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Detecting residential power peaks for innovative tariff designs: A living lab experiment

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ABSTRACT

As smart meters become increasingly prevalent in private households, the availability of high-resolution electricity load profiles creates new opportunities for innovative electricity tariffs. Already established in industry, innovative tariffs could consider power consumption in order to monitor and maintain grid stability. This study explores the crucial role of time granularity in detecting power peaks, which are frequently missed when using coarse temporal intervals, such as 15 minutes. Through the analysis of high-resolution electricity load data from a living lab experiment, this research aims to determine the sampling rate necessary for accurately detecting power peaks. Our findings indicate that a sampling rate of 1 minute generally allows for effective peak identification, while certain cases necessitate even higher sampling rates, such as 10 to 5 seconds, to account for brief yet intense power peaks. This highlights the importance of employing a high sampling rate in the design of electricity tariffs that incorporate peak power consumption from households. Moreover, our study demonstrates that the temporal resolution of sampled data significantly impacts the accurate detection of temporary load unbalance, further emphasizing the novelty and significance of considering time granularity in smart meter data analysis.

1. Introduction

The deployment of smart meters in the domestic sector offers significant potential for grid operators and electricity consumers alike. These devices facilitate the introduction of innovative electricity billing methods by providing detailed measurements of electrical consumption with high spatial and temporal accuracy. This capability opens up various opportunities for new energy- and power-based services. Such innovative tariffs can enhance demand flexibility, which is increasingly vital as electricity supply becomes more volatile due to the growing reliance on renewable energy sources. Moreover, challenges, such as maintaining grid stability during peak hours can be addressed by various tariff schemes that incentivize consumers to decrease or increase their electricity consumption at critical times.

1.1. Current use of smart meters and conventional data sampling resolution

When load dynamic tariffs are contemplated, a significant aspect of evaluating the residents' responsiveness to such tariffs becomes the time sampling resolution of data collected by smart meters, as the ability to detect peak loads depends significantly on the temporal granularity of the provided data. The challenge of interpreting and analyzing domestic electricity load profiles based on their time resolution is well documented. In their work dating from 2007, Wright and Firth [1] assess the effects of time averaging, based on the electricity load profiles of eight households to analyze the effects of on-site generation on local electricity networks by comparing load profiles at 1 min and 30 min resolutions. They conclude that resolutions larger than a minute underestimate the proportions of both exported and imported electricity quantities. Similarly, the study of Hernandez, Sanchez et al. [2] evaluates various studies that examine domestic load profiles, focusing on the loss of informationregarding power peaks relative to the data sampling rate. Their findings suggest that a data granularity of 5 s strikes the best balance between minimizing the loss of information and managing the computational burden, considering data storage and post-processing. As research increasingly incorporates demand response tariffs that include capacity components, these insights are crucial for understanding and implementing such tariff schemes effectively.

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Nomenclature

P_t^T	Power demand in the aggregated time series with a temporal resolution of T at time t
$P_t^{T,a}$	Aggregated load profile of phase a
$P_t^{T,b}$	Aggregated load profile of phase b
$P_t^{T,c}$	Aggregated load profile of phase c
bne	Association of energy market innovators
CBA	Cost-benefit analysis
CPP	Critical peak pricing
CPR	Critical peak rebate
DL	Dynamic load tariff
DLC	Direct load control
ESHL	Energy Smart Home Lab
GB	Grid bottleneck
iMSys	Intelligent metering system
mME	Modern metering system
MsbG	Measuring point operating act
PF	Power flatrate
PMR	Peak-to-mean-ratio
PV	Photovoltaic
RTP	Reak time pricing
SMG	Smart meter gateway
TOU	Time of use tariff
VPP	Variable peak pricing
WAMP	Web Application Messaging Protocol

According to Annex I of the Third Energy Package (2009/72/EC) [3], member states of the European Union (EU) shall ensure that by 2020 80% of consumers are equipped with smart metering system, assuming the cost-benefit analysis (CBA) for their country is positive. However, countries with negative CBAs must repeat the assessment every four years and once the result is positive, the 80% goal shall be achieved withing seven years. Besides the CBA, also other economic, regulatory and technical barriers have delayed the smart meter roll-out in Europe [4]. One key barrier is that the utilities have to recover the costs of the deployment through usage tariffs, although the revenues may be considered insufficient. Therefore, due to the uncertainty of revenues and a lack of incentives, the utilities' interest in the smart meter roll-out can be low [5–7].

Today, there are significant differences in the status of smart meter gateway deployment in different European countries. A number of countries have reached already more than 80% or even finished the first roll-out and have started or planned the second stage (e.g. Denmark, Finland, Italy, Spain, Sweden). Other countries like France, the Netherlands and Switzerland will likely complete the roll-out in the upcoming years. One third of European countries have set their target to complete the roll-out by 2030 or later, with Germany being the most prominent among them. Currently, the share of smart meter gateways is less than 10% in Germany, resulting in the need to deploy 45 million smart meters in the upcoming years until 2032 [4,8]. Due to the current, early status of the roll-out and the need for an accelerated deployment in the upcoming years, we will put the focus on the situation in Germany in this study.

The current average, annual household electricity consumption in Germany ranges from 1958 kWh to 4919 kWh (in 2015, for 1-person households and 3 or more person households, respectively [9]). As long as the annual consumption is below 6000 kWh, there is usually no legal obligation for households to install a smart meter. However, the development of the energy system comprising smart grids, smart homes and a further electrification of households (e.g. by electric vehicles, heat pumps, electricity generation via photovoltaic (PV) systems) will lead to the necessity of installing smart meters in order to closely monitor electricity consumption and make billing for new electricity tariff schemes possible. Having a look at present metering options in Germany in Table 1, we can see that the term "smart meter" does not suffice as description for an upgrade of a previous metering system. Rather three types of metering options need to be distinguished ranging from the analogue ferrari's counter to the digital modern metering system (mME) and the intelligent metering system (iMSys). In general, the former analogue ferrari's counter, still prominent in German private households, is to be exchanged completely by mMEs until 2032 [10]. The mMEs can be upgraded to iMSys by adding a communication entity, also called a smart meter gateway (SMG), that is the interface between counter and communication network. The iMSys comes closest to the term "smart meter", comprising the digital counter, as well as the smart meter gateway to communicate the electricity consumption quarter-hourly via the communication network.

When a household owns an electric vehicle or a heat pump, the electricity consumption rises accordingly. In Germany, as soon as the electricity consumption exceeds 6000 kWh per year, it is accounted for by the Measuring Point Operation Act (MsbG) [11] and the installation of an iMSys is required. Even though the iMSys is not required for households below an annual consumption of 6000 kWh, the participation in new electricity tariffs would require an iMSys in order to allow a correct billing procedure. The iMSys presently accounts for a data transmission rate of 15 min maximum, considering energy metering (Zählerstandsgangmessung) (§ 2 Nr. 27 MsbG) or load metering (§ 55 Abs. 1 Nr. 2). Even though § 55 Abs. 1 Nr. 4 in MsbG states that a metering fitting the requirements of the agreed tariff scheme for electricity supply is supposed to be installed, no further information about the granularity of the data transmission rate is given, implying that the 15 min interval is the maximum granularity accounted for so far. Hence, as the Association of Energy Market Innovators (bne) also formulated in 2020 [12], the current framework just allows special TOU-dependent tariffs and providing information directly to the consumer, so that dynamic electricity price contracts for generation and load management or grid-supporting operational applications are "either limited or non-existent", stressing the inadequacy of the 15 min resolution already for current requirements. With the above mentioned studies such as [1] and [2] also showing that a 15 min resolution would be too coarse to detect power peaks in residential consumption, the doubt arises whether the present smart meter data transmission rate is sufficient for the introduction of power related tariff schemes. Furthermore, the present literature does not yet present a common understanding in this regard, showing the need of further analyzing the information loss caused by a varying data transmission granularity connected to load based tariff schemes.

1.2. Electricity tariffs to induce demand response

Following the assumption that demand response is not established via regulation, but depending on voluntariness, the acceptance and engagement of consumers is needed. This raises a variety of questions, ranging from what incentives are most effective in inducing demand response behavior to how an electricity tariff must be structured to encourage this kind of behavior. Research has shown that volumetric charges, such as time of use tariffs (TOU), give varying results [13,14]. Another option is the introduction of power based tariffs or a combination of volumetric and capacity based tariffs. The latter of these can already be found in the grid charges of the German industry [15]. Since these kinds of tariffs have not yet been introduced in the domestic sector, Scharnhorst, Sandmeier et al. tested multiple capacity and volumetric based tariffs in a field study with two tenants living in a smart home for three months [16]. The data gathered during the experiment builds the basis of our analysis in this study.

Table 1
Overview of metering options for electricity consumers according to Bundesnetzagentur 2022 [10].

	Ferrari's counter	Modern metering system (mME)	Intelligent metering system (iMSys)	Smart meter gateway (SMG)
Metering type	Analogue counter	Digital counter without communication entity	Digital counter with communication entity	Communication interface
Counter displays	Current count	Current count	Current count	*Interface between the counter and communication network*
Data processing	Current count	Saved values: daily, weekly, monthly and annual specific, two years retrospectively	Retrievable, quarter-hourly values: daily, weekly, monthly and annual display	*Automated data transmission to metering operator*

1.3. Consideration of load unbalance

In addition to capacity-based tariffs as an add-on to present electricity tariffs, a further topic to be considered is the option of pricing load unbalance. Domestic costumers in German low-voltage grids are commonly supplied through three-phase connections. Load tariffs usually consider power consumption as the sum across all three phases. Within the costumers' electrical installation, however, household appliances and lights are usually connected to single-phase circuits. These circuits are distributed approximately evenly among phases by electricians. Still, temporary load unbalances can occur because usually not all household appliances and lights are turned on at the same time.

Load unbalance situations are potentially becoming more significant with increasing penetration rates of residential PV systems, electric vehicles (when loading without a three-phase wallbox), heat pumps and storage systems. Load unbalance comes with unbalanced currents, which results in unbalanced voltage drops across the lines. For distribution grid operators, this can lead to problems with maintaining the voltage quality in accordance with European standard EN 50160 [17,18]. The latter standard specifies the voltage quality that can be expected by grid costumers at any public supply terminal in the low-voltage grid, and there are specific limits for voltage unbalance among phases. Arghvani and Peyravi [19] see both costumers and distribution grid operators as responsible for load balancing in low-voltage grids. Therefore, they suggest creating incentives for balanced load consumption through consideration of load unbalance in price structures of future load tariffs.

1.4. Open access to the electrical consumption data

For the sake of transparency and the further use in scientific studies or models, we provide parts of the data that we gathered during our experiment described in [16] and used in this paper as an open source data set to the scientific community [20]. The published data contains the unit-specific electrical consumption data aggregated to 15 min (arithmetic mean) as well as the maximum power demand values per 15 min for every device that was in use during our experiment over the whole experimental period of three months. Further information about the data and devices can be obtained from Section 2.1.

1.5. Purpose and structure of our study

Accurate detection of residential power peaks is essential for implementing dynamic pricing models, reducing grid stress during high-demand periods, and achieving energy efficiency goals. With the EU-wide rollout of smart meters, understanding the impact of load profile granularity on these objectives is increasingly critical. Moreover, the ability to accurately identify peak consumption at different temporal resolutions can help inform regulatory decisions and dynamic tariff designs, enabling a smoother energy transition across diverse grid contexts. Load unbalance at the household level presents challenges for maintaining voltage quality, particularly with increasing penetration of renewable energy technologies such as photovoltaic systems and electric vehicles. Investigating how load profile granularity influences the detection of load unbalance is crucial for developing potential tariff mechanisms that encourage more balanced energy usage. Therefore, the purpose of this study is to investigate the impact of data sampling rates on residential power peaks and load unbalance detection. The data was gathered during a field study in Germany by Scharnhorst, Sandmeier et al. [16] from one household with two tenants, where various tariff schemes were tested and the electricity consumption was metered with a sampling rate of 1 s. Albeit the data has been collected in Germany, the relevance of our findings is also applicable to other countries with similar smart meter adoption plans. The field study took place in the living lab "Energy Smart Home Lab", a controlled environment and with the limitation to two participants, which enabled detailed monitoring and close interaction with the tenants. This was crucial, to test the innovative electricity tariffs and control for user acceptance simultaneously. Our methodology, including a description of the experimental setup, the underlying data set, power-based electricity tariffs and calculation methods, will be further explained in Section 2. In Section 3, we carry out various analyses with regard to peak loads for different data sampling rates to assess the information loss with declining temporal resolutions and give an assessment on a suitable compromise between data accuracy and data storage and processing demands. During the field study, load tariffs were applied to the power sum across all three phases a, b, c. However, in Section 3.4, we separate the load profile data gathered during the field study by phase to analyze the impact of load profile time resolution on the assessment of load unbalance. The discussion in Section 4 consists of an interpretation and classification of our results as well as a comparison with the results of similar studies. Our conclusions are then drawn in the final section.

2. Materials and methods

In this chapter, we present information about the underlying energy consumption dataset and its origin, as well the different metrices and methods we used to analyze the impact of different sampling rates on the accuracy of the detected load peaks.

2.1. Collection of the energy consumption data

This study relies on a data set for the electrical power consumption of an exemplary private household. The data were collected during a three-month living lab experiment in which two individuals spent their daily lives in the Energy Smart Home Lab (ESHL). The ESHL is a fully functional smart home, as well as a living lab, located on the premises of Karlsruhe Institute of Technology (KIT) [21]. The tenants had 60 m^2 living area at their disposal, with smart household appliances such as time programmable dishwasher, oven, tumble dryer and washing machine. In addition, there is a technical room, equipped with PV, heat pump, metering systems and other technical devices, to which, however, the residents did not have access. An overview of the installed devices in the living area as well as the technical room is given in Table 2. More information about the living lab experiment can be obtained from [16].

Table 2
List of the home appliances and technical devices that were in use during the living lab experiment.

Distributed Generation	Device Name	Technical Specifications	Phase
PV panels	24x Sovello SV-T-195	4.7 kW_{peak}	
PV inverter	SMA Sunny Tripower STP 10000TL-10	10.0 kVA	a,b,c
Home Appliances			
Coffee machine	*Miele CVA 5065*	~ 2.3 kW_{peak}	b
Dishwasher	*Miele G 1834 SC*	~ 2.0 kW_{peak}	b
Dryer	*Miele T 8687 C*	~ 3.0 kW_{peak}	a
Hob	*Miele KM 5955*	~ 5.0 kW_{peak}	a,b,c
Oven	*Miele H5681 BL*	~ 3.6 kW_{peak}	c
Washing machine	*Miele 3985 WPS*	~ 2.2 kW_{peak}	c
Deep freezer	*Liebherr GN 3056-29*	~ 1.6 kW_{peak}	b
Refrigerator	*Liebherr IKS 1720-21A*	~ 1.0 kW_{peak}	b
Water kettle	*Alaska WK2210*	~ 2.0 kW_{peak}	c
Other appliances	Microwave, HiFi, TV, lights, toaster...		a,b,c
Heating System			
Heat pump	*Daikin Altherma 3 RW*	8 $kW_{thermal}$	c
Climate controller	*Kieback & Peter BMR410 and FBU410*	*Modbus* gateway	
Hot water storage tank	*SenerTec SE 750*	750 liters	
Electrical Energy Storage System			
Battery	*BYD B-Box 10.0*	10.0 kW, 9.8 kWh	
Inverter	*SMA Sunny Island SI6.0H-12*	4.6 kW	a
Metering Systems and Sensors			
Electrical metering system	*WAGO 750-8204*	*WAGO-I/O 750*	
Electrical meters	*WAGO 750-494, 750-495*	3-phase electrical meters	
Phasor measurement unit	*Electric Data Recorder*	3-phase power quality meters	
Thermal metering system	*Lingg & Janke eibSOLO*	KNX gateway	
Thermal meters	*Kamstrup MULTICAL 601*	KNX heating meters	

During the living lab experiment, the electrical consumption of each device and socket was measured with a temporal resolution of 1 s. For the house connection, additional information about the load distribution over the three phases was collected. The data was transmitted from the measuring unit via the Web Application Messaging Protocol (WAMP) in JSON format to a SQL-database, where the data is stored and can be retrieved for further processing.

The electrical meters are of type WAGO 740-494 and WAGO 750-494. The maximum measurement inaccuracy in relation to the effective power is specified in the data sheet with 0.5% and 0.75%, respectively [22,23]. For our study, these inaccuracy values can be considered negligible and will therefore not be taken further into account.

2.2. Data processing methods

In this section, we describe the different methods we used in processing the collected electrical consumption data. The methods are based on descriptive data analysis to examine the effects of varying temporal resolutions on load profile granularity. This approach was chosen to focus on the direct observational insights from high-resolution data and enables a detailed understanding of the relationships between data resolution, peak detection, and load unbalance in real-world scenarios.

2.2.1. Time series downsampling

We use the original data set with a temporal resolution of 1 s as a reference in the upcoming analyses. In order to simulate coarser temporal resolutions of the measuring system, we downsample the original time series to the respective resolution. For the resampling operator we use the arithmetic mean. Other possibilities would be e.g. the median or the root mean square. We use the arithmetic mean, since this method does not distort the amount of consumed energy in a time period, which is highly relevant in practice for billing purposes and which can be obtained by calculating the integral over the time series.

The calculation formula for obtaining the aggreggated data time series is given in Eq. (1), with P_t^T representing the power demand in the aggregated time series with a temporal resolution of T at time t (which has to be an integer multiple of T) and T_0 being the temporal resolution of the original reference time series (in our case 1 s).

$$P_t^T = \frac{T_0}{T} \sum_{i=t}^{t+T-1} P_i^{T_0} \tag{1}$$

We then analyze the observable power peaks in the calculated time series with the different temporal resolutions and compare the results with the original 1 s resolution data. This allows us to make assumptions about the amount of information loss with regard to power peaks associated with each aggregation level. Therefore we compare the maximum power demand values in the aggregated time series with the maximum values in the original 1 s data for different time periods and power ranges.

2.2.2. Peak-to-mean-ratio

One of the metrics we use in order to examine the accuracy or smoothing of different time granularities with respect to the measured power peaks is the peak-to-mean-ratio. The peak-to-mean-ratio is determined by computing the ratio between the maximum power value and the arithmetic mean for a specified period of time, see Eq. (2), where $\mathrm{PMR}_{t_1-t_2}^T$ denotes the peak-to-mean-ratio for the time series with the temporal resolution T for the time period between t_1 and t_2.

$$\mathrm{PMR}_{t_1-t_2}^T = \frac{\max(P_{t_1}^T \dots P_{t_2}^T)}{\frac{T_0}{t_2-t_1} \sum_{t=t_1}^{t_2} P_t^T} \tag{2}$$

2.2.3. Load unbalance

As mentioned in Section 1.3, the state-of-the-art of electricity billing considers the sum of consumed energy across all three phases. Thus, in the literature, we cannot find any established method for calculating load unbalance from electrical consumption data. For this reason, we decided to follow the definition of apparent power unbalance between phases in the German application rule VDE-AR-N 4100 [24] which establishes technical connection requirements for domestic loads, storage and generation units. In terms of installed apparent power of connected devices, this application rule defines a value of 4.6 kVA as maximum permitted apparent power unbalance between phases.

However, electricity tariffs for domestic costumers commonly only focus on active power. Following the definition of power unbalance in VDE-AR-N 4100 [24], but using active power instead of apparent power,

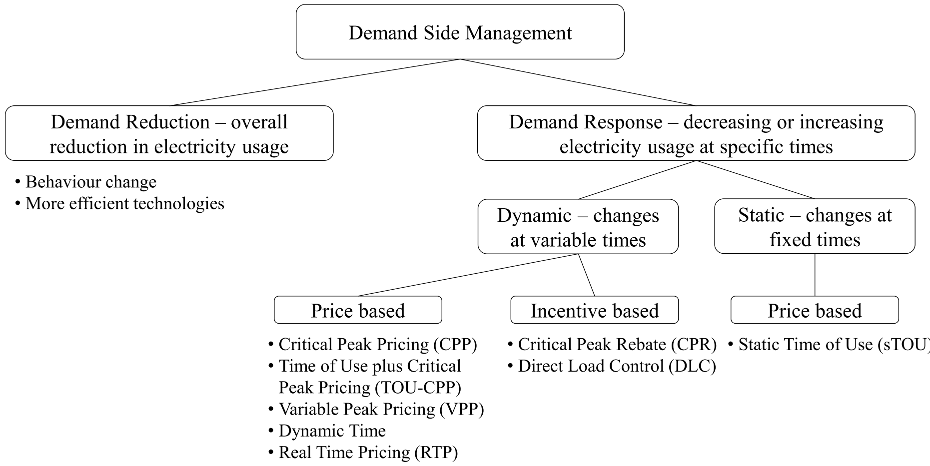


Fig. 1. Classification of demand reduction and demand response - after Parrish et al. 2019 [25].

leads to Eq. (3), where $P_t^{T,\mathrm{a}}$, $P_t^{T,\mathrm{b}}$ and $P_t^{T,\mathrm{c}}$ represent the aggregated load profiles of phases a, b, c, respectively. Similar to critical peak pricing, future "critical unbalance pricing" tariffs could result in a monetary fine for the costumers if $\Delta P_t^{T,\mathrm{unb}}$ exceeds a certain threshold.

$$\Delta P_t^{T,\mathrm{unb}} = \max\{\left|P_t^{T,\mathrm{a}} - P_t^{T,\mathrm{b}}\right|, \left|P_t^{T,\mathrm{a}} - P_t^{T,\mathrm{c}}\right|, \left|P_t^{T,\mathrm{b}} - P_t^{T,\mathrm{c}}\right|\} \tag{3}$$

2.3. Extending electricity tariffs with the power component

Motivating demand response in costumers can be achieved by different kinds of tariff schemes. Parrish et al. [25] present in Fig. 1 a classification of dynamic demand reduction and demand response, as well as pricing schemes for the latter, which can be either dynamic (accounting for demand response at variable times) or static (with predefined changes at fixed times). These again distinguish between price and incentive based tariffs. The incentive based tariffs reward consumers for "estimated changes in demand compared to a baseline level (...)" [25]. The incentive based tariffs comprise Critical Peak Rebate (CPR) and Direct Load Control (DLC) providing an incentive for reducing consumption during critical hours below a baseline level or allowing an external party to control the operating state of certain appliances and thus lower their energy consumption, respectively. The dynamic price based tariffs comprise volumetric charging tariffs such as time of use tariffs (TOU) and tariffs with a power component, such as critical peak pricing (CPP) or variable peak pricing (VPP) [25], also called capacity-based tariffs in [26]. Various studies have already assessed the responsiveness of households to TOU tariffs, coming to varying conclusions [14], [13]. Tariffs can also consist of both the volumetric and capacity charging, such as the TOU-CPP in Fig. 1 [25], [26], similar to the network fee for the industry in Germany [15]. Capacity based tariffs are however not yet applied in private households. Even though the power component is already accounted for in various studies such as [25], [27] or [26], there are still questions of how to implement these kinds of tariffs successfully.

From the monetary incentives and tariff schemes tested during the field study in [16], the power flat rate (PF), the grid bottleneck (GB), the dynamic load tariff (DL) and the TOU tariff are relevant for the analysis presented in this contribution. The first three tariffs have a power component in the form of a threshold in common, meaning that the tenants got a financial benefit or disadvantage from not exceeding or exceeding the threshold, respectively. The economics varied between all tariffs, for a detailed description see Scharnhorst, Sandmeier et al. 2021 [16]. Allocating these tariffs to the categories devised by [25], [27] or [26], the power threshold related tariffs (PF, GB and DL) belong to capacity pricing, such as critical peak pricing (CPP) for GB, and variable peak pricing for DL and PF. The GP and PF were tested either with a financial incentive or price based (meaning in this case a financial disadvantage, when consuming peak power). The DL and TOU tariffs were price based.

3. Results

In this section, we will present the results we obtained from different analyses with regard to power peaks and their characteristics when applying different temporal resolutions in the downsampling of the same original time series. At first, we take a look at the peak-to-mean-ratio, which gives an indication about the measured maximum demand values compared to the average. Afterwards, we will analyze the impact of the different temporal resolutions on the monitored peaks in connection with the power range of the peaks. Then, we will dive deeper into one exemplary peak pricing event and finally, we will take a look at the unbalance of load in peak situations.

3.1. Peak-to-mean-ratio

For each day of the experimental phase, we have determined the mean power demand and the peak demand for each of the aggregated time series and six different temporal resolutions between 1 s and 60 min. With these values we then have calculated the corresponding daily peak-to-mean-ratios for all of the considered aggregation levels of temporal resolutions. The results for one exemplary week are depicted in Table 3.

It is no surprise that the peak-to-mean ratio is always the highest for the 1 s time series and declines for lower temporal resolutions. This effect is all the stronger, the higher the peak-to-mean-ratio. On day 6, for example, the ratio for the 1 s time series is 22.76 and for the 5 min series it is 11.52, which is 49.4% less, whereas on day 4, the 1 s time series ratio is only 9.54 and for the 5 min time series it is 9.05, which equals a deviation of only 5.1%. Another interesting observation is that the peak-to-mean-ratio drops drastically comparing the 15 min and 60 min time series to the other ones, meaning that these two are not capable at all to properly represent peaks in the power demand. On the other hand, up to a temporal resolution of 1 min the deviation of peak-to-mean-ratios compared to the original 1 s time series is rather small. For the 5 min resolution, the deviation is strongly fluctuating with each day, so that no general statement can be made for this particular week.

In Fig. 2 the daily peak-to-mean-ratios over the time span of the entire experimental phase of three months are shown with boxplots for each of the time series. The results strengthen the observations we just made. The difference in the peak-to-mean-ratio of the 15 min and 60 min time series compared to the 1 s series are rather large (53.5% and 73.3%, respectively, for the average values), for the 5 min series the difference is noticeable (27.0%), for the 1 min and 30 s it is rather low

Table 3
Daily peak-to-mean-ratio for different temporal resolutions T for one exemplary week.

	1 s	2 s	5 s	10 s	30 s	1 min	5 min	15 min	60 min
Day 1	20.31	20.31	18.44	16.95	16.03	15.76	15.46	8.49	3.82
Day 2	14.94	14.92	14.90	14.87	14.48	14.22	12.47	7.62	4.11
Day 3	12.51	12.50	12.50	12.50	11.94	10.40	5.81	4.21	2.59
Day 4	9.54	9.54	9.50	9.47	9.41	9.07	9.05	5.27	3.01
Day 5	15.30	15.30	15.27	15.24	15.05	14.63	14.49	7.87	5.25
Day 6	22.76	22.76	21.63	19.91	16.80	16.49	11.52	7.52	4.56
Day 7	13.52	13.52	13.47	13.45	13.42	13.40	10.78	7.51	4.58

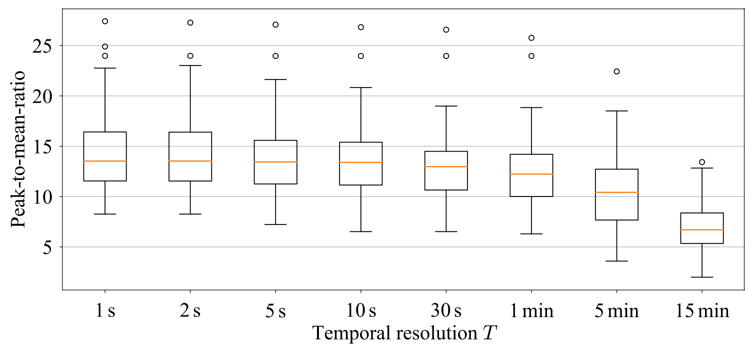


Fig. 2. Boxplots of the daily peak-to-mean-ratio for different temporal resolutions.

Table 4
Average negative deviation (in %) of the maximum power demand per 15 min time slot over the entire experimental phase for different temporal resolutions T compared to the original time series (1 s resolution) and the number of occurrences (# occ.) of power spikes in the respective power ranges.

	2 s	5 s	10 s	30 s	1 min	5 min	15 min	60 min	# occ.
$P_{max} \leq$ 500 W	0.44	2.82	3.93	5.27	6.50	12.21	21.78	26.00	5637
500 W < $P_{max} \leq$ 1000 W	2.61	19.48	27.34	33.40	35.23	40.37	46.52	50.47	816
1000 W < $P_{max} \leq$ 2000 W	3.29	26.66	39.67	52.84	57.68	66.87	73.53	73.97	976
2000 W < $P_{max} \leq$ 3000 W	0.59	5.11	7.41	14.28	23.86	54.16	71.30	75.77	663
3000 W < $P_{max} \leq$ 4000 W	0.57	4.93	7.63	13.59	19.27	42.25	62.14	71.97	228
4000 W < $P_{max} \leq$ 5000 W	0.10	4.33	7.50	12.26	19.48	41.00	61.28	72.70	79
P_{max} > 5000 W	0.74	3.95	6.80	12.27	18.39	34.54	56.45	70.09	36
Every 15 min slot	0.98	7.31	10.55	14.25	16.76	25.25	35.66	42.37	8435
Slots with P_{max} > 2000 W	0.55	4.97	7.44	13.90	22.28	49.73	67.91	74.46	1006

(14.2% and 10.0% for the average values) and for the 10 s, 5 s and 2 s series it is negligibly small (5.3%, 3.5% and 0.5%, respectively).

3.2. Differences in observed peak demand for different temporal resolutions and power demand ranges

We have not only compared the peak demand in the different temporal resolution time series with the mean load, but have also compared the different time series to each other with respect to the peaks in power demand. Therefore, we have divided the entire period of the experimental phase into time slots of 15 min and have determined the maximum in power demand for each time slot for each of the considered time series with temporal resolution T. This has lead to a total of 8435 time slots that have been examined. We have used the results from the 1 s time series as reference and have compared the results of the other series to them by calculating the percentage deviation of the maximum power demand per time slot. The averages of these deviations over the entire experimental phase are shown in Table 4 as well as Fig. 3. We have differentiated between the average of time slots with a maximum power demand in a specific power range (e.g. between 1000 W and 2000 W), the average deviation of all time slots over the whole experimental phase and the average for all slots with a power demand above 2000 W.

As could have been expected, the deviation is negative for all considered time series and increases with the amount of aggregation (the lower the temporal resolution, the higher the deviation). For instance, for the 15 min resolution time series, the average deviation in maximum power demand is 35%. However, in this number also the times of generally low consumption (e.g. night-time) are taken into account. These times are not interesting for the examination of demand peaks and add to a lower average deviation. We can confirm this assumption by taking a look at the numbers for the power peaks lower than 500 W, where the average deviation is very low (< 10%) for the temporal resolutions of 1 min and higher, and fairly low for the 5 min, 15 min and 60 min time series. This changes for higher power peaks, where the deviation for all the different temporal resolutions except the 2 s time series increases significantly. The highest numbers of deviation occur in the range of power peaks between 1000 W and 2000 W with a maximum deviation of nearly 74% for the 15 min and 60 min series and 26.66% for the 5 s. Interestingly, the deviation decreases again for higher peaks in demand. For the more fine-grained temporal resolutions from 1 min to 5 s it decreases rapidly and levels off for the power ranges above 3000 W, even dropping below 10% for the 2 s, 5 s and 10 s ones. For the coarser temporal resolutions from 1 min to 60 min the decrease is much smaller, even staying above 50% for the 15 min and 60 min time series.

The results show that all of the different time series, except the 2 s one, fail to properly represent power peaks in the range of 500 W to 2000 W. The peaks in this range are mostly caused by smaller household appliances that tend to be operated for rather short time periods in the

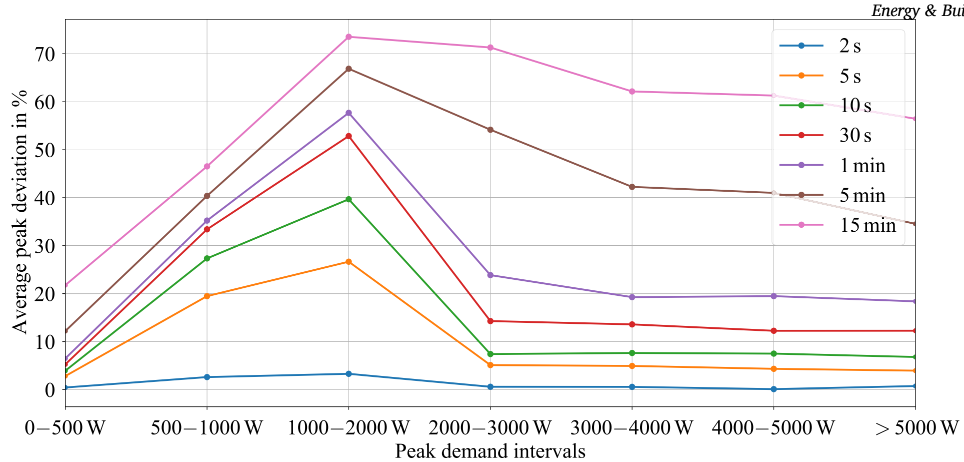


Fig. 3. Illustration of the average percentage deviation of maximum power peaks for different temporal resolutions T compared to the 1 s reference time series, differentiated by the height of the peak in the reference time series. (For interpretation of the colors in the figure(s), the reader is referred to the web version of this article.)

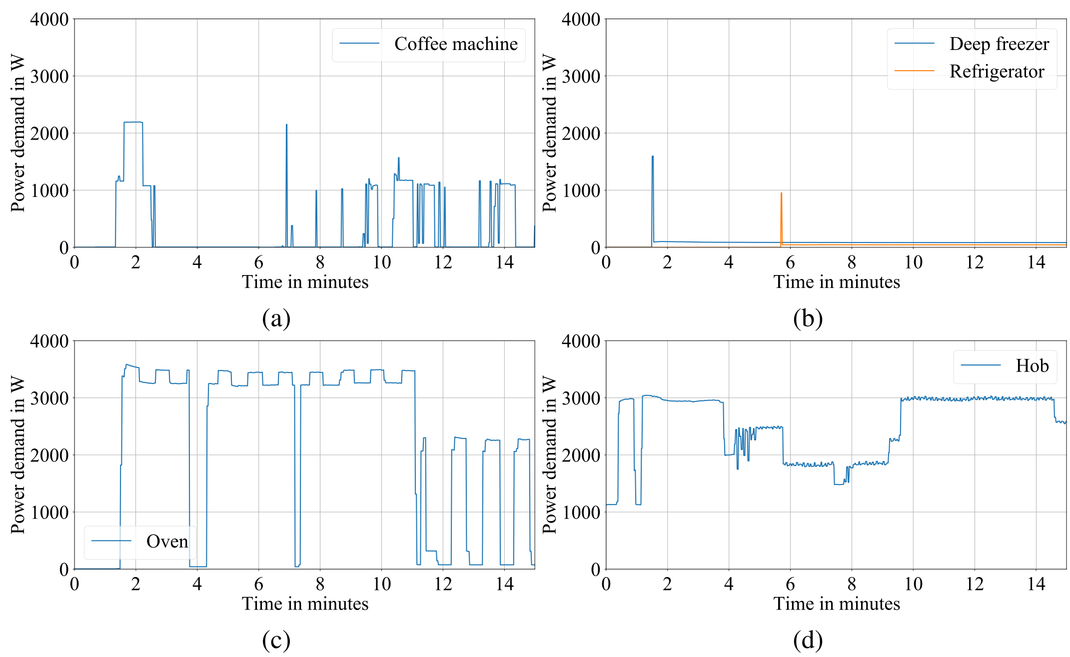


Fig. 4. Load profiles (15 min duration, 1 s temporal resolution) of selected household devices during exemplary usage (Coffee machine (a): switch-on process and preparation of several coffees; deep freezer and refrigerator (b): compressor start-up; oven (c): switch-on and standard operation at approximately 180 °C; hob (d): standard cooking process with different temperature settings).

range of several seconds. Additionally, the power demand of these devices often varies over the runtime, which in combination with the short runtimes leads to the huge deviation in demand peaks in nearly all of the different time series. The biggest impact in this matter had the coffee machine, which was used very frequently and has a highly volatile power demand with high peaks (see Fig. 4a) as well as the refrigerator and deep freezer, both of which cause brief load peaks during compressor start-up (see Fig. 4b). However, higher peaks of 3000 W and more are usually caused by larger appliances like the oven or the hob. They generally have longer runtimes and they tend to maintain a more constant level of power demand, as it can be seen in Fig. 4c and Fig. 4d. That is why the average deviation is much lower for these power ranges. One exception is the 15 min series, which seems to be unable to depict demand peaks in all power ranges. Of course, this also applies to the 60 min series.

In order to mitigate the influence of the previously discussed devices in lower power ranges on the average values, we have calculated the average deviation for all time slots with a peak power demand above 2000 W (see last row in Table 4). These numbers give an overview of the deviation for different sampling times in a power range that is interesting for load-based electricity tariffs. We can see that in the 2 s series almost no information is lost and that for the 5 s and 10 s series the deviation also is below 10% with 4.97 and 7.44, respectively. With sampling resolutions of 30 s to 1 min the information loss is still moderate (13.90 and 22.28%), but sampling resolutions of 5 min and above are not able to properly represent power peaks at all with around 50% deviation for 5 min and even 68% for 15 min.

3.3. Exemplary peak pricing event

Having previously discussed the challenges associated with detecting peaks in the previous sections, we now want to take a closer look at one exemplary peak pricing event. In this case study, we implemented a Critical Peak Pricing (CPP) tariff. This tariff imposes a temporary limit on power demand over a designated period, setting a threshold that,

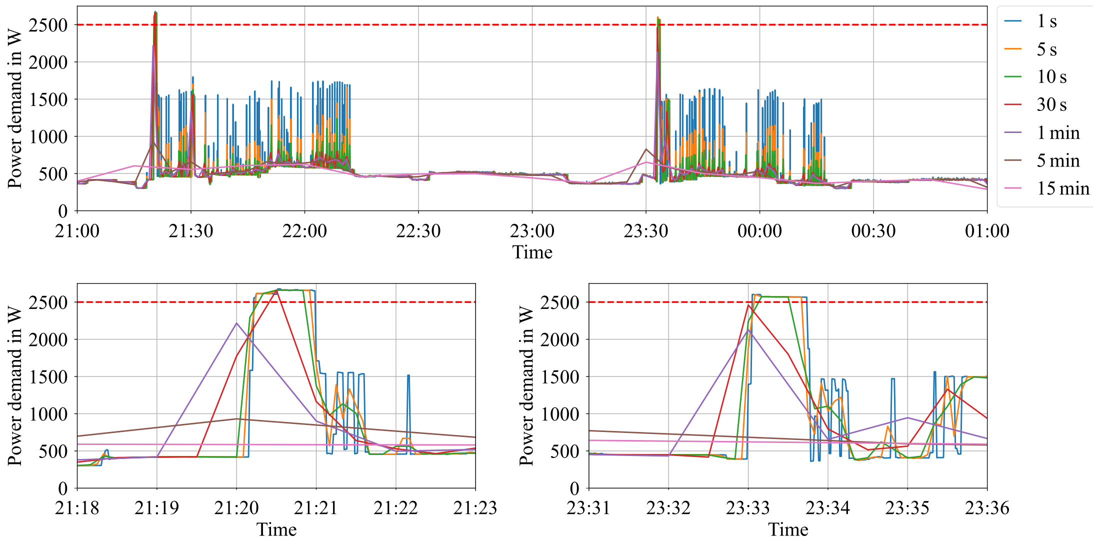


Fig. 5. Load curve of one exemplary evening for different temporal resolutions T. The lower diagrams are zooms around 21:20 h and 23:30 h, respectively. The dotted line represents the power threshold of the dynamic electricity tariff.

if exceeded, incurs a financial penalty for the consumers. Such a tariff could potentially be utilized during periods of grid congestion or when renewable energy generation is low. For the event analyzed here, the duration of the time period was set to two hours and the power threshold to 2.5 kW.

In Fig. 5 the load curve of a designated peak pricing event is illustrated across various temporal resolutions. The power threshold of 2.5 kW is indicated by a dotted line. It is apparent that not all temporal resolutions adequately capture the two significant power demand peaks occurring at 21:20 h and 23:30 h. To facilitate a clearer comparison of these discrepancies, detailed zoom-ins on both power peaks are provided (see Fig. 5 bottom left and right). In the bottom left figure, it is evident that the 1 s, 5 s, 10 s and 30 s resolutions surpass the 2.5 kW threshold, whereas the 1 min, 5 min, 15 min and 60 min resolutions do not. Consequently, under a temporal resolution of 30 s and finer, the inhabitants would incur the associated fee, whereas at a resolution of 1 min and coarser, they would avoid the fee. Regarding the power peak at 23:30 h (see Fig. 5 bottom right) the findings are consistent, except for the 30 s resolution. While in the previous case the exceedance of the power threshold is measured in the 30 s time series, in this case the maximum measured power demand of this series just falls below the threshold, indicating that only resolutions of 10 s or finer are capable of detecting this exceedance.

On the other days on which corresponding power-based electricity tariffs were active and the requested demand in that time period was close to exceed the maximum power threshold, the results are similar. In all cases, the time series that has the lowest temporal resolution but is still able to detect the exceedance of the power limit is either the 10 s, 30 s or the 1 min series.

3.4. Analysis of load unbalance

In contrast to the previous sections, we consider the load profiles of every power phase separately in this section. This allows us to analyze the impact of load profile time resolution on the assessment of load unbalance, which may become relevant for the design of future electricity tariffs (see Section 1.3).

Fig. 6 shows the load curves of every single phase for the exemplary evening analyzed in Section 3.3 for the two “extreme” time resolutions of 1 s and 15 min. From the highest resolution of 1 s in Fig. 6a, it is clearly visible that while load at phases a and c does not exceed 300 W, load at phase b reaches values higher than 2 kW. Using a sampling time of 15 min, however, leads to smoothing out of the short peaks of phase b, and therefore suggests nearly balanced phases a and b (see Fig. 6b).

Fig. 7a visualizes the spread of the measured unbalanced power values from the entire experimental phase according to Eq. (3) for different temporal resolutions through boxplots. The actual boxes show the interquartile range (middle 50% of values). The median is indicated in orange. The whiskers use the conventional length of 1.5 times the interquartile range. There is a considerable amount of outlier values for every load time profile resolution in Fig. 7a.

For a further assessment of time resolution on the effectiveness of possible future critical unbalance pricing tariffs, we take a value of 4.6 kW (see Section 2.2) as an exemplary load unbalance threshold. In the original data set with a temporal resolution of 1 s, unbalance power values reach close to 6 kW, same for time resolutions up to 5 min (e.g. by using the oven and the washing machine or the coffee machine and the dish washer at the same time with no or only few other devices in use, see Table 2 and Fig. 4). The threshold is thus exceeded by more than 30%. Only when using time resolutions of 15 min, consumers would not have to pay the fee since load unbalance remains below the threshold.

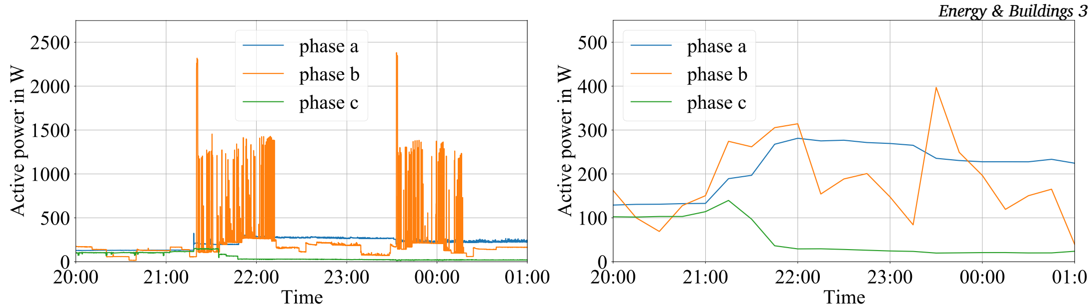
Fig. 7b shows the same boxplots as in Fig. 7a, but zoomed in to the interquartile range. It is to be noted that median and the interquartile range rise with increasing load profile aggregation time.

4. Discussion

Referring to the context of Germany, “smart meter data” is defined as the electrical energy demand per 15 min across all consumers and phases within a household, as per the legislative framework [11]. Our study leverages data with significantly higher spatial and temporal resolution, allowing for a more granular and nuanced analysis of short-term power fluctuations than is feasible with conventional smart meter data. This enhanced resolution facilitates deeper insights into transient power peaks, underscoring the potential of our methodology to contribute valuable perspectives on electrical demand management.

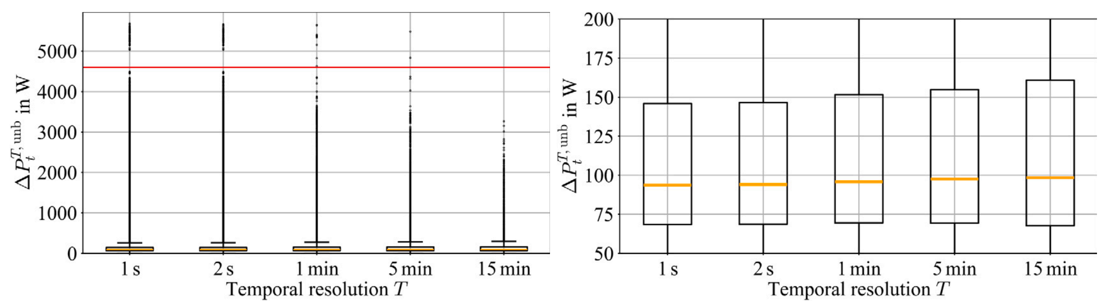
4.1. The influence of different sampling resolutions on observable peak demand

In this study, we show that the sampling rate has a massive impact on the height of observed peaks in power demand in private households. The information loss significantly rises with coarser temporal resolutions. Over the whole period of our three-month experiment we could observe average peak load reductions of 0.55% for 2 s, 4.97% for 5



(a) Temporal resolution $T = 1$ s (b) Temporal resolution $T = 15$ min

Fig. 6. Exemplary load curve (same as in Section 3.3) showing unbalance among phases a, b, c.



(a) Including outliers (b) Zoomed in to the interquartile range

Fig. 7. Boxplots of unbalanced power values (entire experimental phase) for different temporal resolutions T.

s, 7.44% for 10 s, 13.90% for 30 s, 22.28% for 1 min, 40.43% for 3 min, 49.73% for 5 min, 67.91% for 15 min for the respective sampling resolutions, compared to the originally measured data with a temporal resolution of 1 s and only including peaks higher than 2000 W (in the originally measured time series). This way we neglect times where nothing but the base load (refrigerator, freezer) is active and peaks that are solely generated by switch-on processes as described in chapter 3.2. The results show a significant reduction in the detected load peaks with coarser sampling rates. With 7.44% the 10 s series is the one with the coarsest temporal resolution with a deviation that is still below 10%. For a resolution of 1 min the deviation is about 22%, which might still be sufficient to observe peak loads in some occasions as one might argue. The deviation rises to nearly 70% for the 15 min series, which makes it nearly impossible to detect and measure peaks when sampling the data with this resolution.

The results from the considered peak pricing events lead to similar conclusions. In all cases in which a load-based electricity tariff with a power limit (e.g. 3000 W) was active, the coarsest time series which was still able to detect a violation of the power limit was either the 10 s, 30 s or 1 min series. In the time series with a lower temporal resolution, the violations were not observable and thus the tenants would not have had to pay the fee. This suggests that in the range of sampling resolution between 10 s and 1 min the resulting data still contains sufficient information to detect and measure demand peaks appropriately. If one wants to make sure to be able to properly detect all violations and quantify peak loads with almost no deviation, a 10 s temporal resolutions seems to be the best choice. However, if data transmission and storage capacity play a role, a 1 min temporal resolution should still allow for the detection of most threshold violations while the needed capacities are cut by the factor six. One way to tackle the data transmission and storage problem might be to perform all calculations directly in the smart meter. This way only the evaluated, billing-relevant data (e.g. average and maximum power demand values per 15 min) has to be transmitted to the utility. After transmitting, the underlying raw data can be deleted. However, in this case the smart meter has to be equipped with a data storage and calculation module.

In cases where the storage and transmission requirements only play an insignificant role, higher temporal resolutions should be preferred to maintain as much of the information as possible. This information will be key for utilities in the future. On the one hand, with the rising numbers of PV systems and electric vehicles, the stress in distribution networks will increase and thus the network operator needs to be able to observe the network status with as much detail as possible. On the other hand, as our results show, the utility needs to be able to detect load peaks for correctly billing newly introduced peak load based electricity tariffs. Similar to the critique expressed by [12], we therefore suggest to address these problems in the rollout of the intelligent metering systems, in order to make the application of new business models and tariff schemes possible.

As mentioned before, unbalance tariffs were not applied during the residential phase in [16], but could become relevant in the future when voltage quality problems rise with increasing penetration rates of PV systems, electric vehicles, storages and heatpumps. The analysis in 3.4 shows that load profile time resolution has a considerable impact on the assessment of load unbalance and the effectiveness of possible future critical unbalance pricing tariffs. We thus see the same effects as when analyzing the impact of temporal resolution on peak load detection.

4.2. Plausibility check

To evaluate the credibility of our findings, we conducted a comparative analysis with previous studies. For this purpose we used the average deviation for the different sampling resolutions over the whole experiment, without differentiating between peak load ranges. However, drawing parallels with existing literature proves challenging due to discrepancies in the temporal resolutions of the raw data and the sampling strategies employed in different studies. Hoevenaars et al. [28] observed a deviation of the load peaks between 1.28 and 7.45% for a sampling rate of 10 s and between 1.78 and 15.04% for a resolution of 1 min, exhibiting slightly lower deviations compared to our observations (10.55% for 10 s and 16.76% for 1 min). Wright et al. compared a temporal resolution of 30 min to a resolution of 1 min, observing a peak load reduction of 16-47% for different households [1], while Naspolini et al. determined a peak load reduction of 18.56-28.36% when comparing 5 min to 15 min resolution [29]. Although these studies employ coarser temporal resolutions for reference (1 min and 5 min compared to 1 s in our case), the substantial decrease from the 1 min resolution (16.76% peak load reduction) to a 15 min resolution (35.00% peak load reduction) is also clearly evident in our results and aligns well with the ranges reported in the aforementioned studies.

Our analysis on the impact of temporal load profile resolution on the assessment on load unbalance appears to be an unprecedented contribution to the field, rendering direct comparisons with existing research infeasible. Thus, to the best of our knowledge, this aspect of our study presents a novel inquiry into the dynamics of load unbalance in residential power consumption profiles.

4.3. Consideration of battery home storage systems

Undoubtedly, the majority of short-term power demand peaks within households discussed in this study could potentially be mitigated by a home battery storage system. Equipped with appropriate control mechanisms, such systems have the capability to smooth out the household's load profile, thereby alleviating stress on distribution grids and diminishing the need for peak load monitoring. As of the end of the year 2021, there are approximately between 330.000 and 430.000 home battery storage systems in Germany [30,31]. With a total amount of approximately 16 million one or two family houses in Germany [32], this means only 2.1% to 2.7% of suitable houses are equipped with a battery system. In 2030 the number of home battery systems is expected to rise to 1.7 million and in 2050 to 5.0 million (derived from [33]). These numbers are equivalent to 10.6% and 31.3% of all one or two-family houses in Germany, respectively. Despite the anticipated rapid expansion of home battery storage systems, the data suggests that even by 2050, the majority of households will remain unequipped with such technology, thus lacking the capability for peak shaving.

4.4. Limitations

Our study draws upon a comprehensive dataset encompassing 90 logged days from a single household, providing a substantial foundation for our analysis. However, it is crucial to recognize that the results derived from this singular dataset may not universally represent varying household dynamics, which can differ significantly in terms of equipment usage and the number of residents [34]. To enhance the robustness of our findings, future research should extend this approach to include a wider variety of household configurations.

The practical implementation of innovative electricity tariffs may face additional challenges, such as real-time data processing and regulatory adjustments, as well as consumer acceptance and behavior. Consumer behavior and acceptance of such tariff schemes have been explored by a limited number of studies, including Scharnhorst et al. [16] and Royal & Rustamov [35]. Given the scarcity of practical experiments in this area, we recommend further research with a larger and more diverse sample size to better understand these dynamics.

Although the ESHL provided a highly controlled environment, it is important to note that most of the large appliances used in the study, such as refrigerator, dishwasher, dryer and freezer, were installed in 2010. These appliances are representative of standard technology commonly found in many German households today, rather than the latest high-tech or highly efficient models. As such, the energy consumption behavior observed in this study may be more reflective of typical household consumption than initially assumed. However, the ESHL is equipped with some smart technologies and energy management systems that are not yet ubiquitous in all homes. Therefore, while core appliances reflect common household standards, more research is needed to validate the findings in a wider range of household types, including those without smart devices. Future studies should also explore different family sizes, socio-economic backgrounds, and living environments (e.g., rural versus urban) to better generalize the results.

Additionally, when looking at the aggregated load profile from several households, one could argue that there are no high-frequency variations in loads over timescales up to 1 min, and load unbalance among phases can be assumed to be at least partially averaged out. Nevertheless, for a more definitive assessment of these phenomena, additional research is necessary. Moreover, contemporary business models that promote innovative electricity billing practices increasingly focus on individual household metrics, necessitating a detailed understanding of each household's smart meter gateway operations. Variations in domestic load profiles can be substantial even over brief intervals, influenced by different consumption patterns and the scale of appliance use, as noted by Wright [1].

In this case study with one single household, temporary load unbalance of up to nearly 6 kW was observed. It should be recognized that this phenomenon primarily results from most of the standard home appliances in Table 2 being single-phase. It might be difficult to justify that a household might face penalties on their electricity bill solely based on how their standard home appliances were previously distributed. The new devices that are increasingly being added (PV systems, heatpumps, etc.) to domestic costumer installations are usually at least partially controllable, and therefore often integrated into energy management systems. In future situations, unbalance tariffs could help to foster the development of control algorithms which take into account load unbalance at the grid connection point of a household.

5. Conclusion and policy implications

In this study, we investigated the required temporal granularity to discern power peaks and load unbalances within private household load profiles, which are pivotal for implementing load-based electricity tariffs. This investigation utilized data from a living lab experiment with a 1 s granularity, evaluating various time resolutions ranging from 1 s to 60 min. Overall, the results indicate that diminishing the load profile's temporal resolution leads to less accurate detection of power peaks and increases the extent of information loss. A delicate balance must be maintained between minimizing data transmission and storage needs and maximizing the accuracy of the sampled data. When it comes to load-based electricity tariffs, a certain standard in the precision and quality of the data is mandatory in order to guarantee for a fair and transparent billing process. Our results show that a sampling rate of 15 min, which is currently often considered as standard for electric meters, is not sufficient to fulfill these requirements. Too much information is lost in the sampling process, which makes it nearly impossible to ensure proper monitoring and billing. Conversely, a sampling resolution of 1 min, though not fully capturing all the demand peaks, significantly outperforms the 15 min sampling resolution, with an average deviation of 22.28% compared to 67.91% for peaks exceeding 2000 W, and remains feasible concerning data processing, transmission, and storage requirements.

Despite the study's focus on a single household equipped with standard appliances, temporary load unbalance values of up to nearly 6 kW were observed. Such unbalances would likely be smoothed out by the aggregation of multiple household load profiles in a larger grid area. However, the potential for voltage quality problems as a result of unbalanced load scenarios is anticipated to rise with greater integration of distributed generation units, storage systems and electric vehicles. Those new devices are usually at least partially controllable. Unbalance tariffs could help to promote the development of energy management systems which take into account load unbalance at the grid connection point of a household. Our study demonstrates that when designing these tariffs, it should be taken into account that a coarser load profile sampling rate – more favorable in terms of required technical specifications, as mentioned before – considerably decreases the detection accuracy of temporary load unbalance. This also decreases the potential effectiveness to use these tariffs to address voltage quality problems.

We can conclude that the need for a massive and accelerated deployment of smart meters in many European Countries and especially in Germany in the upcoming years is both a challenge and an opportunity. Our findings underscore the importance of high-resolution data for accurately detecting residential power peaks and managing load unbalance. Regulators should act promptly and ensure that newly installed smart meters possess the capability to measure, process, and transmit consumption data at a temporal resolution of at least 1 min – for each power phase and collectively. While not immediately necessary in all instances, this enables the potential implementation of innovative load-based tariffs in the future. Additionally, future regulatory frameworks should incentivize households to adopt energy management systems that can optimize energy use and reduce load unbalance. These findings also have broader implications for grid operators, who must balance the trade-off between data granularity and the associated costs of data processing and storage. Given the rapid evolution of the energy sector and its regulatory landscape, leveraging this potential for enhanced flexibility in the demand sector, including private households, justifies the additional investment and effort required.

CRediT authorship contribution statement

Thorben Sandmeier: Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Leandra Scharnhorst:** Writing – original draft, Methodology, Conceptualization. **Johanna Geis-Schroer:** Writing – original draft, Visualization, Methodology. **Armin Ardone:** Writing – review & editing, Supervision, Funding acquisition. **Thomas Leibfried:** Supervision, Funding acquisition. **Wolf Fichtner:** Writing – review & editing, Supervision.

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Declaration of generative AI and AI-assisted technologies in the writing process

Statement: During the preparation of this work the authors used ChatGPT in order to avoid grammatical and spelling errors. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Datasets related to this article can be found at https://doi.org/10.35097/898, hosted at RADAR4KIT [20].

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