CISBAT 2017 International Conference – Future Buildings & Districts – Energy Efficiency from Nano to Urban Scale, CISBAT 2017 6-8 September 2017, Lausanne, Switzerland

Synthesizing residential load profiles using behavior simulation

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Abstract

This paper introduces a novel approach for synthesizing load profiles based on a psychological model that models the residents as independent, desire driven agents in a true bottom-up approach. The basic idea is then extended to be able to simulate for example office workers, unemployment, retirees or factory shift workers. Additionally, the model can simulate multifamily houses in detail, including details such as illness periods, personal hobbies and device ownership. The results are validated, and some results shown. The model is implemented as a Windows program and is available for download for free.

Peer-review under responsibility of the scientific committee of the scientific committee of the CISBAT 2017 International Conference – Future Buildings & Districts – Energy Efficiency from Nano to Urban Scale.

Keywords: load profile generator; household load profile; agent simulation; residential load curve; hot water load curve

1. Introduction

Many simulations in the field of renewable energy require residential load profiles for electricity and warm water. Typical applications are research about renewable energy systems, simulations of low voltage grids or demand side management algorithms and the research into smart grid systems. Load profiles vary widely between different occupants, such as office workers, shift workers, retirees, singles or families. The use of average profiles yields often misleading results [1]. Since measured profiles are rarely available, synthesis is frequently the only option. For this

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1876-6102
Peer-review under responsibility of the scientific committee of the CISBAT 2017 International Conference – Future Buildings & Districts – Energy Efficiency from Nano to Urban Scale.

load profile generators are used. Figure 1a shows an example of a measured residential load profile for a single day and for comparison purposes the averaged standardized German load profile H0. It is visible that the profile has very steep peaks from for example cooking and the washing machine and the averaged profile are quite different.

This paper will give a brief overview of the state of the art before introducing a novel kind of load profile generator for residential load profiles, which models the persons in a household as independent agents. Then the validation and some of the results will be discussed. The goal of the research is to provide a modeling tool for other researchers to quickly and easily model different households and enable them to use the generated profiles as input for other simulations.

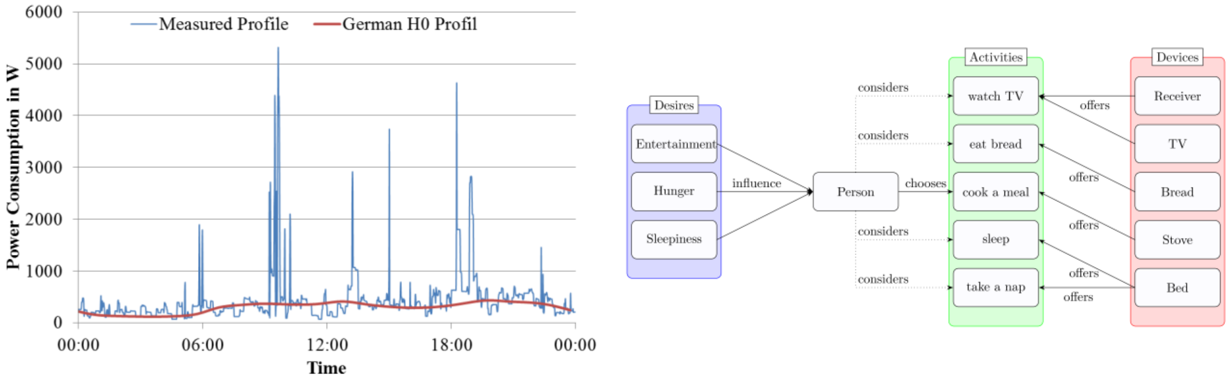

Fig 1. (a) a measured residential load profile for a single day and the German standardized load profile H0 (b) Basic idea for the model

2. State of the art

Research into synthesizing load profiles has been performed for a long time now. One of the earliest papers about electric load profiles is from 1984 [2]. It was (very simplified) built upon the idea of describing device activations with rules such as “90% chance of turning on the TV between 19:00 and 21:00”.

Later research built upon this idea and generated more realistic profiles, using ideas such as combining multiple devices into activities [3]. Another approach was using sophisticated time of use studies as the foundation for generating the activity probability distributions for the different activities [4, 5] . A particularly clever idea was implemented by Stokes [6], who used statistical data about device penetration and combined it with measurements from a substation to split the load profile of the substation into individual household load profiles that add up to exactly the load at the substation. The comprehensive review article in [7] gives a very detailed review of different approaches.

Load profile generators for domestic hot water are rarer, even though the energy required to make hot water for a household is similar to the electric energy consumption. One of the few examples is DHWCalc [8], which uses probability distributions based on measurements from a multifamily house. One of the latest developments has been Synpro by Fischer [9, 10]. They make very detailed combined electricity and hot water profiles using data from the last big German time of use study. These statistical approaches work very well for larger populations if sufficient data is available. For individual households or when only very little data is available, this method is challenging.

3. Methodology

This section first describes first the basic behavior model and then the various extensions built around the basic model.

3.1. Basic Model

The previously mentioned approaches for generating load profiles work well if there is sufficient data available. One way to compensate for missing data is to build more “intelligence” into the model. For this, a desire model was used, which is based on the works of the German psychologist Dörner [11]. The basic idea behind the model is that people will do whatever gives them the greatest satisfaction at any given time. The concept is shown in Fig. 1b. The central element is the person, which has a number of different desires. There are a number of devices, which offer different activities to the person. The person then checks the expected satisfaction from each activity and chooses the one that promises to give the biggest boost. So if a person is tired, then he will sleep, if he is hungry, he will make some food and so on. To make this work every desire grows a bit in every time step, although the amount of growth varies between desires. To create realistic behavior patterns, cooking, for example, needs about 4-6 hours until the desire becomes strong enough to act on, while for sleep it is between 14 and 18 hours.

Of course, the basic idea is not quite sufficient yet to model the complexity of human behavior. Therefore a number of additional elements were added to the model. The first one was weighing the different desires. Only if eating is more important to the simulated person than watching TV, plausible cooking patterns appear in the simulation. Another necessary element was the concept of autonomous devices. Between 50 % and 80 % [12] of the energy consumption in an average household is directly caused by the behavior of the residents, but the rest is generated by devices on standby and devices that operate independently of the residents such as the refrigerator. Therefore, autonomous devices had to be implemented too.

Lightning consumes up to 15 % of energy in a household. This required implementing the concept of different locations with independent light devices. Some testing yielded the result that the energy consumption and the light load profile are most realistic if the condition for turning on the light is below 50-75 W/m^2 global radiation. More details are described in [12].

Various activities depend on some form of state. For example, the dishwasher activation usually happens if it is full. Modelling this requires using a variable that represents the amount of dirty dishes. Then, as soon as the dishwasher is full, the activity of turning on the dishwasher becomes available to the residents and whoever has the largest desire for clean dishes will turn it on the next time they have some spare time. Additional elements that were needed to model a basic household were vacations, holidays, and, last but not least: Joint activities. If the residents are not able to enjoy a meal together they each end up cooking their personal meals, which yields very unrealistic load profiles for families.

3.2. Expansion

To be able to simulate multi-family houses or areas with a couple of hundred houses, not only the household, but also the house infrastructure has to be simulated. For this houses and settlements were introduced. A house contains the infrastructure such as the heating and cooling system, circulation pumps and the warm water boiler. Each house can contain one or more households. Settlements contain multiple houses and are used to simulate larger groups of buildings. This can be very useful for example when studying the impact of changing technical devices on the load profile at substations.

3.3. Device Picking

When a device is activated, it might be activated with different load profiles. For example, the washing machine can run at 60°C and at 30°C and has different device load profiles for each for both water and electricity. To automatically change devices in households for studying different scenarios, it is thus necessary to change the device load profiles at the same time. To model this, the abstraction of device activations and device activation groups was introduced. A device activation combines a device with one or more device profiles. A device activation group describes an abstract concept such as “turn on washing machine” and multiple device activations then implement the concrete concept. With these abstractions, it is easy to automatically exchange all devices in the household for older or newer devices while using the correct load profile for each.

3.4. Household and Settlement Creation

The next step was the enabling the automatic creation of new households, since modeling a low voltage grid requires hundreds or thousands of individual load profiles. For this, a rule based templating approach was used. One example for such a rule is “The mother has between one and three hobbies.” To make this work, it was required to first describe every activity with some tags, which specify which activities are exchangeable. By describing the people in the households with such rules in a template, it becomes possible to automatically create a large number of similar households of one type.

The same idea was scaled up and used in the creation of settlements. Every household is described with tags such as “Single”, “Family” or “One Child”. Then it is possible to create a settlement template with rules such as “40% of the houses should be single family houses and contain a family with one or more children”. With this template matching settlements can automatically be generated and then simulated to create the desired load profiles.

4. Implementation

The model was implemented as a C# Windows program during a Ph.D. thesis and is provided free of charge at www.loadprofilegenerator.de. The development is ongoing. The program includes 60 predefined, validated households based on German statistical data, measurements, and a small survey. The program is about 50.000 lines of code, of which 10 % is the simulation core that performs the actual calculations. The rest is the user interface, the data model, and the various abstractions and template functions needed. For the usability, it proved to be very beneficial to implement a command line interface that can be used to automate the calculation and spread it out over multiple computers. The time resolution of the generated profiles is 1 minute. To evaluate the influence of the resolution of the profile on the self-consumption ratio, a photovoltaic profile with a resolution of 1 min and a simulated household profile with the same resolution was used to calculate the self-consumption. Then the two profiles were averaged to 5 min values, 15 min values and so on, and the same calculation was performed. For 1 min the self-consumption was 20.6%, for 5 min it was 21.3%, for 15 min it was 22.5% and for 1 h it was 25.6 %. Using a fine time resolution is obviously highly important for precise results.

5. Validation

Validation of load profiles is a notoriously difficult topic since individual load profiles are hard to compare. If in Fig. 1a the breakfast cooking spike is 15 min later, the load profile is no less “correct”. And if someone does not eat a warm breakfast, the spike might be missing entirely, but that still does not make the profile “wrong”. It would only mean that the load profile is from a household where they ate cold breakfast that day. A simple comparison with a measured profile obviously will not yield any useful results.

The predefined households in the LPG were validated with different criteria [12]. Three examples will be shown here: Plausibility checking with action carpet plots, yearly energy consumption and power distribution in a duration curve.

5.1. Plausibility Check

One important tool when creating profiles is a simple plausibility check of the behavior. For this, the LPG contains a large number of different reports. Fig. 2a shows a carpet plot of the activities as one example. In this plot it is possible to tell from the different colors the performed activities and if, for example, the person is suffering from simulated insomnia or if the sleeping pattern is regular.

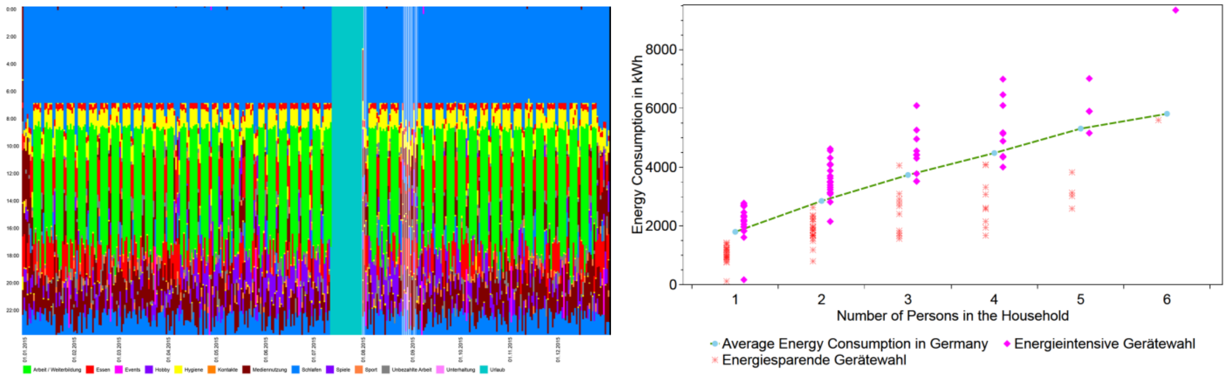

Fig 2. (a) Carpet plot of the activities to check the plausibility of the activities (b) Comparison of the energy consumption of the simulated households

5.2. Yearly Energy Consumption

For Germany, the results of a large-scale survey about the energy consumption are available in [13]. This data has been used to validate the yearly energy consumption of the predefined households in the LPG. Fig. 2b shows the results. For this every one of the predefined households has been calculated twice: Once with old, energy-intensive devices from ca. 1990 and once with new devices from ca. 2010. The households with energy-intensive devices ended up significantly above the average, while the energy-saving households end up below the average. This shows that the yearly energy consumptions are well modeled.

5.3. Duration Load Curve

The third measure is the duration curve. For this, all the values in the year are sorted by size and then charted. As comparison values, the data from a smart meter rollout in Germany by IZES [14] was used. Fig. 3a shows in blue the reference area based on the measured profiles and as colored lines the simulated profiles. It is visible that the simulated profiles and the reference area match very well.

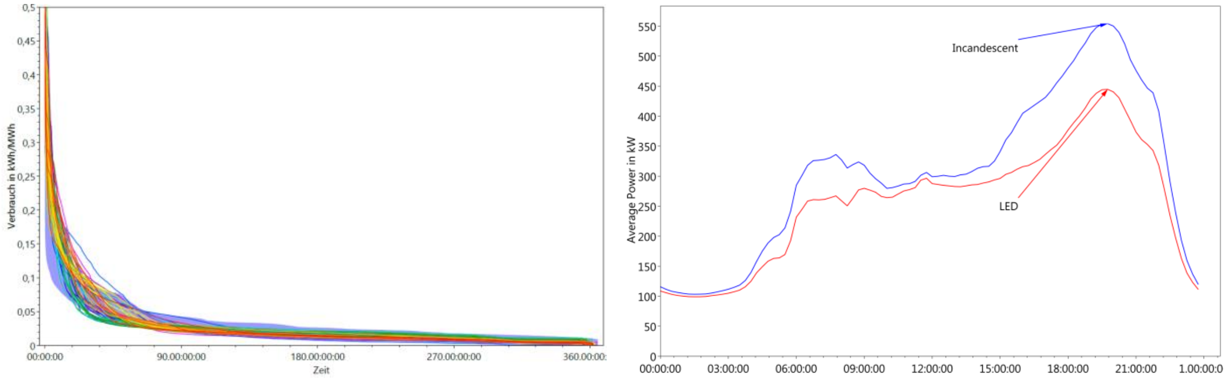

Fig 3. (a) Comparison of the duration curves of all simulated households with data from smart meters (b) Results of a study over 1000 households how the average winter load curve changes if all incandescent light bulbs are changed to LED light bulbs.

6. Results

One of the results from the modeling of the different households was that for different profiles the self-consumption from a photovoltaic system that is sized to net-zero can vary between 18 and 35 % [12]. This has, depending on the local billing model, significant impact on the profitability and thus needs to be considered carefully when planning new photovoltaic systems.

Another result was that the changing the lighting from incandescent bulbs to LEDs will have a big impact on the morning and evening peaks in residential load profiles and therefore measured profiles from before the LED boom are not representative anymore for current households. One example for a comparison between the two cases is shown in Fig. 3b.

7. Conclusion

The paper introduced a novel approach for generating load profiles by simulating the behavior of the residents in the household in very fine detail and generating the load profiles from the behavior. The model and the needed elements were described and the validation was introduced. It was demonstrated that such a behavior-based approach works very well for generating load profiles. The software is freely available and a large number of researchers have used the software in various thesis and papers.

Acknowledgements

We gratefully acknowledge financial support from BFH and the Swiss Commission for Technology and Innovation (CTI - SCCER program). This project is carried out in the frame of the Swiss Centre for Competence in Energy Research on the Future Swiss Electrical Infrastructure (SCCER-FURIES) and with Swiss industry partners. Here, we particularly like to acknowledge the BKW group and Gebäudeversicherung Bern (GVB)."

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