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MODELLING LOAD PROFILES FOR THE RESIDENTIAL CONSUMPTION OF ELECTRICITY BASED ON A MILIEU-ORINTIED APPROACH

N. Haufe[1]*, M. Ziegler[2], T. Bednar[2,]

[1] TU Wien, Department of Spatial Planning, Centre of Sociology, Karlsplatz 13, A-1040 Austria

[2] TU Wien - Institute of Building Construction and Technology; Research Center of Building Physics and Sound Protection, Karlsplatz 13, A-1040 Vienna, Austria

*Corresponding author; e-mail: nadine.haufe@tuwien.ac.at

Abstract
Residential consumption of electricity shows big variance between households. Understanding and integrating these differences into load profiles is important for forecasting residential energy consumption, to improve controllability of power grids and for the successful achievement of energy efficiency targets. This paper combines a sociological milieu based approach to the explanation of the energy consumption with the modelling of load profiles, in order to close the gap between the typical modelling of load profiles based on mean values and the actual residential consumption of electricity.

Keywords:
Electrical Load Profiles; Social Milieus; Residential Energy Consumption

1 INTRODUCTION

Electrical load profiles are used to analyse the specific time of the electrical energy consumption caused by both HVAC system (Heating, Ventilation and Air- Condition) and occupancy. A load curve visualizes the use of electrical energy over time, showing watts on the y-axis and time on the x-axis. Due to simulated and predetermined controlling mechanism regarding the building operation, the time dissolved load profile for the building operation is important. This knowledge can be used for load shifting or demand and respond potentials, not to mention for a better controllable power grid. For the planning of power grids for example, not only the overall quantity of electricity consumed is of importance, it is also important to know at what time of the day the electricity will be demanded. Since the energy demand for the building operation is decreasing due to refurbishments and more efficient technologies, the part of residents-made energy demand and the analyzation resp. visualization of the use of electrical energy over time is getting more important.

One of the current problems of building planers and energy consultants is that current standards for the calculation of the energy performance of residential houses is inappropriate to estimate the individual use of energy consumption. The modelling of household electricity demand is mostly based on mean values for the whole population (e.g. Paatero and Lund [1]. To increase the significance of predicted energy consumption, this approach results in a deviation between the estimated and actual energy consumption, by considering the inequalities of different households.

The wide variation in residential energy consumption is well known, but not well understood [2,3,4]. This paper combines a sociological approach to the explanation of the energy consumption with the modelling of load profiles, as a step to close the gap between the estimated and actual residential consumption of electricity.

2 UNDERSTAND ENERGY CONSUMPTION

Households exhibit extreme variability in energy consumption from one house to another. Many factors contribute to residential energy consumption resp. the electricity consumption, such as climate, the building characteristics (size, age, construction), the number and age of the occupants, and the amount and types of electrical appliances. Goldstein and Fairey state that “the unexplained variance in home energy use, when using only (weather, home size, and number of occupants), is normally greater than 40% of the mean [4]. The variation in energy consumption regarding differences in climate and building characteristics is well studied. However, the effect of various appliances and especially the variation regarding the behaviours of people which are using them (e.g. rebound-effects), is less understood [5].

Many fields try to explain these differences from different perspectives, such as economics, psychology and sociology looking at the influence of income, norms, attitudes and values. In sociology it is assumed that it is possible to describe and explain social differences and behaviour with features of social inequality (single indicators such as income, wealth, education, professional position, ethnic origins, gender, age, household type, etc., respectively indices such as social class, social status, social milieu, etc.). In this case, research into social stratification in modern societies has shown that the complexity of social activities cannot be explained satisfactorily by sociodemographic or socioeconomics variables alone. Attitudinal and value variables resp. lifestyle- and milieu-based approaches have been introduced in order to explain and understand individual behaviour in more depth and to segment the population into meaningful (target)groups (e.g. market research) [6]. Hradil (2009) argued that life goals resp. fundamental values and everyday attitudes define the behaviour of people and presented a three stage model: social status, social milieu, and social action. Under social milieu, he understands a group of people who have the same external conditions of life and inner basic attitudes, out of which forms common field-specific lifestyles (attitudes and behaviour patterns) [7].

For the energy consumption research means that, the milieu resp. fundamental values and everyday attitudes determine the typical behaviour pattern of energy use and the observable energy relevant behaviour (Fig. 1). Socioeconomic structures are no longer primarily responsible for behaviour but remain as boundaries.

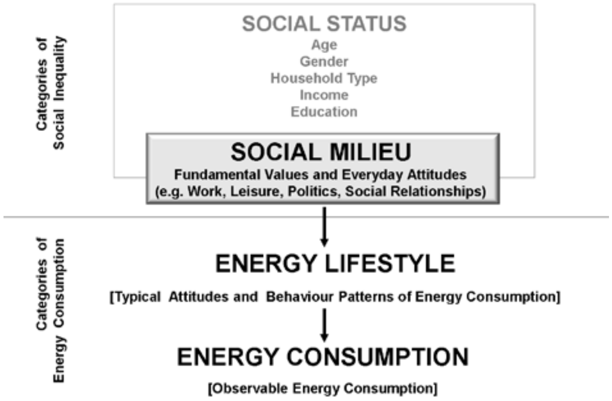

Fig. 1: Theoretical construction to explain energy consumption [6].

Based on this theoretical sociological background, this paper focused how to create electrical load profiles based on a milieu oriented approach.

3 DATA AND METHODS

The modelling of social differentiated load profiles based on a representative quantitative household survey in Vienna. The data collection was carried out by telephone interviews with a total sample size of 977 participants which is representative for the Viennese population aged 14 and above. The duration of the interviews was 35 minutes and the content ranged from demographic data, spatial and building characteristics, general energy consumption (residential demand and mobility), attitudes to the environment, media consumption and typology items. The main goal was to identify types of homogeneous attitudes and behaviour in the field of mobility and residential energy consumption. The survey period extended from the middle of June to the end of July 2015.

The identification of the milieus based on the Sinus-Milieus® in Austria. This segmentation model is based on sociological models describing communities of basic values with shared attitudes concerning different aspects of everyday life (e.g. work, leisure, social relationships, consumption, politics etc.). Figure 2 illustrates the 10 Sinus milieus identified for Austria in 2013.

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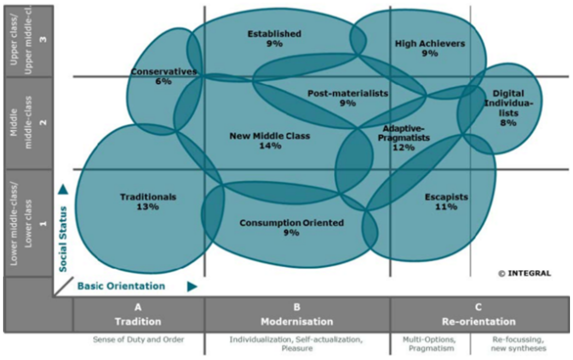

Fig.2: Sinus-Milieus in Austria 2013 [8].

In order to generate electrical load profiles, 977 representative answers from the survey across all milieus have been analysed. The focus here was not only on the behaviour such as when and what kind of electronic appliances do the participants use, but also on the context with building physics and certain energy consumption characteristics.

The most crucial process was an intensive review in terms of plausibility for all answers. Therefore, certain indicators (e.g. maximum number of specific appliances, maximum duration of usage min/week) have been established in order to over write obviously inappropriate answers rather than delete them. Otherwise the number of contradictions will decrease the quantity of useful answers to roughly one third.

$$n(i) = MV(i) \pm SD(i) \qquad (1)$$

Equation (1) describes the procedure if answers seem to be inappropriate with respect to the indicators. Therefore, the mean value for that specific milieu (i) $\pm$ randomly the standard deviation for this question within that specific milieu has been used. In addition to the general attendances of the occupants, the participants indicate in order to generate time dissolved load profiles, not only the running time, but also the time of use. Equation (2) describes the power of all appliances for each time step and milieu.

$$Pi(t) = \sum_{i=1}^{n} Pn(t) \qquad (2)$$

In total, 13 different appliances (e.g. televisions, notebooks, kitchen appliances, cell phones, household devices, etc.) have been considered.

Fig. 3 highlights the time dissolved differences regarding the social differential attendances compared to the mean value including the standard deviation. While each coloured line represents one milieu, the black line represents the mean value. It can be seen, that the general attendance within all milieus is much higher during the weekend.

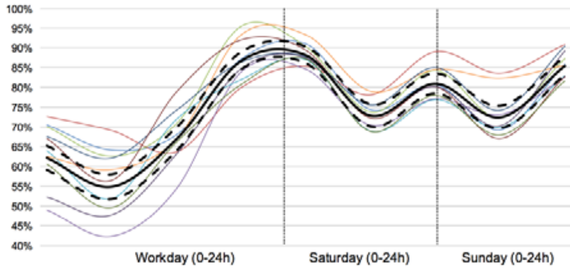

Fig. 3: Attendances for all 10 milieus compared to the mean value (continuous black line) including the standard deviation (dashed black lines) for a Workday, Saturday and Sunday.

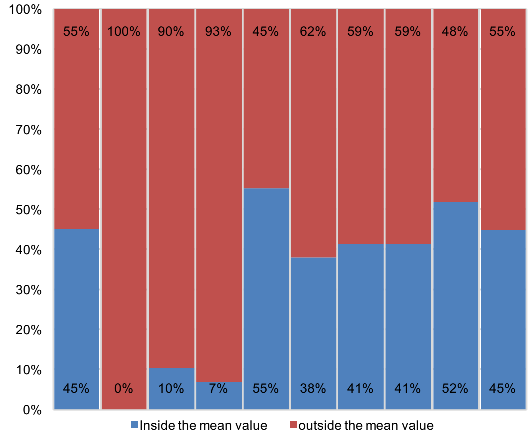

Fig. 4: Deviation of Attendances within the standard deviation for one week.

Fig. 4 indicates the deviation for all milieus regarding their match to the mean value including the standard deviation for one week. In average, 65% are outside that range. It also can be seen that one milieu has no match at all. Considering only a working day, 68% are outside that range, while 57% are outside within the weekend. The specific behaviour for different milieu effects the understanding of a time dissolved load profile significantly.

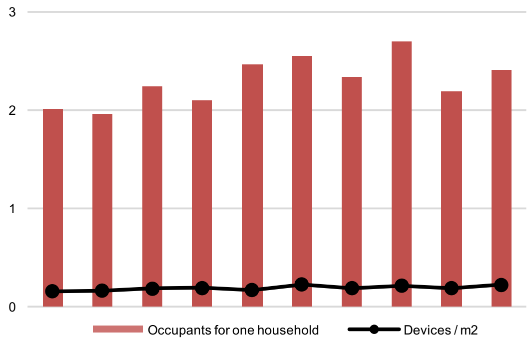

Fig. 5: Comparison between the number of occupants for one household to the number of devices per square meter.

While the deviation of the attendances for all milieus distinguish significantly, Fig. 5 emphasis that the number of devices for one square meter of household remains quite constant, even the

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mean value of occupants differs a lot. As mentioned in the previous chapter, the plausibility of all data had a wide range. Therefore, Fig. 6 shows, that the mean value within all milieus for the running time in minutes per week seems to be realistic, even if some overestimated it.

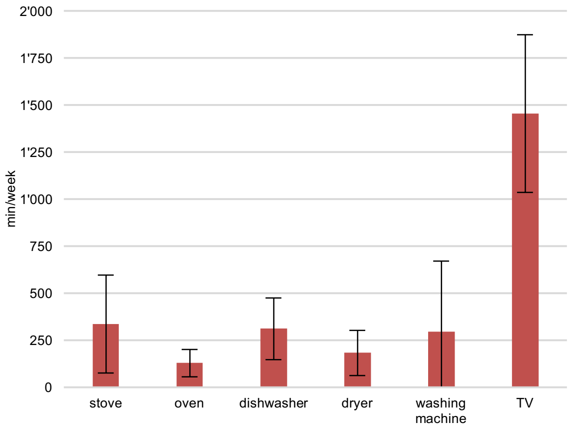

Fig. 6: Running time for 6 different appliances before the correction in the course of the plausibility review.

Therefore, some indicators for the maximum use for each appliance have been established and have been used to limit the maximum running time and thus, to overwrite overestimated values according to equation (1).

	Stove	Oven	Dishwasher	dryer	Washing-machine	TV
min/ week	840	840	1680	840	420	3360

Tab. 1: Maximum running time for appliances in order to limit over estimated time specifications.

As Tab. 1 and Fig. 6 illustrate, the mean values are clearly below the limited values for the running time according to Tab. 1. It becomes clear, that only highly overestimated running times have been corrected according to equation (1).

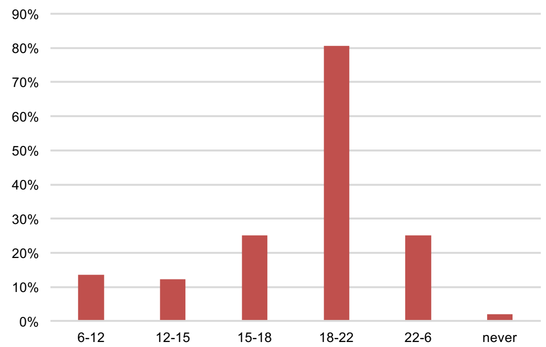

Fig. 7: Mean value within all milieus for the time of use on the example of televisions.

The same procedure has been done for the time of use for all appliances. In the course of the review process, only data with a mismatch compared to the general attendances for each answer has been over write. But in general, the distributed mean values for one day of televisions highlighted in Fig. 7, seems to be realistic.

4 RESULTS

In order to create time and milieu dissolved electrical load profiles, four variables are necessary:

(i) general attendance for each milieu (*Fig.* 3 and Fig. 4)
(ii) the amount and type of appliances for each milieu (Fig. 5)
(iii) running time for all appliances for each milieu (Fig. 6 and Tab. 1)
(iv) time of use for all appliance for each milieu (Fig. 7)

Fig. 8 compares the annual electrical energy consumption for each milieu with statistic data from [9] with respect to the number of occupants for one household. It should be noted, that the energy consumption distinguishes within all milieus significantly. Comparing the deviation for all milieus to the statistic, the results ranges from -13% to 18%.

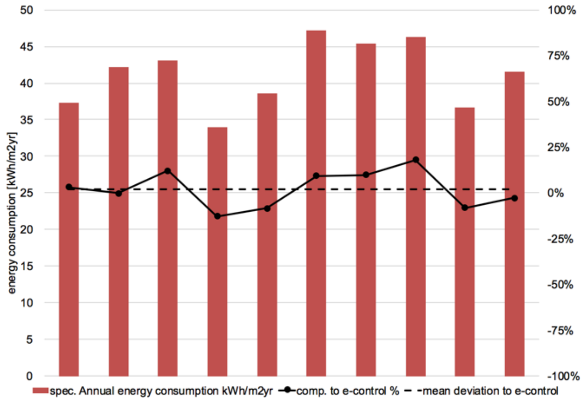

Fig. 8: calculated energy consumption for electrical appliances for all milieus compared to the statistics of e-control [9].

Although the number of appliances remains quite constant within all milieus, the calculated annual energy consumption ranges from 34 to 47 kWh/m^{2}a. This is due to the fact of different running times and attendances within all milieus.

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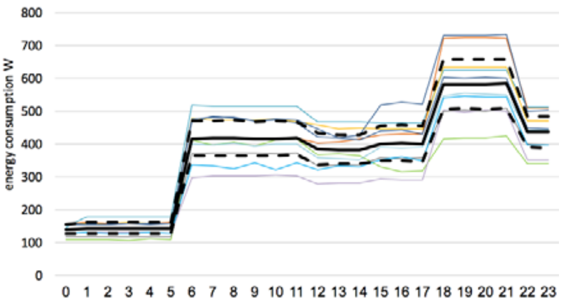

Fig. 9: Daily load profile for a week day considering the variance of all milieus compared to mean value (continues black line) and standard deviation (dashed black lines).

Fig. 9 puts all four variables into one daily load profile for each milieu compared to the mean value including the standard deviation. It is conspicuous that the electrical power differs not only during the evening, but also during the day. Furthermore, the peak load during the evening hours ranges from 400 to almost 800 Watts.

5 DISCUSSION

The results show, that the quality of the developed load profiles is definitely comparable to other research results [10,11], but by considering the variance of different milieus, the quantity differs a lot. In order to get a much better understanding concerning an aggregated load profile for residential buildings, the results can make a contribution towards load shifting, smart metering and not to mention demand side management. The results also highlighted the differences for different milieus regarding their behaviour and thus, their significant effects on that specific load profile. In addition, the results can be used for electrical grid operators for an improving load balancing towards the implementation of more decentralized energy storages and volatile renewable energy (e.g. Photovoltaics) within cities and districts. Therefore, further research will be to disaggregate the results for each milieu to highlight the effects and variances on a more detailed level, as well as to validate the results with well monitored buildings.

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