

Residential load profile tools - A review and comparison of applied tools

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Abstract

The energy demand of the residential sector contributed to about 29 % of Germany's final energy consumption in 2020. For the planning and optimization of energy systems, an understanding of the temporal energy consumption is necessary. This paper discusses tools for estimating these load profiles. Load profiles for electricity, space heating and domestic hot water (DHW) are investigated. A total of ten tools were applied. It turns out that the selected load profiles are dependent on the field of application. Load profiles influence the results of energy system modeling and therefore it is important to differentiate load profile tools. Standardized load profiles are well suited when a large number of buildings are considered. Stochastic load profiles, behavioral load profiles and the reference load profiles are well suited for building-specific simulations. Physical load profiles are well suited for single building models, but as soon as several buildings are considered, the input effort for a sufficient accuracy is high.

Keywords: load profiles, urban energy system, urban building energy modeling, urban energy system modeling

1 Introduction

The energy demand of the residential sector contributed to about 29 % of the final energy consumption in Germany in 2020 [1]. An understanding of the residential energy consumption provides the basis for actions that can be taken to improve efficiency. The energy consumption can be combined to form a load profile showing the course of consumed electricity and heating energy within certain periods [2]. Load profiles are input variables for energy system modeling and play an important role in planning and evaluating of urban energy systems (UES). For the determination of capacities and operation modes, load profiles should be available at least with an hourly temporal resolution [3]. The comparison of real measured data

and estimated load profiles has shown that electricity load profiles of residential buildings are difficult to model. This is because people use electric appliances at different times depending on their individual schedules and lifestyles. The individual use of appliances results in temporally different peak loads in the load profiles of households [4]. For example, the modeled share of self-consumption of a given photovoltaic systems can vary between 18 and 35 % by using different electricity load profiles. Heat load profiles also vary between different occupants, so average load profiles often cause misleading results [5]. A variety of different load profile tools exist [6]. It is important to model realistic load profiles for each use case so supply technologies can be accurately planned or forecasts for electricity purchases can be as accurate as possible. Thus, the quality of results of energy system modeling increases with high quality load profiles.

In this article, different tools for generating load profiles are investigated. The generated load profiles serve as input data for urban energy system modeling (UESM) tools in order to optimize these systems. Thus, the load profiles are supposed to reflect realistic conditions. This paper examines which tool most accurately reflects these realistic conditions. At first urban energy system are defined and different tools to generate load profiles are presented. Then, the generated load profiles are analyzed and compared. Finally, the different load profiles are classified and assigned to a field of application.

2 Urban energy systems

UES consider combined processes of energy production and usage in spatial units (e.g. residential buildings) with a high density and differentiation of consumption sectors as well as energy sectors (e.g. heat, electricity, fuels) [7]. According to Ferrando et al. [8] three methods to model and optimize UES can be differentiated:

- urban energy system modeling (UESM)
- urban energy building modeling (UEBM)
- land-use and transport analyses

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UESM aims on the optimization and design of energy systems. Buildings and their energy consumption are usually only represented in a highly simplified way in UESM, due to the size of the modeled energy systems and the resulting complexity. This causes the results to be significantly less accurate in terms of energy demand than with UEBM, which only addresses the modeling of individual buildings [8].

The basic approach of UEBM is to use physical models for energy flows to determine heat and electricity consumption of buildings [9]. Accordingly, UEBM are used to quantify the energy consumption of buildings through building-based simulations. This can be implemented using bottom-up and top-down approaches. Usually, UEBMs are bottom-up models providing an analysis of the current state of the building stock [10], based on the calculation of individual buildings energy consumption. Top down-models do not need any specific building data [8]. Those models consider the status quo of the building stock and how it changes when, for example, one type of building is converted to another. Top-down models are less suitable when an analysis focuses on a specific district [9]. Therefore Reinhart and Cerezo Davila [9] propose the bottom-up UEBM approach for several dozens to thousands of buildings. Kazas et al. [11] also proposed the bottom-up UEBM for predicting energy demand, evaluating the energy performance of buildings and districts, and applying measures to reduce energy demand and CO₂-emissions.

3 Methodology

To begin, the literature was searched for articles that have already reviewed different tools to generate load profiles. Basically, there is a large amount of tools to optimize energy systems [6], but only a certain number of tools is relevant for this article. Therefore, criteria were defined, whereby a large number of tools can be excluded. The requirements for the tools are shown in Table 1. There are databases with building-specific data that can be used for calculating load profiles, but there is no access because of privacy issues. The lack of data requires that load profiles can be determined with limited input data [10]. The simulation of energy systems often leads to run-time problems. A higher temporal resolution, for example minute values, would increase these problems. Furthermore, it is required that the tools are open and have a short initial effort for usage so users can easily reproduce the results of this article. All requirements could influence the quality of load profiles. Thus, it has to be clarified how strong the restrictions are and whether the load profiles are still realistic or not. A total of ten tools were identified and subsequently applied. It was ensured that the same input parameters were used as far as possible. For some tools, for example,

Tab. 1: Requirements established in this article.

nr.	requirement	reason
a)	low detailed building-specific input data (e.g. year of construction, geometry, location)	because of lack of open data, data privacy
b)	single building resolution	high quality
c)	hourly time-resolution of the output data	simulation run-time
d)	free application of the tool	easy access
e)	requires a short initial effort for useage	easy access

the consumption type could be selected. A single-family building with four occupants is considered as an application example. However, the calculation of the annual energy demand differs in the tools and was therefore standardized to 10 MWh. The different time series were then prepared and visualized with a Jupyter notebook [12]. Finally, a conclusion about the field of application of the tools was made based on the courses.

4 Results of the literature review

The results section is divided into two parts. The first part describes complete UEBM and UESM tools in order to generate load profiles. In the second part, tools are described that exclusively determine load profiles.

4.1 UEBM and UESM tools that meet the requirements

Ferrando et al. [8] investigate modeling tools to improve the energy supply of cities. In their article, they reviewed user-friendly, bottom-up-based UEBM tools developed for urban applications. All eight tools allow detailed modeling of the building stock and generation of load profiles. UESM tools often rely on approaches that do not focus on building modeling. The mainly focus is on the optimization of energy systems with respect to certain optimization variables (e.g. costs and emissions), in which technologies for electricity and heat supply are sized. In this context, UESM tools make use of existing tools for the generation of load profiles and implement these load profiles as input data. In this work, these approaches are considered as stand-alone tools. The eight tools reviewed by Ferrando et al. [8] were evaluated for the requirements in Table 1. The results are shown in Table 2.

Tab. 2: Overview of tools considered in [8] in context with the requirements in Table 1.

tool	a)	b)	c)	d)	e)
CitySim	✗	✓	✓	✓	✓
SimStadt	✓	✓	✗	✓	✗
umi	✓	✓	✓	✗	✓
CityBES	✓	✓	✓	✓	✗
OpenIDEAS	✓	✓	✓	✓	✗
CEA	✓	✓	✓	✓	✓
URBANopt	✓	✗	✓	✗	✗
Teaser	✓	✓	✓	✓	✗

Appendix A shows brief explanations why tools do not meet the requirements. Among the tools listed by Ferrando et al. [8], only CEA (City Energy Analyst) is considered as a possibility to calculate load profiles. After using CEA and according to the article of Mosteiro-Romero and Schlueter [13], it can be seen that the program has been further developed. Meanwhile, it is also possible to compare district heating or heat pumps as investment alternatives, for example. Therefore, CEA can be considered as an UESM tool rather than an UEBM tool. In **CEA**, an approach based on archetypes is used to calculate load profiles [14]. An archetype building is a representative building for a group of similar buildings. Load profile tools make use of archetype buildings due to the lack of sufficient input data on building level, reducing the actual variability of the existing building stock [10]. Within CEA five different databases are used to model the buildings, and thus to generate load profiles. The databases contain weather data, GIS data, archetype data, time series data and measured data for industrial companies, for example. A total of 16 consumption types are defined, which each have a hourly time series for energy consumption. The calculation methods to generate heat load profiles based on local building standards (Switzerland) and is supplemented with averaged measured data for domestic hot water (DHW) [14, 15]. For the electricity load profiles, the calculation methods from local building standards in Switzerland are used as well [14]. Unfortunately, it is not clear which specific values are used out of the Swiss building standards.

The Spreadsheet Energy System Model Generator (SESMG) is another UESM tool considered in this work. The SESMG allows the use of the demandlib [16] and Richardsonpy [17] in order to generate load profiles. Almost all considered tools separate heat demand into demand for DHW and space heating, except SESMG. By considering them separately, heat pumps, for example, can supply the space heating demand, and instantaneous electric water heaters can supply the demand for DHW. SESMG is an open source prod-

uct, so users are allowed to develop the tool. Thus, the heat demand was subdivided into space heating and DHW. For this, the interface between SESMG and demandlib had to be reprogrammed. The daily heat demand (\dot{Q}_{day}) can be calculated due to customer value (KW), h-value ($h(\theta)$), week day factor (F) and hourly factor (SF). The equation is explained in detail in [16].

$$\dot{Q}_{day} = KW \cdot h(\theta) \cdot F \cdot SF \quad (1)$$

$$h(\theta) = \frac{A}{1 + \left(\frac{B}{\theta - \theta_0}\right)^C} + D \quad (2)$$

The summand D represents the temperature independent DHW consumption. For simplification, it is assumed that D is constant throughout the year. If $D = 0$, only the space heating is shown. If the other coefficients of the sigmoid function are set to zero, the DHW can be modeled [18, 19].

As mentioned above, demandlib and Richardsonpy are considered individually. The **demandlib** generates heat and electricity load profiles by scaling the Germany's Federal Association of Energy and Water Management (BDEW) load profiles to a desired annual demand. The basis for these standardized approach is formed by the representative load profiles for end consumers defined by distribution system operators [18]. In the generation of the electricity load profiles by the BDEW, the focus was on the electric power system management of the distribution system operators. Consumer groups were formed from 1 209 individual load profiles and the load profiles were averaged. As soon as between 200 - 300 buildings are considered, the load profiles are representative [20]. Another tool within SESMG to calculate electricity load profiles is **Richardsonpy**. In contrast to demandlib, Richardsonpy can only be used to create electricity load profiles [17]. However, large deviations from the German average of 4 000 kWh/a occur for a four person household. For this reason, Richardsonpy was not used for the calculation of the annual demand within SESMG, but only for the relative, temporal course of the consumption [21]. Richardsonpy was validated with measurement data from 22 households in England. Probability curves are used to consider the use of electric appliances [22].

In summary, the UEBM and UESM tools can be classified in the overview in Figure 1. New approaches are used to implement UEBM in UESM. Besides UEBM tools, other tools that do not deal with building modeling can also be implemented in UESM tools.

4.2 Other tools that meet the requirements

In addition to UEBM and UESM tools, other tools were researched. These tools are used exclusively to generate load profiles and also meet the requirements in Table 1.

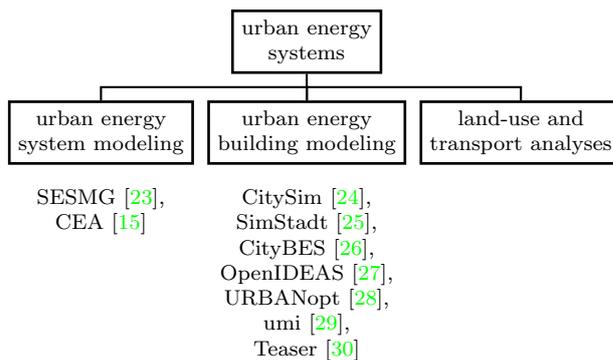


Fig. 1: Overview of tools to calculate load profiles according to [8] and the SESMG. Land-use and transport analyses are not considered in this article.

Jordan and Vajen [31] developed **DHWcalc** as a tool to create realistic conditions for DHW. The data basis for the calculations in the tool come from various studies of real residential DHW consumption [31]. Jordan and Vajen [32] investigated DHW load profiles in different time scales. They created load profiles on a time scale of a hour by taking hourly averages from the minute profiles. Due to this, flow rates will be very small when averages are calculated and cannot be considered as realistic flow rates. However, the error becomes smaller as the total load increases, so hourly values are suitable for larger simulations. Comparing minute time scale and hourly time scale, the shapes of the curves are quite similar, but the flow rates differ significantly [32].

Assmann [33] applied **DIN 4108** to calculate space heating and DIN 18599-10 (DIN 4108-6 is replaced by DIN 18599) for DHW in his bachelor thesis. The focus of DIN 18599-10 refers to the calculation of annual demands. Those are calculated by the effective building area. The annual demand is divided by 8 760 hours per year to obtain the hourly demand. Consequently, with this tool, the DHW consumption is constant throughout the year.

Thermos uses a standard day approach (e.g. normal weekday, winter weekday or peak day) and different building types (e.g. residential and commercial). Based on these data, there are predefined heat profiles [34]. How exactly these profiles were calculated is not clear from the thermos publications.

The Load Profile Generator (**LPG**) is based on a desire model from the field of psychology and makes it possible to avoid calculating any probability distributions [22]. The basic idea of this model is that people do what gives them the greatest satisfaction at any given time. People have a number of different desires, for example the desire to eat something or to watch television. The load profile is then generated depending on the satisfaction of the desire [5].

In the **Ms-Tool**, the hourly space heating demand is calculated using the outdoor air temperature, the heating limit temperature and the annual heating de-

gree hours. The heating degree hours are determined in the tool analogously to the procedure of the VDI 3807 for the calculation of heating degree days only in hourly resolution [35]. The MS-Tool offers electricity load profiles for four consumption types (two for families, working people, pensioners). The basis for these four load profiles are 74 electricity load profiles from the University of Applied Sciences Berlin (HTW Berlin). These 74 load profiles were divided into the above-mentioned consumption types using the cluster algorithm k-means. The 74 load profiles of the HTW Berlin have a second-by-second resolution. For the MS tool, these 74 load profiles were reduced to an hourly resolution, aggregated and normalized to an annual consumption of 1 MWh/a [35, 36].

The demandlib provides a tool to generate load profiles according to the guideline **VDI 4655** [2]. However, the tool is still in the development stage but it is possible to test the branch. The VDI 4655 does not require an hourly weather data set from a specific location. The location of the building gets considered by choosing one of 15 climate zones by the German National Meteorological Service (DWD). For each zone there are ten typical day categories. A typical day category is, for example, a cloudy working day in the winter. Those days occur, for example in Münster, 58 times per year and have a mean temperature of 2.8 °C. The daily energy demand of typical day categories is determined as a share of the annual energy demand by factors. Thus, all typical day categories have different energy demands. The daily energy demands are then multiplied by reference load profiles. A reference load profile comes closest to the typical course of the measured days. This ensures that the characteristics of a profile are preserved and have no loss of detail through averaging and the associated smoothing. The reference load profiles contain the normalized energy demand (ratio of instantaneous energy demand and daily energy demand) in different temporal resolution. The reference load profiles exist for different building types [2]. The approaches from VDI 4655 for heat and electricity load profiles are similar.

SynPRO is a stochastic bottom-up model for generating electricity and heat load profiles for German households. It is based on the assumption that electricity consumption in households is caused by the operation of technical devices. Each device has its individual load curve, which depends on the kind of device, the duration and the intensity of use. The usage depends strongly on the behavior of the user. The general model approach is based on a separation of consumption into user-controlled and user-independent devices. SynPRO also integrates behavioral models and energy balance models (transmission losses, ventilation losses, solar and internal gains). For the behavioral models, synPRO uses data from the last „Harmonised European Time Use Surveys“ in Germany [3, 37].

Most of the presented tools only consider residential load profiles, except the demandlib (Appendix B) and

CEA (e.g. Administrative, Hotel, Restaurant, Sport arena, Store/department store) have profiles for non-residential buildings.

4.3 Applied tools

To sum up, CEA and the SESMG (demandlib, Richardsonpy) as well as all tools described in subsection 4.2 can be used to generate load profiles. Table 3 shows the considered tools and the required input data. The output data is always a time series.

5 Comparison of applied tools

In this chapter, the load profiles are compared based on their courses. The load profiles can be found in the appendix (Appendix C).

Due to the high number of tools considered, a large effort is required to adapt all tools to the same conditions. For a more detailed analysis, for example, it would be necessary for all tools to use the same location and the same reference year. Most tools (CEA, demandlib, DIN 4108, LPG, MS-Tool, thermos) allow user defined weather data as input. This is important to compare the individual tools. However, VDI 4655 uses a different consideration of the weather data. This means that an analysis using the temperature curve is not possible. Figure 2 shows an example of the correlation between temperature and heat demand. It can be seen that space heating is strongly dependent on the outdoor temperature, but DHW is almost constant over a year and does not highly dependent on the outdoor temperature.

5.1 Domestic hot water load profiles

Appendix C.1 shows eight different six-month courses and three-day courses. Looking at the six-month courses, it is noticeable that only three tools (DHWcalc, LPG, synPRO) take vacation days into account. For a realistic course it is necessary to consider the vacation days. Furthermore, it is noticeable that, following to the demandlib, the DHW consumption decreases in the cold months. Normally, the demand is increasing in colder months. In addition, the high peak loads of the VDI 4655 on days in November and December are striking. These are all days from the same typical day category, Sundays when the sun shines. According to the VDI 4655, on these days are probably a particularly high consumption. Considering three-day courses in Appendix C.1, it becomes clear that the tools can be divided into three categories.

1. constant load (DIN 4108, MS-Tool)
2. low peak loads, daily load profile (demandlib, CEA)
3. high peak loads, draw-offs (DHWcalc, LPG, synPRO, VDI 4655)

Jordan and Vajen [31] studied the impact of DHW load profiles on solar heating systems. Most of the profiles used for simulations were very simplified, with long draw-offs periods and constant flow rates (categories 1 and 2). These simplifications have strong impact on the system performance of solar heating systems. Figure 3 shows the hourly comparison of two DHW load profiles (categories 2 and 3). It can be seen that DHWcalc only considers DHW at 36 % of the hours in March. Demandlib assumes DHW at every hour of the month. The peaks are also very different. DHWcalc considers larger peaks up to 20 kW, the demandlib peaks up to 2 kW. This is due to the different calculation methods. Input data are consumer type, annual demand and the climatic location, but not the individual consumption behavior. These standard load profiles only provide a statistical representation of an individual reality and are therefore only suitable to a limited extent for representing individual consumers [19]. In contrast, DHWcalc represents the consumption behavior by means of a probability function. Thus, there is no continuous load as with demandlib, but a draw-off profile is represented, i.e. the hourly used volume flow of DHW [31].

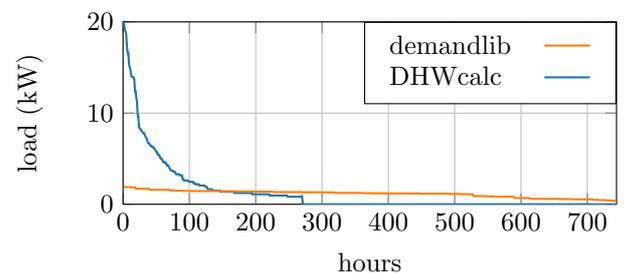


Fig. 3: Hourly comparison of DHW load profile in March between demandlib and DHWcalc.

5.2 Space heating load profiles

Figure 2 clearly shows how dependent the space heating load profiles are on the outdoor temperature. Temperature dependence is considered in most load profile tools by a location-based weather dataset. Appendix C.2 shows eight different six-month courses and three-day courses. Looking at the six-month courses, the load profile calculated by the VDI 4655 differs from the other load profile tools. The reference load profiles of the typical days can be seen. According to Fischer et al. [37], the VDI 4655 load profiles are not suitable for energy system modeling because only limited numbers of reference buildings and days are provided. Consequently, for same climate data and building type the resulting load profiles are identical shaped [37]. The six-month courses in Appendix C.2 also show that the thermos results are different from

Tab. 3: Applied tools for calculating space heating (SH), domestic hot water (DHW) and electricity (E) load profiles considered in this work.

tool	SH	DHW	E	input
CEA [15]	✓	✓	✓	depending on the required accuracy of the simulation, just location is necessary
demandlib [16]	✓	✓	✓	annual demand, building type; heat only: building and wind class, customer values, h-value, week day factor, temperature factor, hour factor
Richardsonpy [17]	✗	✗	✓	annual demand, number of occupants, direct and diffuse solar radiation
DHWcalc [38]	✗	✓	✗	conditions for the draw-offs (flow rates, duration etc.), conditions for the probability function (daily probabilities for draw-offs etc.)
DIN 4108 [33]	✓	✓	✗	building geometry, weather data, solar radiation, U-values etc.
thermos [39]	✓	✗	✗	annual heat demand, geographical location, building's height
LPG [40]	✓	✓	✓	household type (60 predefined households), all settings customizable
MS-Tool [41]	✓	✓	✓	annual demand; heat only: cold and hot water temperature, loss factor, daily volume (DHW), air temperature, heating limit temperature and heating degree hours, loss factor (SH)
VDI 4655 [2]	✓	✓	✓	occupants, units, annual demand, test reference year, house type, holidays
synPRO [3, 37]	✓	✓	✓	climate region, temporal resolution, number of occupants, occupant type; heat only: circulation (DHW), building type, renovation status and night reduction (SH)

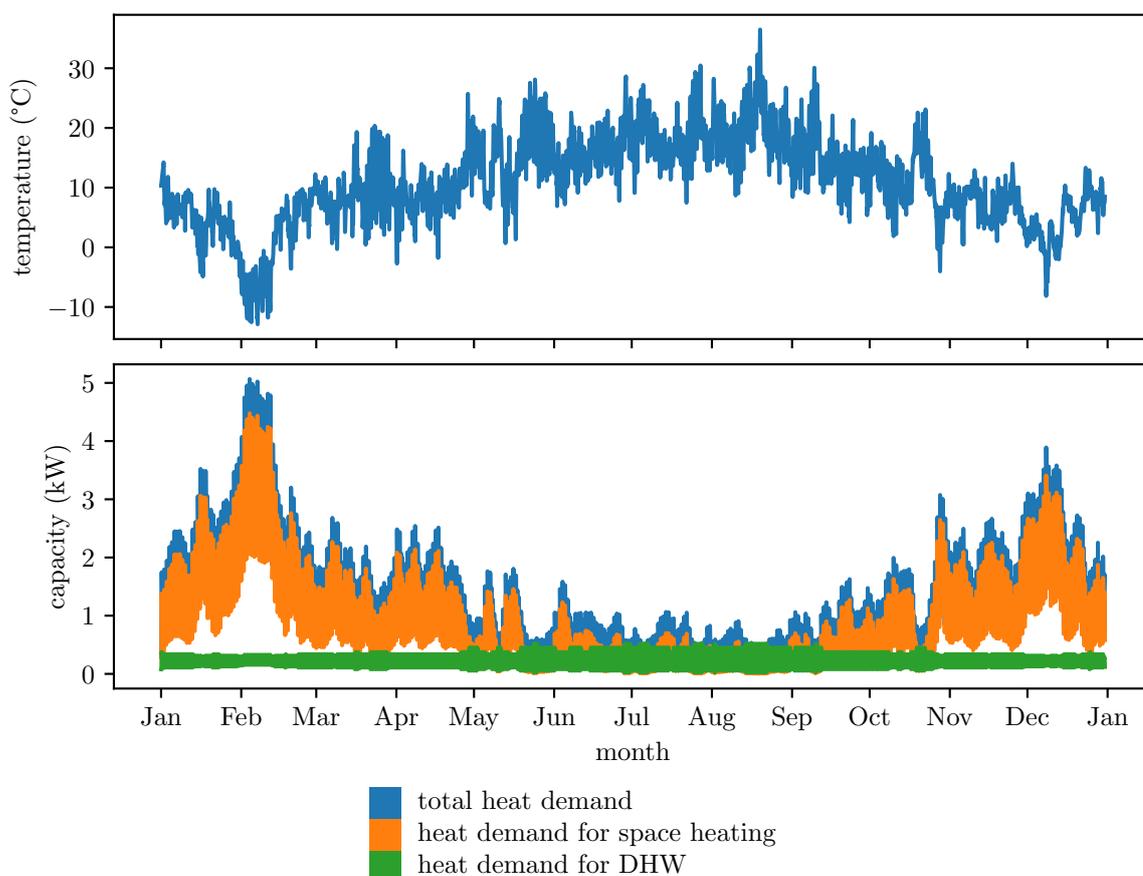


Fig. 2: Temperature course and heat load profiles of one year created with the demandlib (8 MWh space heating 2 MWh DHW).

other load profile tools. A peak load of more than 25 kW occurs. This is due to the fact that thermos is primarily used for the calculation of district heating networks. The peak loads represent the simultaneity, so that pipes are not undersized. Renewable energies cannot be sufficiently considered with thermos, because temporal and seasonal changes cannot be represented. Thus, no continuous year is considered. In addition, thermos is more suitable for larger scales and not for building-specific simulations [39]. CEA and synPRO also assume that space heating supply is interrupted at certain times during the summer months. Thermos, demandlib and DIN 4108 assume a space heating demand in summer. Assmann [33] manually set the space heating demand to zero in his calculation according to DIN 4108. For demandlib, the reasons have already been suggested: standard load profiles represent a large number of buildings or users and therefore usually show little variation. They only partially reflect the individuality of buildings due to their different building physical properties or the inclusion of solar gains [37].

Considering three-day courses in Appendix C.2 shows that only the Ms-Tool does not reflect the typical daily pattern of a household. This course can be seen in all other tools. For MS-Tool, the course is based on the applied VDI 3807. Only the heating degree hour approach is taken into account, but not the user behavior. Here, a heating limit temperature is defined. As soon as the temperature rises above this limit, no heat is supplied [42]. In LPG and VDI 4655, the approach based on heating degree hours is also selected, but with consideration of user behavior.

5.3 Electricity load profiles

Appendix C.3 shows seven different six-month courses and three-day courses. Looking at the six-month courses, the load profiles can also be divided into categories. The course of the load profiles generated by demandlib is similar to those from CEA. Richardson, LPG, and synPRO obviously follow different approaches. If the six-month courses in Appendix C.3 are examined, it is clear that the CEA electricity load profiles are constant over a year and no seasonal changes are considered. Furthermore, it is noticeable that only the LPG considers vacation days. The user can determine when the occupants go on vacation. During this period, only standby devices are considered.

Considering three-day courses in Appendix C.3 shows that no daily changes are considered for CEA either. Consequently, the user behavior of individuals is not represented. The demandlib is using standard load profiles. Standard load profiles are an important example of a top-down model. These are developed for modeling the energy consumption of a large number of households at the same time [43]. The available

standard load profiles are not well suited for building electricity load profiles because it assumes that every household follows the same electricity consumption patterns, regardless of the number of occupants, their socioeconomic status, or the number and type of electric appliances they use. In reality, an individual residential load profile can vary greatly from building to building. In addition, most of the measurements used by BDEW to create the standard load profiles were collected in the decades before 2000. This ignores the impact of the increasing number of electrical appliances in the residential buildings since 1999 on household electricity loads [4]. Therefore, for example, the change of lighting from incandescent bulbs to LEDs is not considered correctly. Today lighting consumes up to 15 % of the energy in households. As a result, it is also important to consider the global radiation and consequently the location. After all, below a global radiation of 50 - 75 W/m², it is most likely that occupants will turn on the lights [5]. This behavior of the occupants is represented, for example, by Richardsonpy, LPG and synPRO. However, Richardsonpy has the disadvantage that the seasonal variations and thus the changing global radiation is not taken into account. Thus, the fact that less electric light is required in summer is also not taken into account.

5.4 Classification of the applied tools

In summary, the output, i.e. the hourly load profile, is specified for each tool (Table 4). The load profiles are specified with respect to their calculation approach. Unfortunately, no calculation approach could be found in the literature for thermos. Energy system modeling can be used for a wide variety of applications. Application fields are differentiated, for example, by the spatial resolution. Thus, it is possible to consider the energy demand of a city district for the whole district, for every building, or even for every consumer [6]. These distinctions have to be made for load profiles as well. Different load profiles are required for entire districts than for individual buildings.

Standardized load profiles are based on average measured values and are unsuitable for a building-specific simulation. In this case, the load profiles are not realistically represented. Standardized load profiles serve the purpose of making forecasts for distribution network operators. A large number of buildings are taken into account in the forecasts. Consequently, the scope is limited to energy system models that do not handle building-specific analyses but, for example, investigate national impacts.

Like the standard load profiles, the reference load profiles are based on measurements. A representative annual load profile is selected from these measurements. From this, representative days for different climate classes are extracted and recomposed according to the desired climate data [37]. Although the

Tab. 4: Type of load profiles (lp). Abbreviations: space heating (SH), domestic hot water (DHW).

tool	DHW	SH	electricity
CEA [15]	standardized lp	physical lp	standardized lp
demandlib [16]	standardized lp		
Richardsonpy [17]	-	-	stochastic lp
DHWcalc [38]	stochastic lp	-	-
DIN 4108 [33]	constant lp	physical lp	-
thermos [39]	unknown	unknown	-
LPG [40]	behavioral lp		
MS-Tool [41]	constant lp	physical lp	standardized lp
VDI 4655 [2]	reference lp		
synPRO [3, 37]	stochastic lp		

load profiles represent peak loads better than standard load profiles. The major disadvantage of these profiles is that only a few days are represented and the load profiles are therefore not realistic for an entire year.

In addition to the tools shown in Table 4, UEBMs also use physical models. Physical models use building models based on lumped energy balance equations and physical building properties [37]. For these models, characteristics such as building insulation or number of windows are important to calculate transmission losses. The difference between losses and, for example, solar gains, represents the physical load profile. However, the user behavior of the occupants is often not taken into account.

Stochastic load profiles are often on the approaches described above, but try to take user behavior into account by, for example, using statistical probability functions. These statistical approaches work well for larger populations when sufficient data is available. However, for individual households or when only few data are available, these load profiles lead to problems [5].

For the optimization of energy supply systems, it is necessary to consider the user behavior [2]. Between 50 % and 80 % of the energy consumption in an average household is directly caused by the behavior of the occupants. The rest is generated by appliances in standby mode and appliances that operate independently of the occupants, such as the refrigerator [5]. Behavioral load profiles refer almost exclusively to the behavior of the occupants. No statistical functions are used, but an entire behavioral model is set up. This attempts to reflect the behavior of the occupants as accurately as possible. However, important building characteristics that significantly influence the load profile are missing.

6 Conclusion

At the beginning of this work, the question was asked which load profile tools are most suitable for energy system modeling. Due to the large field of application of energy system modeling, it was found that load profiles have to be selected based on the field of application. The developed classifications enable users to select suitable load profiles for energy system modeling, thus reducing the probability of misinterpretation of the results and sizing the technologies more realistically.

7 Outlook

The article shows, that a combination of the CEA and the LPG approach would be useful. The CEA defines different archetypes for buildings. A similar approach is created with the LPG for occupants. If both approaches are combined, building characteristics and occupant behavior, could be modeled in detail. The user would only specify the type of building and what kind of people live there. The requirement is that this data is available.

In the coming decades, the electricity load profile will change radically due to the increase of

- electric vehicles,
- ownership of electric devices or
- remote work.

To study and understand these changes, a solid understanding of the electricity load profile and its modeling in its current state is required [4]. Especially tools that rely on old measured values have to be outdated, otherwise there will be large deviations that could negatively influence the sizing of the technologies. Electric vehicles are considered in the context of energy

systems under the heading of land-use and transport analyses (Figure 1). It would make sense to use the data from the analyses as input data for UESM. This would allow a holistic view of energy systems so that the different synergies could be identified.

This paper focuses on residential buildings. However, demandlib and CEA have the advantage of also considering buildings in other sectors. Fraunhofer ISE (synPRO) is also planning synGHD [44], a tool to create load profiles for commercial buildings. For the holistic consideration of energy systems, the load profiles of the other sectors are indispensable and must also be considered. There is still a need for improvement at this point.

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Appendix

A Tools reviewed by Ferrando et al.

- **CitySim** is building a 3D model, needs lots of input data (export of a drafting software application, CityGML data, indoor air temperature, ideal heating needs, internal gains, satisfied heating needs)
- **SimStadt** is not publicly released (04/2021)
- **umi (Urban Modeling Interface)** is using Rhino 7, which is only free for 90 days
- **CityBES (City Building Energy Saver)** uses EnergyPlus for simulation
- **OpenIDEAS (Open Integrated District Energy Assessment Simulations)** requires knowledge of the programming language Modelica and Python
- **CEA (City Energy Analyst)** meets all requirements
- **URBANopt** is not publicly released and needs high performance computer (04/2021)
- **Teaser (Tool for Energy Analysis and Simulation for Efficient Retrofit)** requires skills of the programming language Modelica and Python

B Standard load profiles demandlib

Tab. 5: Electricity standard load profiles as provided by Germany's Federal Association of Energy and Water Management (BDEW) [20].

Profile	consumer group
H0	households
G0	commercial general
G1	commercial on weeks between 8-18 hrs
G2	commercial with strong consumption in the evening
G3	commercial continuous
G4	shop/hairdresser
G5	bakery
G6	weekend operation
L0	agriculture general
L1	agriculture with dairy industry/animal breeding
L2	other agriculture

Tab. 6: Heat standard load profiles given by Germany's Federal Association of Energy and Water Management (BDEW) [18, 19].

Profile	consumer group
EFH	single family house
MFH	multi family house
GMK	metal and automotive
GHA	retail and wholesale
GKO	Local authorities, credit institutions and insurance companies
GBD	other operational services
GGA	restaurants
GBH	accommodation
GWA	laundries, dry cleaning
GGB	horticulture
GBA	bakery
GPD	paper and printing
GMF	household-like business enterprises
GHD	Total load profile Business/Commerce/Services

C Load profiles

All considered load profiles do not show significant differences of the half-year curves. Therefore and due to the file size of this document, only half-year curves are shown. In addition, the courses of three days are shown to allow a detailed consideration.

Tab. 7: Abbreviations for the following diagrams.

Abbreviations	full name
slp	demandlib [16]
richardson	Richardsonpy [17]
lpg	LoadProfileGenerator (LPG) [40]
mstool	Mieterstrom-Tool (MS-Tool) [41]
cea	City Energy Analyst (CEA) [15]
vdi4655	VDI 4655 [2] created with demandlib [16]
synpro	synPRO [45]
dhwcalc	DHWcalc [38]
din4108	DIN 4108
thermos	thermos [39]

C.1 Domestic hot water

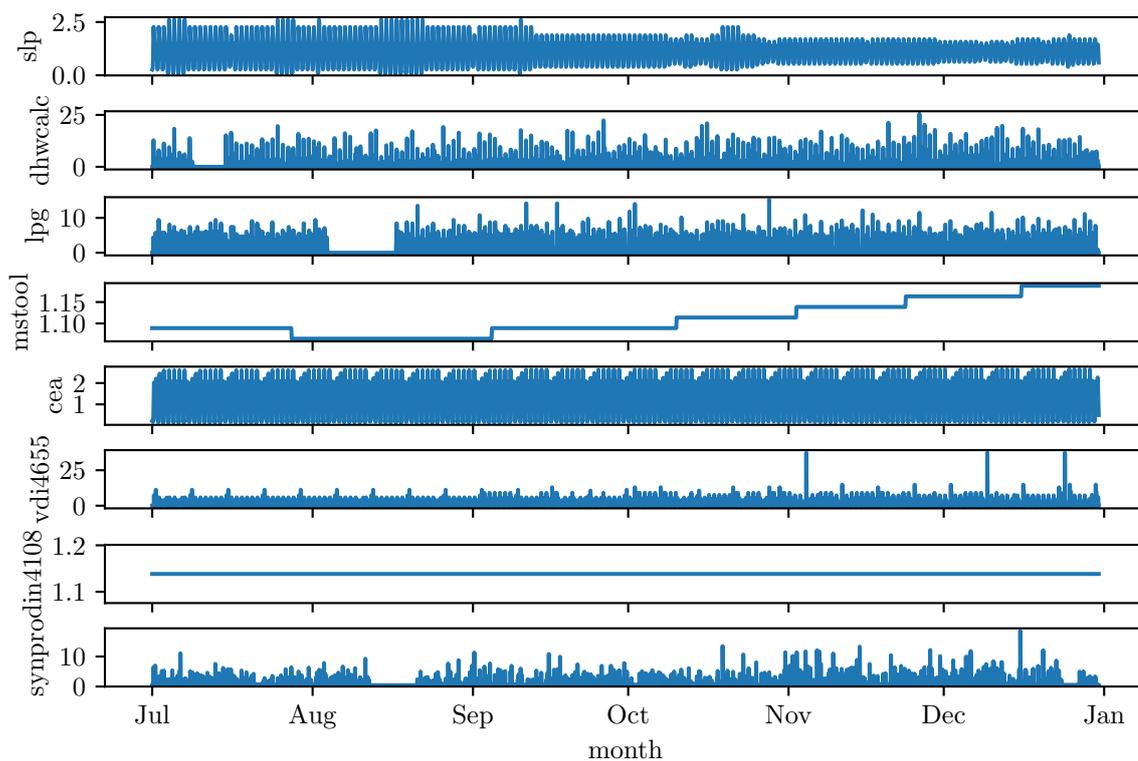


Fig. 4: Domestic hot water load profiles (kW) of half a year (01.07.2012 - 31.12.2012).

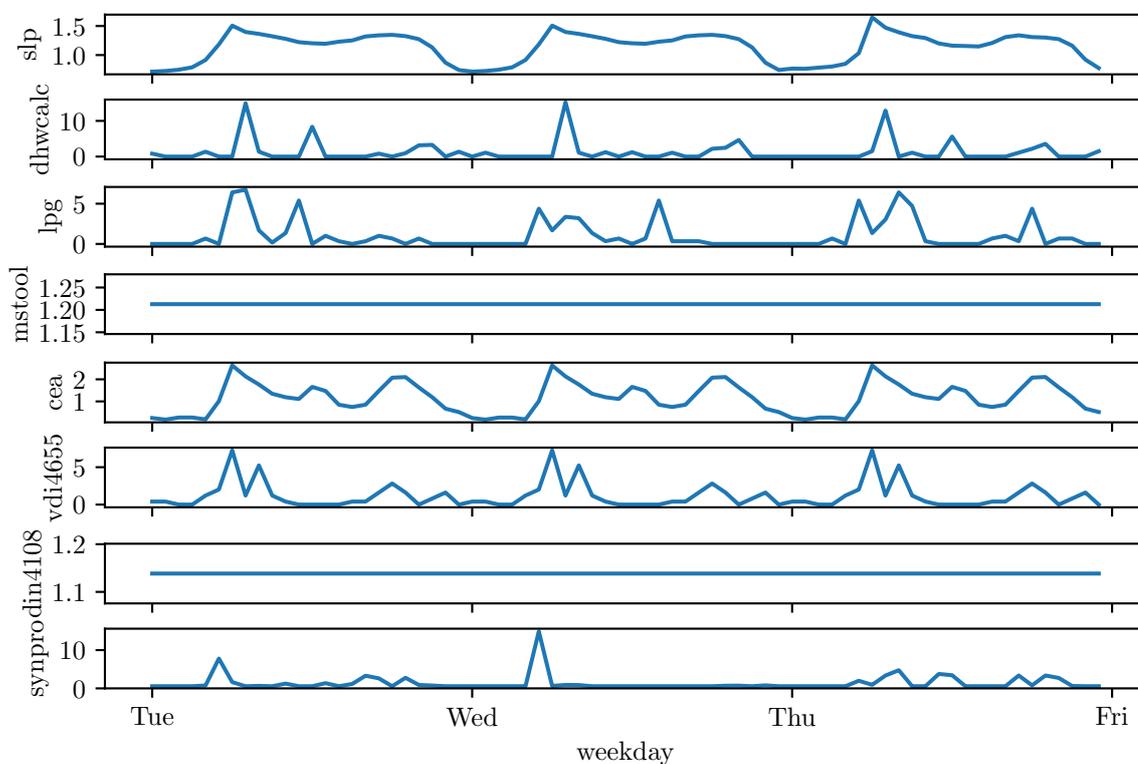


Fig. 5: Domestic hot water load profiles (kW) of three days (31.01.2012 - 02.02.2012).

C.2 Space heating

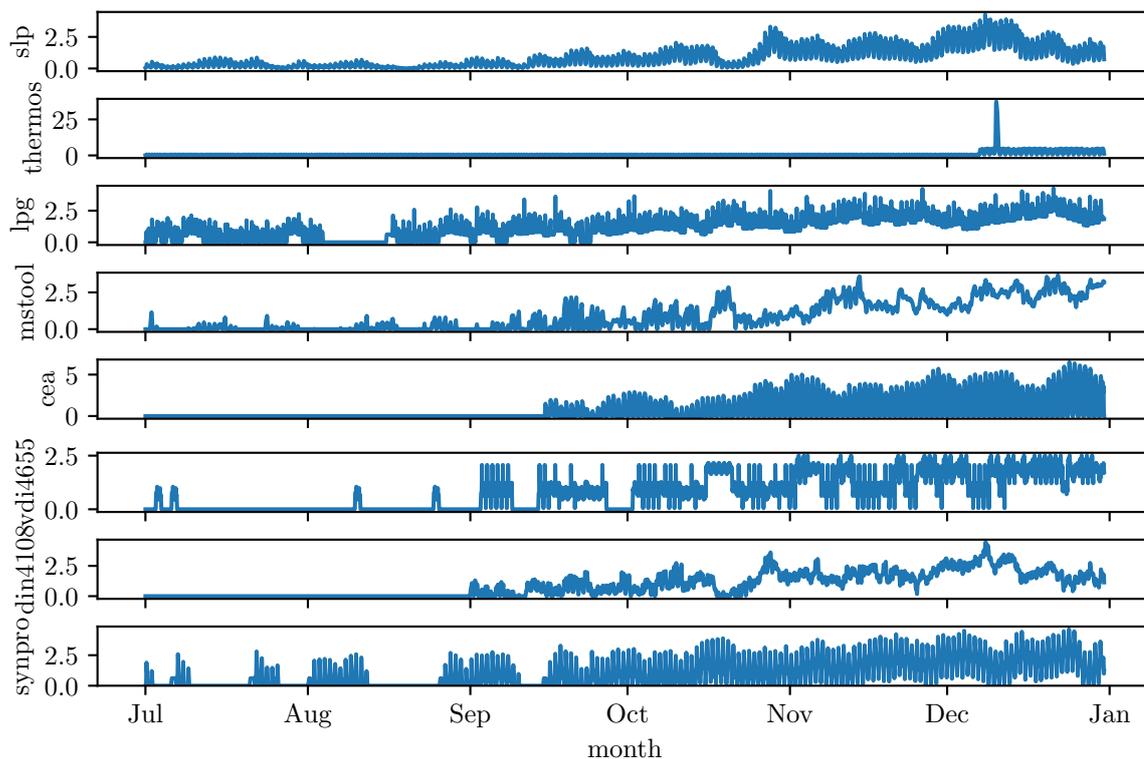


Fig. 6: Space heating load profiles (kW) of half a year (01.07.2012 - 31.12.2012).

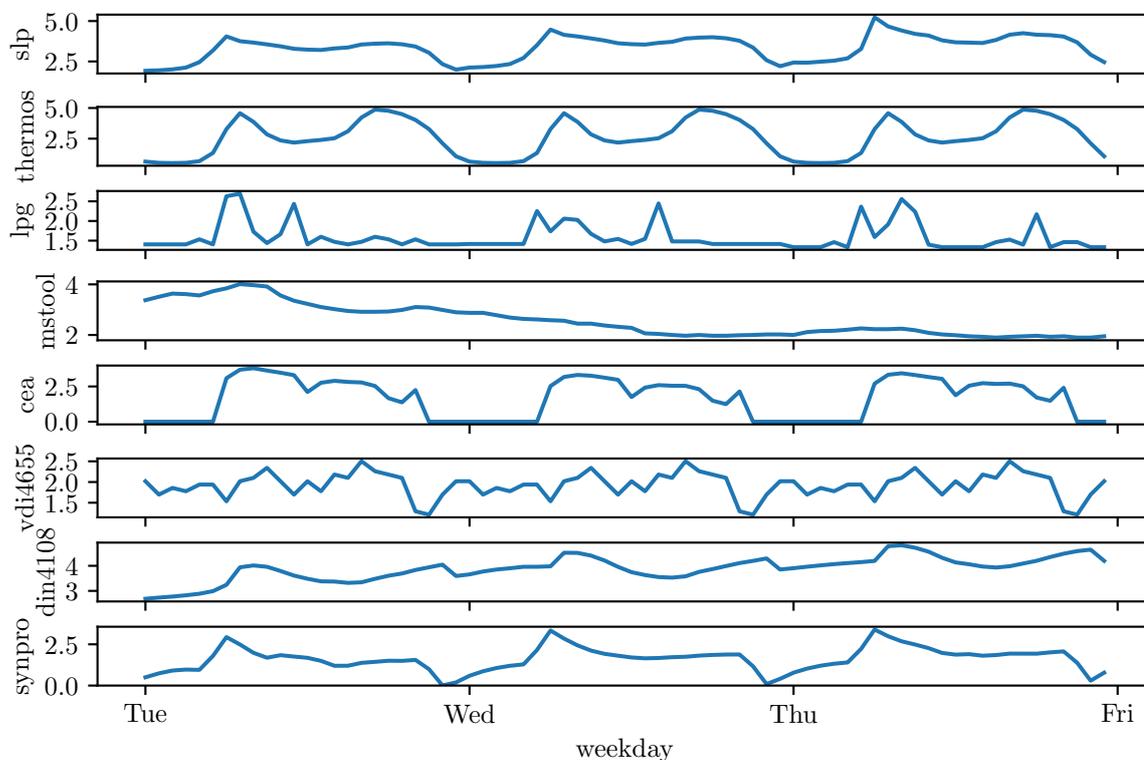


Fig. 7: Space heating load profiles (kW) of three days (31.01.2012 - 02.02.2012).

C.3 Electricity

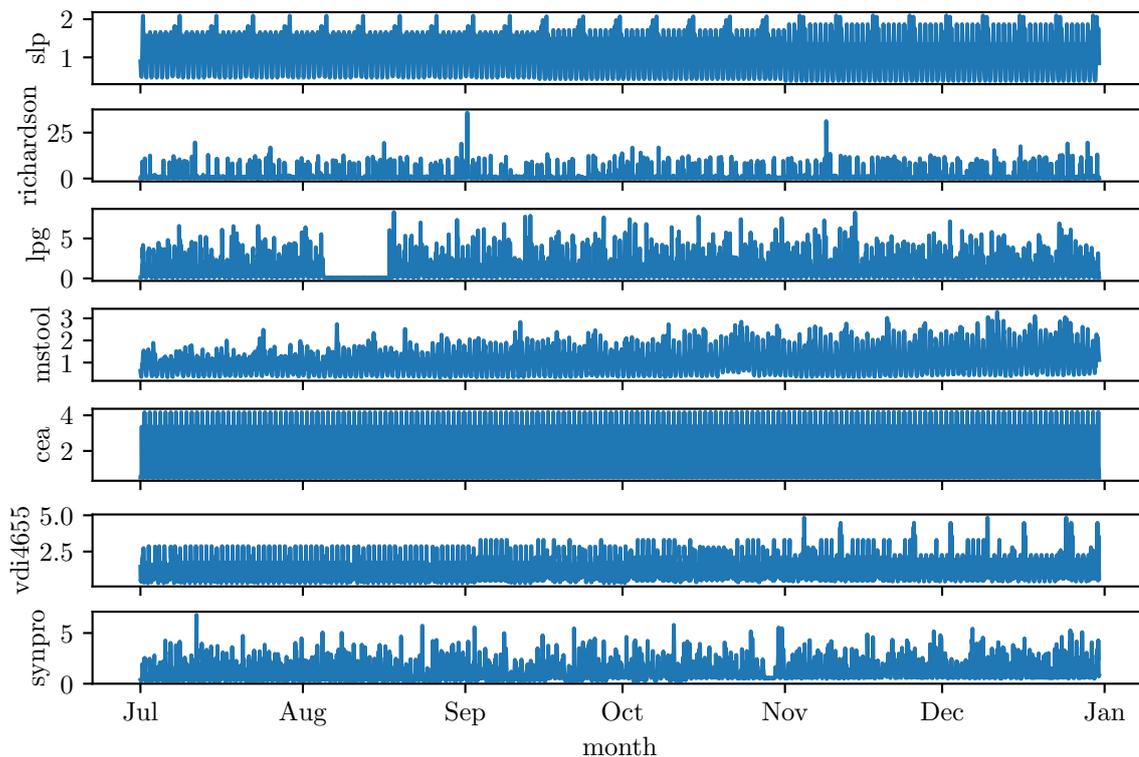


Fig. 8: Electricity load profiles (kW) of half a year (01.07.2012 - 31.12.2012).

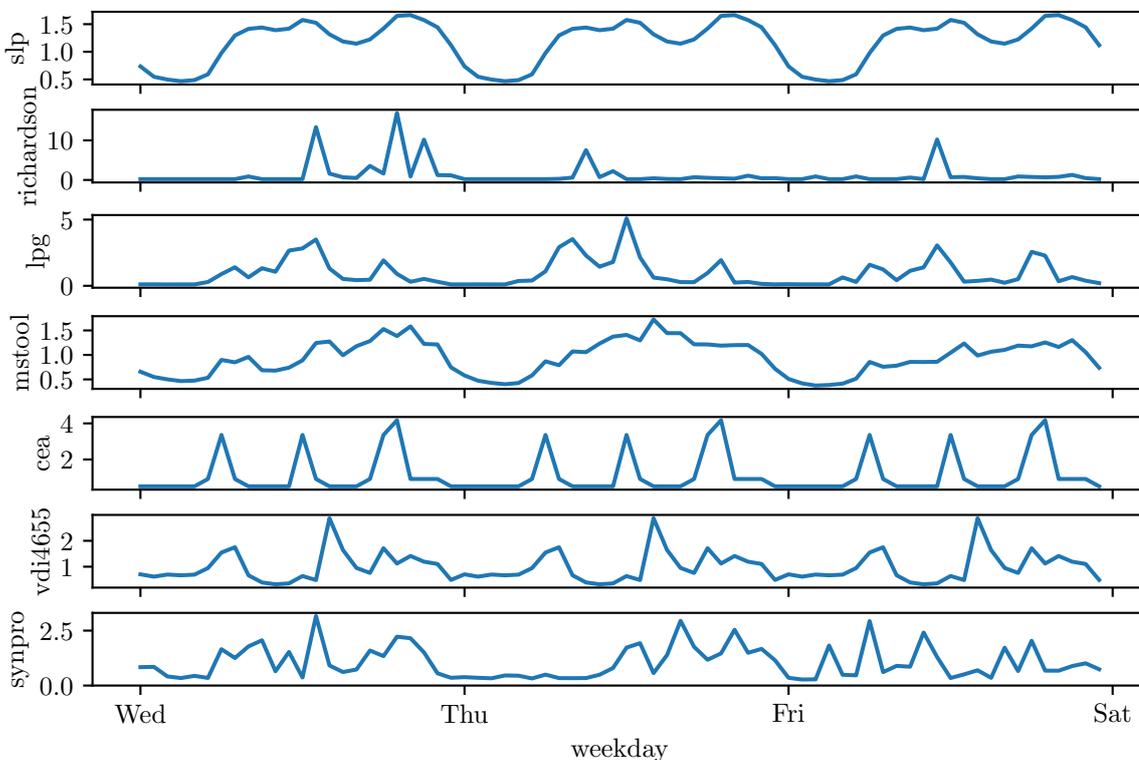


Fig. 9: Electricity load profiles (kW) of three days (25.07.2012 - 27.07.2012).