional electric appliances, e.g., a second refrigerator, TV or entertainment system [31,33]. The employment status as well as household size strongly determine the time of use of an appliance as the likelihood of its utilization increases in general with a larger number of persons and the employment status affects the time spend at home allowing for the use of that appliance [39].

Various approaches exist to categorize appliances. Yao and Steemers [40] define five categories based on functional similarities, i.e., brown goods (electronic consumer goods), cold appliances, cooking appliances, wet appliances and miscellaneous appliances. Lünsdorf and Sonnenschein [41] differentiate between task-driven, user-driven and program-driven appliances. Task-driven appliances, e.g., dish washers, are used to perform a task at a given time; user-driven appliances, e.g., TVs, are used depending on user preferences and program-driven appliances, e.g., refrigerators, have to maintain a specific target state. Zeilinger and Einfalt [42] and Esslinger and Witzmann [43] use a very detailed categorization with up to eleven categories, e.g., lighting, cold appliances, dish washers, office appliances. With regard to this paper the best categorization has been done by Firth et al. [39] as their approach is based on use patterns and underlying similarities in the load profiles of the categorized appliances. As the objective of this paper is to identify reasons leading to similar load profiles on household level, the categorization of electric appliances according to their load profiles proves beneficial. The identified categories of Firth et al. [39] are:

- Continuous appliances: Continuously switched on with constant power consumption, e.g., broadband modems;
- Standby appliances: Actively switched on by household members but remaining power consumption when not in use, e.g., DVD recorder;
- Cold appliances: Continuously switched on with alternating consumption between zero and a set power level, e.g., refrigerator;

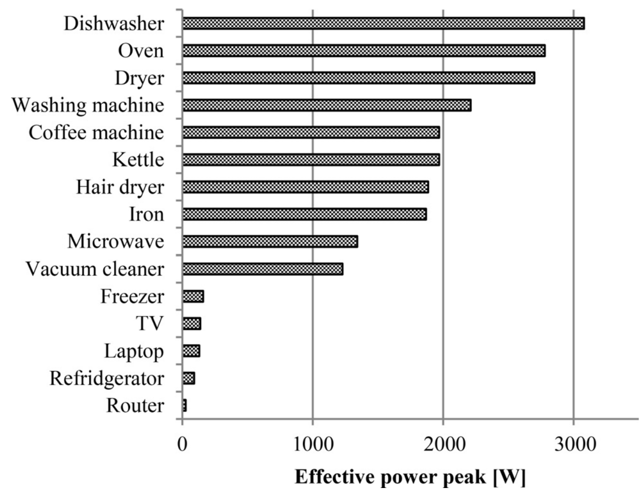

Fig. 5. Illustrative peak demand of selected electric appliances – own measurements.

- Active appliances: Actively switched on by household members but no power consumption when not in use, e.g., dish washer.

Based on this high level differentiation and their research, Firth et al. [39] state that the equipment of households, the number of occupants and occupancy patterns are important factors determining households' electricity consumption. The average split of households' electricity consumption by application type in Germany is shown in Fig. 3. Due to the high utilization time of computers, notebooks and TVs the cluster "TV/audio + office", belonging to active appliances, represents about one quarter of total electricity consumption. Additionally, many households possess more than one of these appliances at a time and even use them at the same time. According to the German Federal Statistical Office households own on average 1.6 TVs and 1.5 computers or notebooks [35]. Not surprisingly the next biggest electricity consumers in a household are appliances for "Cooling + freezing" (cold appliances), "Washing, drying, dish washing" and "Warm water" (active appliances). While the cold appliances produce such a high demand due to their high utilization time, the other two application types require high power peaks, mainly for heating purposes. This can be seen in the selected load profiles in Fig. 4; while the load profiles of the tumble dryer and the dish washer have very high peaks (active appliances with heating process), the refrigerator's load profile has a very steady, alternating consumption over the entire time with very low effective power demand (cold appliance).

Very important in terms of creating variances in load profiles and total electricity consumption between households are appliances with extremely high peak demand. Nowadays these appliances are mainly electric space heating systems, boilers for hot water, electric cooks and ovens as well as tumble dryers, washing machines and dish washers [31]. The peak demand of selected appliances is shown in Fig. 5. This is also a reason for the identified peaks at dinnertime and in the morning – most probably determined through electric showers and kitchen equipment [30]. While currently electric space heating systems play only a minor role in German households – only about 3.5% of German households use electric space heating systems [45] – in the future it is likely to detect new technologies having a huge impact on households' electricity consumption, e.g., heat pumps.

The findings of this section highlight that the equipment of households with electronic goods and their specific time of use, both depending on socio-demographic characteristics of a household, are the basis for residential electricity consumption and load profiles. Even though it seems difficult in practice to collect this information on household equipment, much statistical data regarding this topic is available from federal statistical offices. Nevertheless, electric appliances cannot be the only segmentation criteria for households due to the strong correlation to the socio-demographic characteristics of households. However, combining both approaches might lead to valuable insights. Moreover, the decision to adopt new technologies or technological innovations is also linked to households' characteristics [46]. Consequently, the impact of some selected technologies will be analyzed in the following.

5. Segmentation based on new technologies for residential electricity and heat supply

Upcoming technologies for electricity and heat supply on household level with the potential to significantly change households' electricity demand and load profile are mainly heat pumps, micro-CHPs, PV systems, batteries and e-cars (cf. [47–49]). In the heating sector heat pumps might become more common, resulting in a higher market penetration. Though their use might have a positive effect on primary energy use of households they will lead to an increasing electricity demand [50,51]. On the other side, micro-CHPs and PV systems might produce additional electricity that can be used in households directly. This effect is reflected by the introduction of the term "prosumer", i.e., electricity consumers equipped with new technologies producing electricity [52].

On the production side the increasing use of PV systems in households can change their electricity demand from the grid if more self-produced electricity would be used directly by the producing households. This leads to an increasing self-consumption as well as an increasing self-coverage of households[5]. In combination with storage systems, in this case batteries, it can even further change the load profile [48,53].

Last but not least, e-cars might change households' electricity consumption. Depending on their utilization in the power system they could act as batteries but could as well strongly increase households' electricity demand as well as their load shifting potential if they are recharged at home. In Germany, for instance, the objective exists to have around one million e-cars in the market by 2020 [54]. Assuming an annual mileage[6] of 15000 km one e-car would require around 3000 kWh per year[7] equaling almost the annual electricity consumption of an average German two person household (cf. [56]). The peak load of e-cars during the charging process depends on various factors like technical restrictions, e.g., the battery capacity, and the charging strategy and infrastructure, e.g., fast charging. Lunz et al. [57] calculated for different use cases loads between 0.7 kW and 170 kW. Due to this high variety of possible charging loads and the uncertainty of where e-cars will be charged – at home, at work or at public charging stations – a detailed consideration of the impact of e-cars on households' load profiles would go beyond the scope of this paper. We therefore focus on PV, heat pumps, micro-CHP and batteries. For further reading regarding the impact of e-cars please refer to Jochem et al. [49] for instance.

To illustrate the impact of the abovementioned upcoming technologies on households' total consumption and their load profile, a

[5] The term self-consumption describes the share of used self-produced electricity to total self-produced electricity. The term self-coverage is defined as the share of used self-produced electricity to total electricity demand of a household [53].

[6] The annual average mileage in Germany for a petrol-engine vehicle is 14,652 km [36].

[7] Assuming a consumption of 20 kWh per 100 km [55].

Table 2
Specifications of model elements used in PLEXOS® Integrated Energy Model.

Model elements	Specifications	Sources
Household electricity load profile (SLP)	Single family house 4950 kWh/a 1.83 kW_{peak} Hourly resolution	VDI 4655
Household heat load profile	Single family house 10,000 kWh/a 5.6 kW_{peak} Hourly resolution	VDI 4655
Local grid	Nominal capacity: 20 kW	Assumption
PV panels	Nominal capacity: 4.9 kW_{peak} Hourly resolution Generation profile of year 2011	Assumption
Battery	Capacity: 5.4 kWh Depth of discharge (DoD): 80% Charging efficiency: 90% Maximum charging capacity: 5 kW	Assumption
Heat pump with heat storage	Maximum nominal power consumption: 5 kW_{el} Coefficient of Performance (COP): 2–3 kW_{th}/kW_{el} Storage capacity: 10 kWh_{th} Storage loss rate: 1% per h	Assumption
Micro-CHP with heat storage	Nominal capacity: 1.7 kW_{el} Heat rate: 15 MJ/kWh Power to heat ratio: 0.3 Heat storage capacity: 10 kWh_{th} Storage loss rate: 1% per h	Assumption
Electricity tariff	Flat: 0.25 €/kWh	Assumption
Gas tariff	Flat: 0.07 €/kWh	Assumption

model was set up with PLEXOS® Integrated Energy Model[8] as only limited literature was found analyzing these effects. While the software is normally used for energy market modeling, e.g., electricity price forecasting or capacity expansion planning, it has been scaled down for this paper to optimize a single household. The basic functionalities of the software are described, e.g., by Drayton-Bright [58]. The model setup for our analyses and selected results will be presented in the following.

5.1. Model setup

The developed model is derived from a model developed by Bertsch et al. [59]. It is based on one single-family house (SFH) that is equipped with different technologies depending on the respective use case. The required electricity is provided by the local grid, own PV panels, a battery or a micro-CHP. If own electricity generation exceeds local demand, defined through guideline VDI 4655 [34], the electricity not used in the household is fed into the grid. The heat demand of the household, specified as well by guideline VDI 4655, is covered either by a heat pump or a micro-CHP, both combined with heat storage. The specifications of the used model elements are given in Table 2. The assumptions for the specifications of the different model elements are based on typical market values that are similarly used in other literature (cf. [53]). The use cases are modeled as classical linear programming problems with the objective to minimize variable costs for electricity and heat supply. The optimization problem is described by the target function (1). The model runs on hourly time steps for the period of one year. For more details on the calculated optimization problem and the associated constraints see Bertsch et al. [59] and more specifically Hayn et al. [60].

$$\min \left(\sum_{t \in T} \sum_{i \in I} (E_{t,i} * p_{t,i}) + \sum_{t \in T} (f_t * p_{t,gas}) \right) \tag{1}$$

with: $E_{t,i}$: electricity supply of resource i at time t (variable); f_t: fuel consumption (gas) at time t (variable)); $p_{t,i}$: price of resource i at time t (parameter)); $p_{t,gas}$: fuel price (gas) at time t (parameter)); t: time index of hour $t \in T = \{1, 2, \ldots, 8760\}$ of one year); i: index of electricity supply resource $i \in I = \{\text{PV, Grid}\}$.

5.2. Use cases and selected results

Six different use cases were modeled and analyzed. Each use case is defined by a combination of the abovementioned technologies and can be described as follows:

- UC1: Base case without any new technologies equaling the SLP;
- UC2: SFH with own PV panels;
- UC3: SFH with own PV panels and battery;
- UC4: SFH with own PV panels, heat pump and heat storage;
- UC5: SFH with own PV panels, battery, heat pump and heat storage;
- UC6: SFH with micro-CHP and heat storage.

The impact of a PV system in combination with battery storage (UC3) on households' load profile is already shown by Staudacher and Eller [53]. Own calculations with the described model provide very similar results. For instance, Staudacher and Eller [53] calculated a self-consumption of 56% and a self-coverage of 54% based on a flat electricity tariff while the results of the model developed by the authors of this paper indicate a self-consumption of 57% and a self-coverage of 37%. The differences probably rely on different

[8] See: http://www.energyexemplar.com. The authors thank Energy Exemplar for the provision of the software and their support.

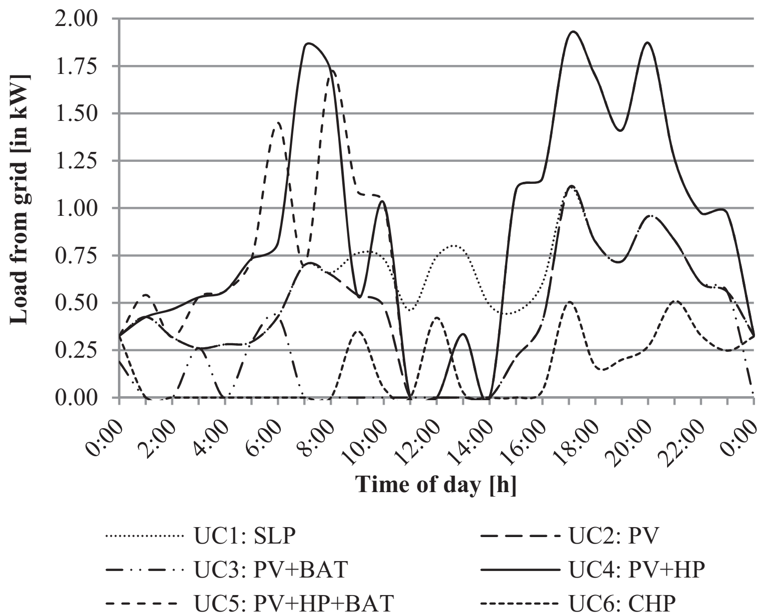

Fig. 6. Modeled load profiles of load demand from the grid for one SFH for defined use cases of one selected winter day on January 18th.

parameter values used in the models, e.g., for the PV generation profile or the battery itself. Bertsch et al. [59] use a similarly build up model but focus in their analysis on the optimal size of heat storages. Elsland et al. [51] developed a bottom-up model to simulate the load profile of the German residential sector until the year 2040 but did not analyze a households' individual load profile. Other models analyzing the effect of new technologies on households' load profiles similar to the other defined use cases were not found.

The resulting load profiles of the six modeled use cases for one selected winter day are visualized in Fig. 6. On first sight, it becomes obvious that the different technologies result in huge variations in load over time. Already the simple modification of the household by installing a PV system (UC2) leads to a significant change in demand around noon because the produced electricity is used directly in the household. Adding a battery to store parts of the electricity surplus generated by the PV system (UC3) further modifies the load profile. The electricity demand in the morning can now partly be satisfied from the battery. Adding a heat pump with heat storage instead of a battery to the PV system significantly increases the electricity demand of the household as the heat pump converts electricity into heat. Nevertheless, the installed PV capacity is sufficient to also lower the demand around noon, similar to UC2 and UC3. The combination of UC3 and UC4 is represented by UC5, including a PV system, a battery and a heat pump with heat storage in one use case. While the resulting load profile is very similar to the one from UC4, especially from 10 a.m. onwards where it is the same, the effect of the battery can be seen in the morning hours. The peak at 7 a.m. is covered with electricity from the battery. Finally, the use of a micro-CHP with heat storage is modeled in UC6 leading to a load profile that is different to UC1 at all times of the selected day. The co-production of electricity, a consequence of the satisfied heat demand of the household, is in many hours of the day sufficient to cover all electricity demand. Consequently no electricity from the grid is consumed in these hours. Summing the described results up, new technologies have a significant impact on both, the total electricity demand from the grid, e.g., by the use of heat pumps, and the load in a specific hour of the day from the grid, e.g., by the use of PV.

Nevertheless, the use of new technologies in combination with flat electricity tariffs does not lead to a decrease of the peak consumption per se as shown in Fig. 7. As the time of households' peak demand does not overlap with times of PV generation, the peak demand from the grid is not lowered in UC2. Also an installed battery (UC3) does not change the peak demand because the flat electricity tariff used by the model does not incentivize a specific time for the utilization of the battery. Consequently, it would be only by chance that the battery is used in times of peak demand of households. The increased peak demand in UC4 and UC5 can be explained by the additional electricity demand of the heat pump and the effects described for UC2 and UC3. Only the use of a micro-CHP (UC6) lowers the maximum load taken from the grid which can be explained by the correlation of heat and electricity demand in households.

As described above, flat electricity tariffs do not incentivize a peak load reduction. Therefore, in order to demonstrate the impact of different electricity tariffs in combination with new technologies on electricity load profiles, particularly the peak load, two additional use cases were modeled. For illustrative purposes, UC3 including PV and battery storage, was used as a basis for this analysis. The additional use cases are:

- UC7: Same as UC3 (PV + BAT) but instead of a flat electricity tariff a simple time-of-use tariff with a peak (0.25 €/kWh) and off-peak price (0.20 €/kWh) is simulated;
- UC8: Same as UC3 (PV + BAT) but instead of a flat electricity tariff an interruptible load tariff with time-of-use prices as above is simulated (max. grid demand set to 3 kW as in Italian households).

Fig. 8(a) shows the resulting load profiles of the abovementioned use cases, UC1 and UC3. Fig. 8(b) compares their average and peak demand. The simulated time-of-use tariff leads to a further load shift in UC7 and UC8. The battery is now used to store electricity from the grid during off-peak periods in order to reduce electricity demand from the grid during peak price periods. This operating strategy is beneficial in this simplified battery model as it leads to reduced variable costs (arbitrage effect). In real life, where other effects, e.g., irreversible capacity loss, would occur, another operating strategy might be better. As long as capacity demand from the grid is not priced or limited, e.g., due to interruptible tariffs, the charging load of the battery is limited neither. This can be seen in Fig. 8(b); the peak demand in UC7 is three times higher

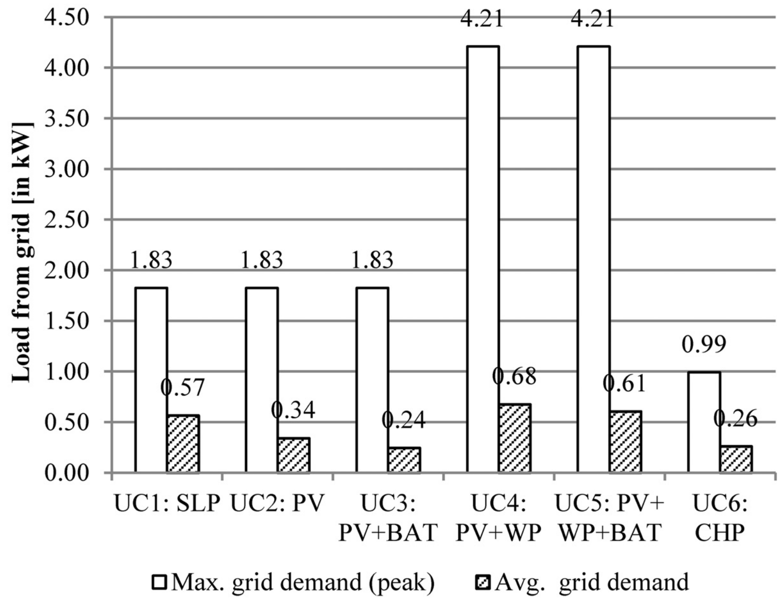

Fig. 7. Modeled maximum and average grid demand for defined use cases [60].

than in UC1 or UC3 due to the fast charging of the battery. Time-of-use tariffs alone do not necessarily lead to more predictable or reduced peak demand. Contrariwise, in UC8 the utilization of the grid is limited to maximum 3 kW. Hence, in order to further use the battery to store cheaper off-peak electricity, the battery is charged more frequently with a lower maximum load, cf. Fig. 8(a) and (b). While in this analysis the grid capacity was limited exogenously, similar effects of peak load reduction may be achieved by an introduction of capacity-based price components in households as described in Section 1.

5.3. Summary on new technologies for residential electricity and heat supply

The presented results clearly show that new technologies for residential electricity and heat supply influence the load profiles of households. Depending on the available technologies, load is reduced through an increased self-consumption, e.g., by using PV or micro-CHP, increased due to additional electricity consumers, i.e., heat pumps, or even shifted due to storage technologies, i.e., batteries and heat storage. However, also the limitations of the existing electricity market design regarding a load reduction on household level become obvious. Flat electricity tariffs provide no incentive for households to reduce their peak load; hence, new electricity tariffs need to be analyzed. Time-of-use and real time tariffs are in focus of many studies, e.g., Hillemacher et al. [61], but often require active interventions of households as long as electric appliances do not automatically react to different electricity prices. Nevertheless, even though such active interventions were necessary, Hillemacher et al. [61] have shown that time of use tariffs change households' electricity consumption visibly. While the differences in consumption observed by Hillemacher et al. are based on the price elasticity of demand, the modeled results in this paper point out the effect of new technologies for heat and electricity supply, more specifically the effect of the related storage technologies. It is shown that also automated technological solutions can be used in order to increase the flexibility of electricity consumption in households. Due to these reasons it can be stated, that new technologies for electricity and heat supply need to be considered in household segmentation approaches. Hence, the market penetration rates of new technologies and their relation to the socio-demographic background of households need to be understood in order to analyze the evolution of load profiles. Concerning the penetration of PV systems, for instance, the reasons for households to install PV modules have been already analyzed by Schelly [46]. According to her findings such a decision is not only driven by its environmental or economic value but also by the household dependent characteristics like socio-demographics, lifestyles and available communities of information.

6. Conclusion and outlook

Summing up the reviewed methods to describe households' electricity demand it becomes obvious that households' electricity consumption is not easy to capture by one single method. All four characteristics – lifestyles, socio-demographic factors, electric appliances and new residential heat and electricity generation technologies – influence households' load profiles and total electricity consumption. While data on socio-demographic factors and the equipment of households with electric appliances and new technologies is comparable on an objective level, lifestyle clusters always appear subjective. This is mainly due to the four reasons explained in detail by Otte [18] – lacking comparability of identified clusters, questionable correspondence to reality of selected lifestyles, lack of supporting theoretic approaches, and high effort of data collection. Nevertheless, lifestyles at least partly result from underlying socio-demographic characteristics like age or income of the household members and are as such included in segmentation approaches based on socio-demographic factors.

According to our findings presented in this paper, there are three socio-demographic factors with the biggest influence on households' electricity consumption and load profiles:

1. Household size: With an increasing number of persons living together the overall amount of used electricity increases, while the per capita amount decreases. Also the likelihood of having people spending time at home during the day and using more appliances at the same time increases and influences the load profile. Additionally the number of electric appliances and their use is affected by households' size.
2. Net income: Within some limitations, an increasing income correlates with higher electricity consumption. This can be

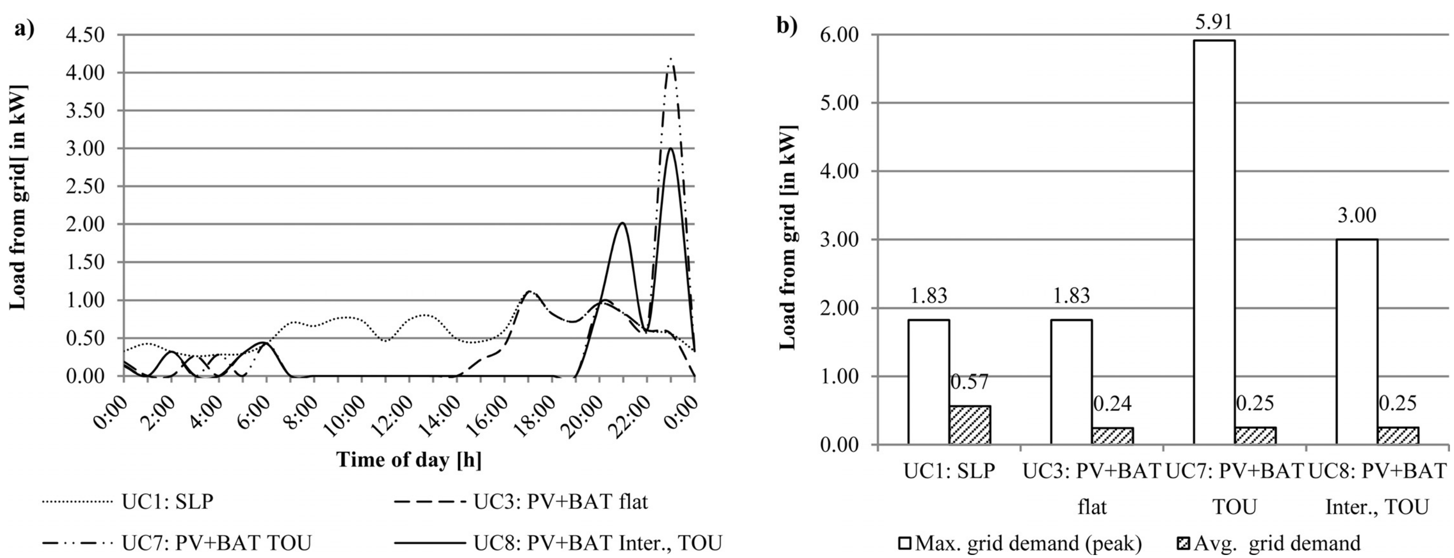

Fig. 8. (a) Modeled load profiles of load demand from the grid for one SFH for defined use cases of one selected winter day on January 18th. (b) Modeled maximum and average grid demand for defined use cases.

explained by the ownership of more electric appliances on the one hand side. On the other hand side, the net income correlates with household size, so a higher income often goes along with more people living in the household resulting in higher electricity demand.
3. Employment status: The employment status directly influences the occupancy time of households and consequently their load profiles. Longer times of absence during the day, e.g., due to a full-time employment, shift loads to the evening.

Both, lifestyles and the equipment of households with electric appliances are related to socio-demographic factors. The electricity consumed in one household is the sum of the electricity used of all appliances in that household. While the number and type of appliances is strongly linked to income and household size, the use patterns depend very much on the employment status.

Besides the regular household appliances, future analyses should also include upcoming technologies such as PV, micro-CHP, heat pumps and batteries. Their impact on load profiles is much higher than the one of regular appliances mainly due to two reasons. Firstly, the peak demand of regular appliances is lower than the one of the modeled new technologies. And secondly, the possibility to shift loads with regular appliances is also comparably limited as for most of them, the time of use strongly depends on immediate needs, e.g., cooking dinner. Contrariwise, most of the shown new technologies come along with either a thermal or an electric storage and can therefore be utilized in order to optimize electricity demand of households.

Summing this up, a household segmentation should be characterized through the socio-demographic factors household size, income and employment status and the respective equipment with electric appliances and new technologies. The link between socio-demographic factors and ownership of appliances or technologies, which could be established through probabilities based on country specific statistical data, will play an increasingly important role. As this paper is mainly based on a qualitative review of previous studies it would be helpful to test the stated segmentation criteria with real life data from households. The advantages of the suggested segmentation criteria are the reproducibility due to their objectivity and the broad availability of the required data from federal statistical offices.

Going forward, including this segmentation approach in residential bottom-up load models can provide insights in various topics. For instance, the simulated load profiles can be used to evaluate the impact of specific household segments on residential load demand from the grid. This knowledge can help for example to better forecast required reinforcement measures in low voltage grids, to test the effect of different electricity tariffs on residential demand or to simulate distributed energy markets.

Appendix A. Analysis report of the impact of socio-demographic factors on energy demand

The impact of socio-demographic factors on energy demand, shown in Table 1, was evaluated based on the statements in the reviewed literature. The following table highlights the main statements of the reviewed sources for each mentioned criteria. As the evaluation cannot always be based on quantitative figures but sometimes relies on the statements in the reviewed sources only, three categories were used for the evaluation in this paper:

- Significant impact on energy demand: +
- Low to no significant impact on energy demand: –
- Not investigated: Empty

The decision for "+" was based on keywords like "important", "significant", "related" or "dependent" occurring in the reviewed literature in relation with the respective criteria. Statements like "small influence" or ambiguous statements for one criterion result in "–". If a criterion was not analyzed in a specific paper the field in Table 1 is empty. In case of German sources, the statements are freely translated into English Table 3.

Table 3
Analysis report for Table 1.

Source, criteria and evaluation		
Kavousian et al. [32]	Household size	+
	• Significant in daily maximum	
	• Not significant in daily minimum	
	Dwelling size	+
	• Considerable correlation	
	• Most important factor among building characteristics	
	• Effect on daily min. and max. consumption	
	Income	–
	• No statistically significant correlation	
	• Income effect is minimal in samples with similar socioeconomic status	
	• Effect of income is mediated by ownership of appliances	
	Age	+
	• Significant correlation	
	Employment status/occupancy	+
	• Occupancy rate influences electricity consumption	
	• Presence of occupants impacts consumption in excess of daily minimum	
	Rural vs. urban	
	• Zip code as a proxy	+
	• Considerable correlation	
	• Explains up to 46% of the variability	
	Ownership structure/dwelling type	–
	• No significant impact on electricity consumption	
	• Significant factor on winter daily maximum where heating load dominates	
	Other	–
	• Building age: No significant correlation	
McLoughlin et al. [31]	Household size	+
	• Fewer number of occupants results in lower total electricity consumption	
	Dwelling size	+
	• No. of bedrooms used as a proxy	
	• Significant	
	• Strongly influences total electricity consumption	
	• Load factor increased on average for each additional bedroom	
	• Most significant variable to influence maximum electricity demand	
	Income	+
	• Social class used as a proxy	
	• Significant	
	Age	+
	• Electricity consumption for younger households significantly lower	
	• Strongly influences load factor	
	• Time of use shows high significance for age	
	Employment status/occupancy	+
	• Employment status: Little effect	
	• High collinearity to social class	
	• Increased occupancy patterns result in higher electricity consumption	
	Education	–
	• Little effect	
	• High collinearity to social class	
	Ownership structure/dwelling type	+
	• Maximum demand significantly influenced by type	
	• Significant impact	
	• Load factor influenced by dwelling type	
	Other	+
	• Household composition: Significantly influences maximum demand	
	• Time of use shows high significance for household composition	
	• Most significant to influence maximum demand	

Table 3 (*Continued*)

Source, criteria and evaluation		
Yohanis et al. [30]	Household size • Profiles for all groups are similar • Households with four or more occupants consume largest amount of electricity	+
	Dwelling size • Annual electricity consumption depends on dwelling size	+
	Income • Very important impact • Households with large incomes use 2.5 times more electricity on average in the evenings	+
	Age • Influence on consumption	+
	Employment status/occupancy • Higher average electricity consumption in homes with no daytime occupants	+
	Rural vs. urban • No significant impact on majority of daily profiles • Exception: high daytime demand of homes in the country	+
	Ownership structure/dwelling type • Average consumption on a per m^2 basis is the same • Difference in demand of 24% in winter and 30% in summer • Average 24-h profiles are very similar • Significant variation of total average load • Privately owned houses with demand profile over 100% greater in the evenings compared to rented homes, 60% greater throughout the rest of day	+
	Other • No. of bedrooms: very similar profiles • Total consumption very much dependent	+
Austrian Energy Agency [23]	Household size • Electricity consumption increases with an increasing household size	+
	Dwelling size • Positive correlation with total consumption • Specific consumption (per person) not correlated	+
	Income • Evident correlation with total consumption • No evident correlation with specific consumption	+
	Age • Higher total consumption of middle aged reference persons • Weaker correlation when considering household's average age	+
	Education • Weak connection with total consumption • No correlation with specific consumption	–
	Rural vs. urban • Higher total consumption in rural areas • Specific consumption not related	+
STATISTIK AUSTRIA [28]	Household size • Important determinant • Total consumption increases with size	+
	Dwelling size • Total consumption increases with size	+
	Age • Elderly households have on average a higher electricity consumption	+
	Employment status/occupancy • Households with unemployed persons have highest electricity consumption per person	+
	Education • No significant impact	–
	Rural vs. urban • Higher electricity consumption in rural areas	+
	Ownership structure/dwelling type • No significant differences	–
	Other • Year of construction: Total consumption on average 27% lower in houses build after 1990	+

Table 3 (*Continued*)

Source, criteria and evaluation		
Gram-Hanssen [33]	Household size • Strongest explanation • $R^2 = 27.6\%$	+
	Dwelling size • Third most important factor • $R^2 = 2.5\%$	+
	Income • Second most important factor • $R^2 = 5.8\%$	+
	Age • Little extra explanatory power • $R^2 = 1.3\%$	–
	Education • Little extra explanatory power • $R^2 = 0.02\%$	–
Abrahamse and Steg [29]	Household size • Positively associated • Related • Correlation = 0.40	+
	Income • Related • Correlation = 0.41	+
	Age • Correlation = 0.07	–
	Other • Gender: Correlation = 0.13	–
Gatersleben et al. [27]	Household size • Primarily/most strongly related • Only significant predictor	+
	Income • Primarily/most strongly related • Only significant predictor	+
	Age • Not significantly related	–
	Education • Not significantly related	–
Brandon and Lewis [26]	Household size • Proved significant • *T*-value of 3.89	+
	Income • Proved significant • *T*-value of 4.78	+
	Age • Proved significant • *T*-value of 2.36	+
	Ownership structure/dwelling type • Renters *t*-value of 1.99 • Owner-occupiers t-value of 2.52	+
Schipper et al. [15]	Household size • Important/significant determinant	+
	Dwelling size • Key determinant	+
	Income • Certainly a determinant • May not drive important changes in energy use alone	+
	Age • Important/significant determinant	+
	Employment status/occupancy • Important/significant determinant	+
	Ownership structure/dwelling type • Small influence	–
	Other • Family composition is an important determinant	+

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