Analysis of Power Consumption Data from Smart Metering of Parking Garages with Regard to Influencing Factors

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Abstract

This paper examines load profiles of three commercial parking garages and, in this context, created individual load profiles for them. A considerable proportion of the operating costs of parking garages is accounted for by energy and maintenance costs. The lighting systems and the ventilation system are the main cost drivers. The aim is to use these load profiles to estimate energy consumption and its structure over the course of the day, week and year, as well as to identify efficiency measures and potential savings with regard to operational energy costs. The necessity of such individual load profiles results on the one hand from the lack of current representative commercial profiles for this industry, and on the other hand from the heterogeneity of the individual buildings. Here it becomes clear that the construction and energy concept of the parking garages have a great influence on the consumption patterns. Therefore, parking garages were equipped with a detailed metering infrastructure in the project "SmartPark"[1] funded by the BMWK.[2]

Keywords: Load Profiles, Parking Garage, Load Metering, Energy Efficiency

[1]Part of the pilot programme "Einsparzähler (*engl.* energy-saving meters)
[2]German Federal Ministry for Economic Affais and Climate Action

1. Introduction

1.1. Motivation

Companies need transparency about their energy consumption to sustainably reduce costs and emissions. In the past, standard load profiles were frequently used to analyze consumption behavior. Load profiles are a temporal representation of the power used by a consumer over a certain period of time. They are used to determine individual power requirements and thus enable simulation and optimization of consumption patterns. The "Bundesverband der Energie- und Wasserwirtschaft e.V." (German Association of Energy and Water Industries; in short: BDEW, formerly: VDEW) created standard load profiles (in short: SLP), with which the energy demand of individual typified customers can be represented. The days of a year are divided into so-called type days and additionally distinguished between seasons. Even though the SLP of the BDEW are a good tool for the general estimation of energy consumption, they cannot take into account customer-specific particularities. These special features can include the type of construction and efficiency measures of the buildings supplied, but for commercial customers also the capacity utilization, working hours and business models. Thus, for business costumers in particular, it is therefore advantageous to record their own energy requirements in concrete terms in order to identify individual consumption patterns and, if necessary, to derive energy-saving measures from them. The data on consumer load profiles required for this can be processed and evaluated by an energy management system, while these are recorded via so-called smart meters. From this, individual load profiles of the companies can be created, which can be standardized if required.

Parking garages could play a critical role in the future of the electrification of the mobility sector by providing the charging infrastructure. In the past the primary focus has been on the installation of sufficient parking space to enhance the life quality of inner cities and other places where a lot of individual traffic is concentrated. On the other hand, the electricity consumption profile and the energy efficiency of parking garages has not been a central focus of the parking garage operators. as charging of electric cars redefines the role of parking garages. The needed upgrade in the electricity grid infrastructure to install a significant number of charging points mean significant investments for each parking garage. The optimization of the installed grid load in regards to a set number of charging points requires the full use of flexibility and efficiency potentials. In the wake of rising electricity prices, the efficient use of electricity will also play a more central role in the future of parking garage operations.

1.2. Scope

Within the scope of this work, load profiles of three selected parking garages from three cities in Germany will be evaluated and associated individual load profiles will be created. A brief assessment of the measurement quality is made by putting the shares of electricity consumption measured by sub-metering in relation to the total consumption. Afterwards, the data are to be examined for outliers by mapping the load profiles as a weekly progression. This work is not intended to create representative load profiles for the parking sector, but rather individual load profiles for each facility, which should enable the operator to identify consumption patterns and, as a result, efficiency measures. The above-mentioned influences on consumption patterns are only intended to demonstrate the necessity of a separate consideration.

Thus, we can define the following research questions

Research Question 1: To what extent do individual load profiles of selected parking garages differ from their standard load profiles?

Research Question 2: Are there external parameters such as temperature and humidity influencing the electricity consumption?

Research Question 3: How did the electricity consumption develop during the COVID lockdown and what does that mean regarding the dependency of electricity consumption and occupancy?

In this paper we first introduce the data and methods in section 2 used to create the results in section 3. We then conclude this paper with and extended discussion of the stated Research Questions and beyond in section 4.

1.3. Literature review

In the past decades most of advances in metering technology lead to installation of registered load meters (RLM) allowing real-time measuring of electricity consumption throughout almost all sectors making it possible to overcome standard load profiles (SLP, [1]). According to Peters [2], load profiles are "a temporal representation of the power used over a period of time, such as a week or year". Load profiles are generally subject to strong diurnal fluctuations, which in turn depend on the day of the week and vary seasonally. They are used for demand forecasts as well as for design and planning calculations and thus represent an important operating parameter in the load management of energy grids [3]. Meier et al. [4] used data series, which were already collected from 1980 onwards by various utilities in Germany, to create representative load profiles. Households as well as commercial and agricultural enterprises, which were distributed over the entire federal territory, were already examined. As a result, three standard load profiles for farms (L1 - farms with dairy farming/sideline livestock breeding, L2 - other farms, L0 - farms), one profile for Household customers (H0) and seven standard load profiles for commercial enterprises (G1 - commercial on weekdays 8-18, G2 - with heavy to predominant consumption in the evening hours, G3 - commercial continuous, G4 - shop/barber store, G5 - bakery with bakery, G6 - weekend business, G0 - general trade). For a comparison of the parking garages investigated in this work, the SLP G3 would be the most suitable, which is characterized by "consumption points that show a relatively even course throughout the year and also in the course of the week with a noticeable continuous base" [4].

According to Hellwig, the application of load profiles is subject to some limitations [5]. Since they are created from a large number of different consumers, individual consumption characteristics are sometimes lost through averaging or averaging. In addition, these profiles sometimes only inadequately cover the trade sector, which includes other service and retail businesses.

Böckmann et al. [6] developed a framework for modeling industry- and technology-specific load profiles for the commercial, trade, and services sector and applied it to five of the six most energy-intensive industries in this sector in Germany for 2018 (office-like businesses, trade, accommodation, hospitals, and schools). One thus expanded the pool of load profiles for commercial enterprises. However, if these profiles are used for comparison, it must be noted that they include not only electrical energy, but also heat and operational cooling in the energy demand. However, due to the mostly constant patterns of these consumption categories, a characteristic of electricity consumption can be derived.

Lübke, Holst and Tolzmann [7] developed synthetic standard load profiles for households using the city of Greifswald as an example and recognized a vertically and a horizontally acting component, which cause the actual electricity consumptions to deviate from those of the VDEW load profiles. The vertical component explains upward/downward deviations in consumption levels due to the geographical location of cities and consequently different meteorological conditions. The horizontal component, which describes temporal shifts of local maxima and minima, can be attributed to different sunrise and sunset times within a larger geographical area as well as socioeconomic differences, e.g. working hours.

In [8], Litzlbauer modeled load profiles for charging electrically powered vehicles and analyzed different charging scenarios by comparing them with BDEW household profiles. He elaborated that unregulated charging would greatly increase the residential peak load during the evening hours. Regulated overnight charging would minimize this peak load and draw constant power during the night hours. However, this would require a communication system between the charging stations and the central utility. This finding is also relevant to this work. Due to the higher proportion of electric vehicles on the road, parking garage operators will also have to adapt their business model to this by installing charging stations. In this respect, the consideration of individual load profiles of parking garages provides an outlook on the possibility as well as the energy and economic sense of installing such charging stations.

In [9], Mincu and Boboc used load profiles of seven types of consumers to model a so-called smart city, using real collected data. They divided the consumers into gas stations, restaurants, bank buildings, schools, accommodation, public lighting and business offices.

While research is moving forward bigger advances are often hindered as the source code often remains unpublished [10]. Thus, projects building upon already published findings often have to start from scratch and replicability of some projects, as it is gold standard in other data-driven fields of research, is not guaranteed.

2. Data and Methods

In order to investigate the research questions stated previously we first introduce the different kinds of data. Afterwards we present the methods used and refer to the source code on GitHub (`https://github.com/IIRM/EnergyMetering`).

As part of the project, smart meters were installed and their electricity consumption was recorded via registered load metering (RLM) over periods of 19, 32 and 35 months in each of the years 2018 to 2021. These parking garages differ not only in size and capacity, but also in their location in Germany and within their city, as well as in construction type and equipment. The data for the individual parking garages are briefly summarized in Table 1.

Table 1: Meta data of the parking garages.

Parameter	**Site A**	**Site B**	**Site C**
Opening hours	full day	full day	full day
Parking lots	670	912	512
Metering units	6	5	13
Metering start	2019-01-01	2020-01-10	2018-09-12
Metering end	2021-08-30	2021-08-30	2021-08-30

2.1. Energy consumption data

The energy consumption data for this study is obtained using RLM metering. Hence the data was obtained for every quarter of an hour from every metering point. Often outliers can be observed in cases of load peaks where machines are started up or, vice versa, fail to work. Therefore, we remove both, 5% and 95% quantile, from the data for each time slice before further analysis. Also, we used SLP data from [1] in order to compare the load profile for G3 under which parking garages were listed originally.

2.2. Weather data of the sites

All parking garages considered in this study are located in Germany. Hence, we applied historical data from closely located weather stations. The data series are provided by the German Weather Service. By using the stations ID the correct historical data can be downloaded [11].

2.3. Modeling the hourly utilization of parking garages

As there is no public data set for the utilization of parking garages within the opening hours, we estimate that parameter by using numbers of entries and exits per day, which are provided by the operator of site C.

Based on [12], we find that parking garage utilization behaves like a bimodal curve that can be modeled using two normal distributions $\mathcal{N}_1(\mu_1, \sigma_1)$ and $\mathcal{N}_2(\mu_2, \sigma_2)$ with expectation μ and standard deviation σ. From the graphs we can see that the expectation values, i.e. μ_1 and μ_2, are around 11:30 am and 5:00 pm. As our data were recorded in 15 minute intervals we set $\mu_1 = 46$ and $\mu_2 = 68$. Further, we set $\sigma_1 = 6$ and $\sigma_2 = 12$. To adjust for the fact that both peak are of the same height we need to reweight $\mathcal{N}_2$, s.t. $f(\mu_1) = \mathcal{N}_1 + 5 * \mathcal{N}_2 = f(\mu_2)$. Figure 1 shows $\mathcal{N}_1$ in blue, $\mathcal{N}_2$ in orange, and the combined graph $f(x) = \mathcal{N}_1 + 5 * \mathcal{N}_2$ in black.

This crude approximation of the overall utilization during one day is then scaled up depending on the number of entries and exits observed throughout one day. In a perfect scenario the link between utilization and number of entering and leaving cars is the numerical differentiation of the utilization curve. Yet we model it in the same 15 minute intervals as the consumption data. Thus we need to account for the possibility of a certain number of cars leaving the parking garage while the same amount of cars enters. The overall utilization remains the same for this period of time. Hence we only consider 85% of the observed entries and exits.

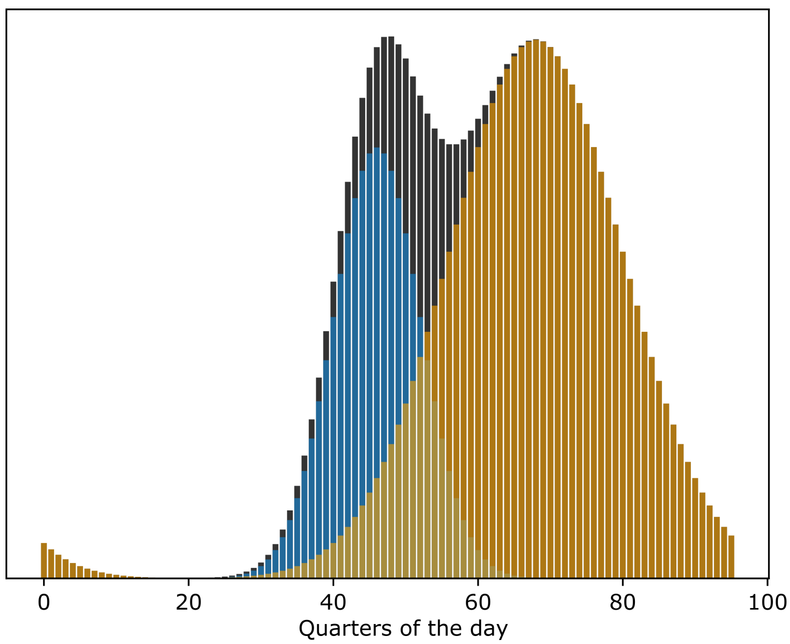

Figure 1: Underlying model for estimating the hourly utilization which was later scaled up such that the Euclidean distance between every two time steps amounts to the observed entries and exits per parking garage.

3. Results

3.1. Descriptive Analysis of RLM Data

In a first step we looked at the meter data. Since the incentive was to measure electricity consumption for different technical groups we can classify in main meters and sub-meters. Sub-metering should ensure that all groups

Table 2: Share of energy consumption recorded by sub-metering.

Site	Sub-Metering quota
A	28.6%
B	26.7%
C	60.4%

of consumers are measured individually and therefore explain the overall consumption. Categories for technical groups of sub-meters are various lighting lines, ventilation, pumps, exhaust air, elevators, heaters, and the gate. Yet we still see a discrepancy between the energy consumption covered by sub-meters compared to the main meter (Table 2).

The highest number of sub-meters installed within the pilot project "Einsparzähler" was in parking garage C. Consequently, the degree of coverage by the sub-meters is also the highest. For this site, by far the largest share of consumption is accounted for by the exhaust air system with around 24.1 % of total consumption, while the supply air system is the second largest with 8.4 %. Compared to that, the lighting systems on the lower basement floors and the elevators have low consumption shares. Due to their small share in the total consumption of the parking garages, a more detailed consideration of the load curves of most points of consumption is omitted in the following.

For a visual comparison of the measured values, typical weekly profiles are considered, showing also the 5% and 95% quantiles (Figs. 2-4, gray data). We remove outliers that can be attributed to special events such as a breakdown of the measuring infrastructure or short burst in consumption. This would also enable to verify similarities between each of the parking garages.

Figure 2 shows one of the two main meters of parking garage A over the course of a typical week. It indicates a base consumption of about 5 kWh/quarter-hour with a higher consumption level over the day of about 15 kWh/quarter-hour.

The load curves of parking garage B differ from those of A in that a significantly higher base consumption of 28 kWh/quarter hour can be observed here, which is never fallen short of. During the course of the day, the energy consumption increases and reaches two peaks during the morning and early evening on weekdays. On Saturdays, another peak can be observed, while on Sundays only a weaker increase is visible on average. The observed peak load was about 75 kWh/quarter hour.

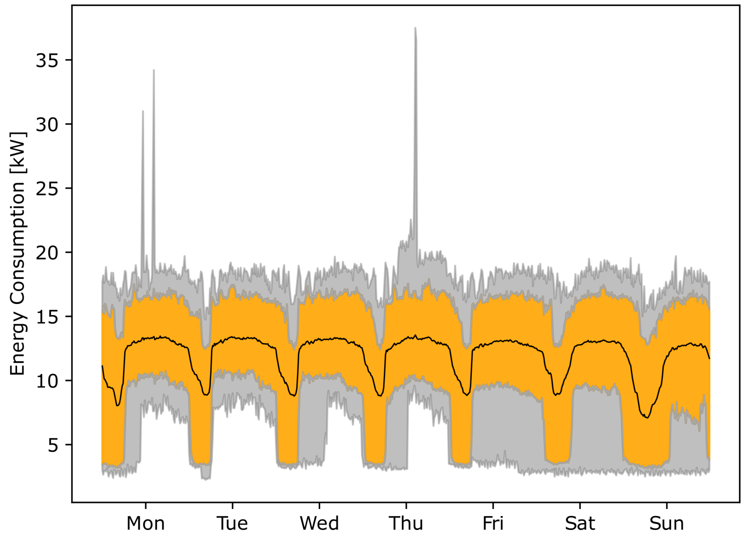

Figure 2: Aggregated energy consumption [kW] of site A. As first cleaning step, 5% and 95% quantiles (gray) were removed. The remaining data (orange) was used in the remainder of the study. The black line marks the mean.

A similar pattern can be found in the load curves of parking garage C, but the range and consumption level are different compared to parking garage B. 90% of all data are in the interval between 25 and 50 kWh/quarter hour, with the lowest consumption measured around midnight. Swings downwards mostly do not fall below the consumption of 18 kWh/quarter hour, but no consumption is measured on a Friday. For this day, it can be assumed that there was a power outage or other event that prevented a measurement. On the other hand, upward outliers occur over the course of the entire week and sometimes show a peak load that is twice as high. Lower overall fluctuations occur over the course of the week than in the other two parking garages, and the flattening of load curves toward the weekend is similar to that of Parking Garage C. The position of the median in comparison to the quantiles suggests that the data show a left-skewed distribution.

3.2. Deriving individual load profiles

Following the descriptive analyses performed so far, the individual load profiles of the parking garages will now be discussed.

Figure 5 shows the load profiles of parking garage A, differentiated by day type and season. The periods of higher consumption worked out in section 3.1 are also well recognizable here. They reach values between 25 and

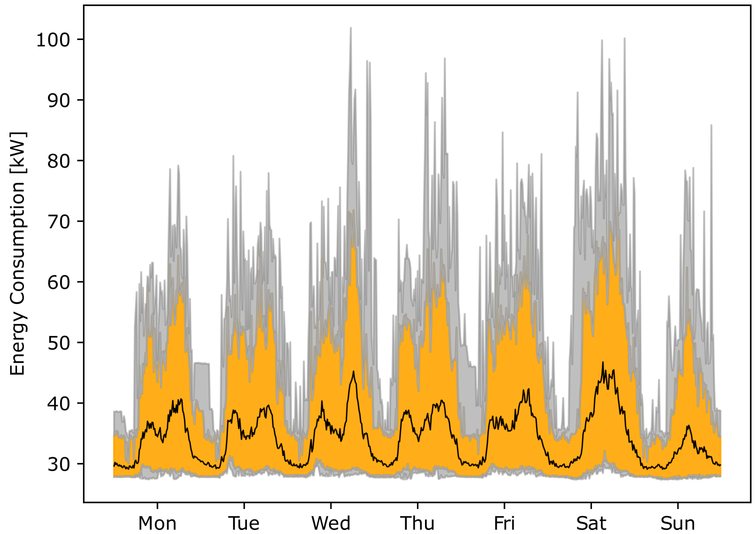

Figure 3: Aggregated energy consumption [kW] of site B. As first cleaning step, 5% and 95% quantiles (gray) were removed. The remaining data (orange) was used in the remainder of the study. The black line marks the mean.

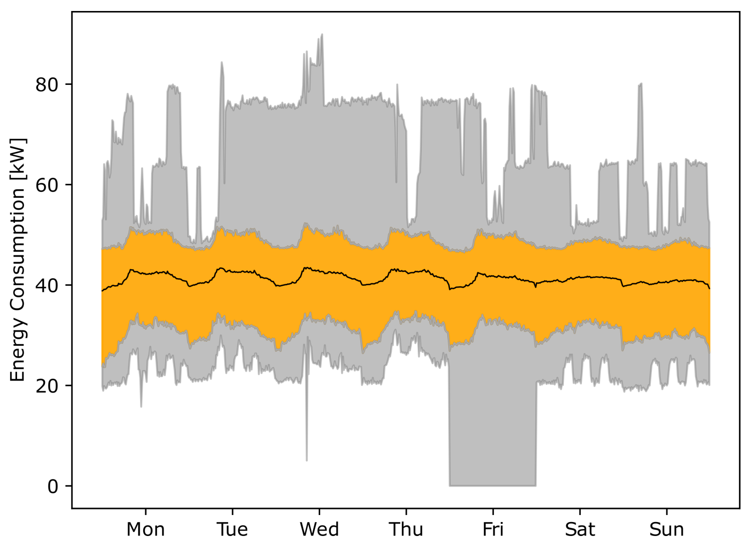

Figure 4: Aggregated energy consumption [kW] of site C. As first cleaning step, 5% and 95% quantiles (gray) were removed. The remaining data (orange) was used in the remainder of the study. The black line marks the mean.

30 kWh/quarter hour in the morning and about 45 kWh/quarter hour in the evening and are thus in the range of the median consumption. There are hardly any differences between the days of the week and the seasons. Winter consumption hardly exceeds that of the other seasons, and if it does, it is only insignificant and limited in time.Overall, these load profiles provide a good estimate of the energy demand of parking garage A. The lack of significant deviations in the course of the week as well as the year indicates on the one hand a strict clocking of the electricity consumption and on the other hand a resistance to external factors. In combination with the small range of the measured values between the 5% and 95% quantile, it can therefore be concluded that the energy demand in this parking garage is usually represented well to very well by the load profiles.

A different picture emerges in the load profiles of parking garage B (Fig. 6. The already mentioned base of 28 kW is also found in the load profiles, as well as the characteristic peaks during the week. Consistent with the observations of the weekly curves, there are two pronounced peaks on weekdays around 9 a.m. and between 6 p.m. and 7:00 p.m., on Saturdays a long-lasting peak in the afternoon hours as well as a smaller increase in consumption on Sunday afternoon. The highest consumption is measured on Saturdays around 6 p.m. In addition to the differences between the days of the week, some can also be found between the seasons. Contrary to expectations, the higher energy consumption do not occur in winter but mainly in summer, especially on weekdays around 6 p.m. The local maxima also shift over the course of the year. They occur earliest in winter and latest in summer. It can be assumed that due to the later sunset time either the visiting times in the parking garage reach a later maximum or the exhaust air system shifts its running times due to the high temperatures in summer, especially in the afternoon and evening hours.

Parking Garage C shows the smallest relative changes in electricity consumption over the course of the day (Fig. 7). The base load of the parking garage of 38 kW forms a range of only 7 kW with the peak load of just over 45 kW, within which the average consumption moves. In contrast to parking garage B, significantly higher consumption occurs in winter than in summer, regardless of the time of day or season. In addition, there are deviations in consumption patterns between seasons and day types. Summer and the transitional period are the most similar in this respect, with a pattern that reaches its daily maximum between 7 and 8 a.m. on weekdays, slowly decreasing and reaching its minimum over midnight. In winter, on the other

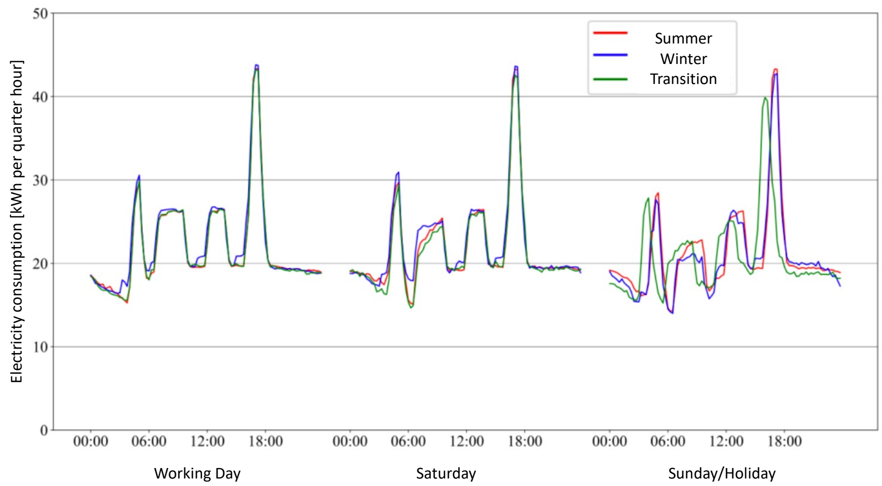

Figure 5: Individual load profile for site A.

hand, consumption rises again in the late afternoon hours before reaching its maximum around 6:00 p.m. and then dropping off. The load profiles of Sundays are similar to those of Saturdays, but at a slightly lower consumption level.

3.3. Correlation with External Parameters

In order to check whether external parameters are responsible for possible differences within series variation we used a linear regression model. To account for seasonal changes we separated the data in seasons as done in [1]. As already mentioned in Sec. 2.3, an investigation of the influence of the utilization of the parking garages on their electricity demand can only be carried out for Site C, since data for entries and exits are only available for this parking garage. One example for a correlation in a transition period can be seen in figure 8. It shows that there is little to none correlation between energy consumption and the respective sum of entries and exits. Moreover, there seems to be a divide in the data set which we were able to link to spring and fall. While this is not significant for the regression, it implies that there are significant differences in the level of energy consumption between

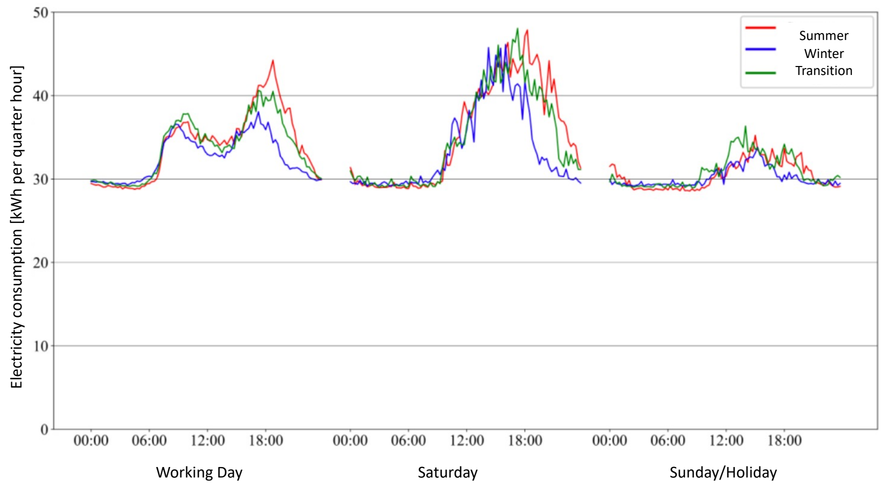

Figure 6: Individual load profile for site B.

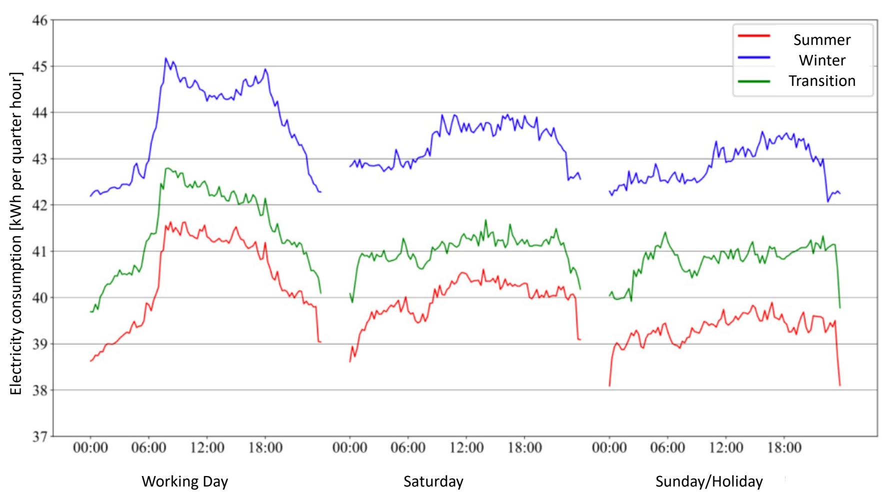

Figure 7: Individual load profile for site C.

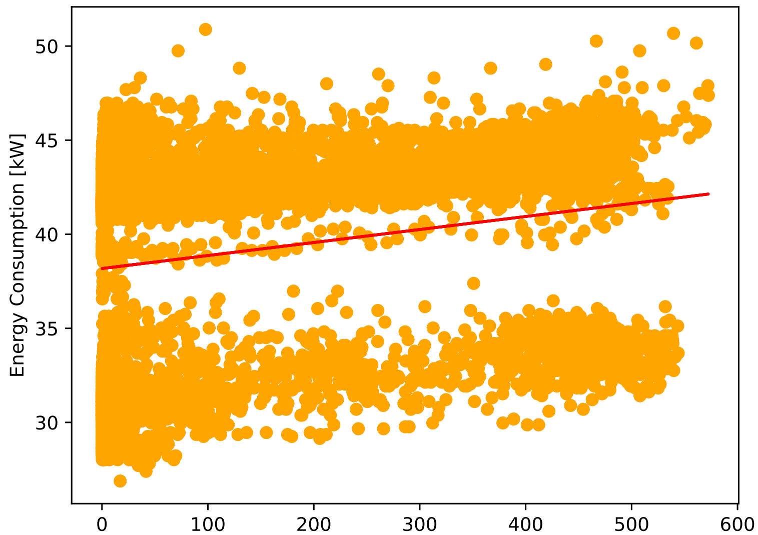

Figure 8: Correlation between energy consumption [kW] and occupation (as sum of entries and exits).

spring and fall that could not be identified by the general approach to load profiling. As a result of this finding, it may be useful to create separate load profiles for spring and fall for this parking garage.

For all (sub-)meters we calculated each coefficient of determination (R^2) indicating whether the measured variation in the model can be explained through variables. We find that there are none of the external parameters, i.e. humidity, temperature, and occupation, can explain the variation in the energy consumption (see Tab. A.3).

4. Discussion and Outlook

The results from the various evaluations of the load profiles and regressions underscore the importance of registered load metering (RLM) in the commercial sector. Not only did the parking garages studied exhibit fundamentally different consumption patterns, which were reflected in the individual load profiles, the heterogeneity of these implies the need for a building-specific and thus also facility-specific energy concept for companies. Looking at the data material, it can be seen that despite great efforts, at best only slightly more than half of the electricity consumed could be recorded by smart metering. The consumption of the sub-meters thus recorded cannot be used to explain the total energy demand of the buildings.

By looking at the load profiles over the course of a week, it was possible to identify initial consumption patterns and estimate the range, location and distribution of the data. These findings were used in the analysis of the individual load profiles in order to be able to explain particularities in their course.

The first striking feature was the stringent timing of electricity consumption in parking garage A. Here, hardly any differences were found between weekdays and seasons. Parking garage B stood out due to its power peaks linked to store opening times, which showed similar distributions over the course of the day and week compared to their load profiles. Parking garage C showed a different pattern of electricity consumption. While the other underground parking garages had base consumption rates in the range of 20 or 28 kW, this value for parking garage C was between 38 and 42 kW, depending on the season. In contrast, the local maxima of all three parking garages reached similar values on average. In the course of this observation, the question arises as to whether the operator of parking garage C should create an energy concept which, as in parking garage A, clocks certain technical systems in order to be able to reduce the total consumption of electricity.

Regression of energy consumption with a modeled load factor did not yield significant results. The correlation between utilization and energy consumption is slightly positive, but not sufficient to explain changes in electricity consumption. This aspect can be partially explained by the inaccuracy of the data material, since it was thus necessary to model consumption.

Also we did not find any obvious link between COVID and energy consumption when comparing load curves for months of lockdown versus normal occupation over all years of metering. Even though this project has been going on over several years already we pledge for a longer data gathering period since we have to analyze data of each parking garage individually.

In section 2.3 we described one way of modeling utilization of parking garages. This model is rather simplified and yet it can be readily extended in order predict utilization throughout a year. At the same time we see an increase in electric car registrations leading to obvious future problems of car park operators: How can we predict energy consumption when offering charging stations for electric cars? When combining the presented utilization model with know electricity consumption during a charging cycle we can extend the current predictions.

It might be even possible to move a step further: knowing cars often spend several hours in a car park a coupling of charging station with spot market prices could lead to a decrease in electricity costs. At the same time the costs are lowered the carbon footprint at the production sites is usually low as solar and wind power plants provide a larger proportion of electricity in the grid.

5. Acknowledgments

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Appendix A. Appendix

Table A.3: This table captures all R^2 values for all correlations for summer (S), transition (T), and winter (W). The largest value is 0.447 for heating and signs 2 in winter for utilization at site C and therefore none of the values is significant.

	Meter	Humidity			Temperature			Utilization		
		S	T	W	S	T	W	S	T	W
Site C	main	0.013	0.007	0.004	0.0	0.013	0.017	0.095	0.0	0.081
	light 1	0.318	0.25	0.098	0.274	0.167	0.085	0.249	0.164	0.109
	light 2	0.182	0.063	0.023	0.142	0.138	0.029	0.207	0.298	0.127
	light 3	0.011	0.028	0.01	0.003	0.0	0.021	0.005	0.003	0.005
	light 4	0.147	0.063	0.048	0.132	0.06	0.016	0.343	0.343	0.402
	light 5	0.065	0.012	0.032	0.059	0.056	0.017	0.201	0.286	0.408
	air supply	0.031	0.004	0.02	0.016	0.028	0.246	0.031	0.003	0.005
	exhaust	0.005	0.0	0.018	0.022	0.011	0.037	0.013	0.012	0.008
	lift 1	0.17	0.04	0.03	0.139	0.052	0.052	0.244	0.023	0.39
	lift 2	0.0	0.005	0.016	0.093	0.022	0.001	0.056	0.021	0.136
	sockets	0.203	0.186	0.082	0.115	0.069	0.004	0.052	0.06	0.046
	heating/ signs 1	0.0	0.006	0.15	0.059	0.006	0.001	0.001	0.015	0.075
	heating/ signs 2	0.114	0.0	0.057	0.093	0.037	0.032	0.326	0.32	0.447
Site A	main 1	0.108	0.0	0.002	0.083	0.063	0.007			
	main 2	0.026	0.0	0.0	0.009	0.003	0.0			
	vent 1	0.074	0.007	0.004	0.036	0.017	0.001			
	vent 2	0.09	0.001	0.0	0.057	0.03	0.011			
	vent 3	0.0	0.0	0.001	0.001	0.002	0.002			
	pump	0.001	0.001	0.0	0.007	0.0	0.0			
Site B	main	0.193	0.104	0.026	0.196	0.078	0.003			
	exhaust 1	0.065	0.004	0.005	0.087	0.047	0.007			
	exhaust 2	0.073	0.002	0.015	0.1	0.057	0.003			
	exhaust 3	0.001	0.128	0.041	0.0	0.001	0.007			
	gate	0.156	0.166	0.008	0.265	0.035	0.005			