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An Analysis of Energy Consumption in Small- and Medium-Sized Buildings

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Abstract: Building energy efficiency has grown strong in a context of soaring energy prices, especially in Europe. The use of energy-saving devices strongly influences its improvement, but in many cases, it is far from sufficient., especially if the energy comes from renewable sources with forced production. In the case of buildings, these are usually photovoltaic (PV) sources. For this reason, energy management systems (EMS) are becoming increasingly popular as they allow the increase in self-consumption and reduce the size of energy storage. This article presents analyses of historical energy consumption profiles in selected small- and medium-sized buildings powered by renewable energy sources. The implementation limitations of this type of systems, depending on the profile of the building, were identified and guidelines were presented to assess low-cost solutions dedicated to small buildings and considering the actual conditions of existing systems. Statistical analyzes were conducted for the energy demand profiles of 15 different buildings. The analyzes consisted of the preparation of box plots for each hour of working days and the calculation of the relative standard deviation (RSD) index for annual profiles of 60 min periods. The analyzes showed that the RSD index has low values for commercial buildings (e.g., hospital 7% and bank 15%) and very high values for residential buildings—even over 100%. On this basis, it can be concluded about the usefulness of energy profiles for demand forecasting. The novelty of the proposed method is to examine the possibility of using measurement data as data to forecast energy consumption based on statistical analysis, dedicated to low-cost EMS system solutions.

Keywords: electrical energy management; energy system; renewable energy sources; reduction in electrical energy consumption; low-cost electrical power systems; energy strategy; energy efficiency; strategic management; analysis of methods of energy management; electrical energy consumption; limitation of probabilistic method; integrated approach; transformation; European Green Deal

Citation: Kampik, M.; Fice, M.; Pilśniak, A.; Bodzek, K.; Piaskowy, A. An Analysis of Energy Consumption in Small- and Medium-Sized Buildings. *Energies* **2023**, *16*, 1536. https://doi.org/10.3390/en16031536

Academic Editor: Abu-Siada Ahmed

Received: 27 December 2022
Revised: 27 January 2023
Accepted: 31 January 2023
Published: 3 February 2023

1. Introduction

The continuous increase in the price of electrical energy makes the issues of saving energy and proper energy management extremely important to ensure uninterrupted operation of power systems, thus ensuring the appropriate quality of electricity for consumers. Implementing the European Green Deal strategy is also crucial [1]. Energy-saving mechanisms include a number of activities that aim to rationalize the use of resources and increase the share of renewable energy sources in total production and activities that lead to a reduction in the consumption of these resources [2–4]. The energy market cannot function properly without proper management of energy consumption at every level, from a single household to an integrated power system. This order was used not without reason as the widespread use of distributed energy sources (especially renewable sources) requires changing the place of managing and forecasting electricity demand to the lowest level - this is especially true for prosumer installations [5].

The management of electricity in buildings is becoming increasingly important, mainly due to the rapid increase in energy purchase costs. Cost reduction can be achieved by reducing consumption or using cheap, prosumer renewable sources, such as photovoltaics or micro biogas plants. Cheap prosumer renewable sources are sources with limited supply, most of which are limited by weather conditions. The energy management of a single building or premises requires reliable forecasting of energy production and consumption, which, together with the appropriate model, allows one to make the right decisions about its use. This article analyses the demand side because of the possibility of using simple methods to predict production. There are many models that use Industry 4.0 technologies, the integration of IoT (Internet of Things) technologies, artificial intelligence and modelling supported by a digital twin, enabling the creation of intelligent environments that increase energy efficiency [6–8].

There are many available devices on the market that provide the ability to manage and monitor nonintelligent loads, such as Fibaro, Sonoff, Pacific Sun, Ocean ABB or Xiaomi MI Smart plugs. There are also many works showing the use of these smart plugs in energy management systems [9–11]. Smart plugs enable the retrofitting of electrical resources and provide basic functions, such as planning or creating rules. However, smart plugs, in addition to their capabilities, are not able to acquire and transfer information regarding the context of the resource, i.e., where and how users use the resource. The implementation of inexpensive and generally available solutions is relatively simple, but the problem is the limitations in the information on the use of the resource by the user. The energy management system is highly dependent on available data on the context of the object. To be able to forecast and optimize energy consumption, general knowledge of the building context is necessary and partial information provides limited possibilities for forecasting consumption and appropriate energy management. Moreover, the aggregation of several systems and devices of different brands and their different standards of output data is also a big challenge.

Several solutions are used to connect energy loads in buildings with the energy management system defined by the IEC 61970 standard. The first concerns the modification of individual loads by adding measuring and communication units, making them intelligent; such solutions have been proposed in works [12–15]. The second solution concerns the incorporation of intelligence into the power line, which requires modification of the electrical infrastructure of the building [16–18]. The third approach presented, among others, in [19,20] uses DR and intelligent measurement units connected between the power supply and the load. Currently, there are many relatively inexpensive hardware solutions that enable the creation of an EMS system and the control of loads, but the challenge is to use and adapt these systems to forecast demand. They provide limited possibilities and the forecasting itself is possible to a limited extent. That is why in the article we present the problems of deployment such solutions in various EMS systems implemented in several projects completed in recent years. The implementation of these systems in buildings with an annual consumption of several MWh is debatable because high hardware requirements are associated with high investment costs and thus, the solution can be uneconomical.

The importance of predictive methods in forecasting electricity demand is dictated by the fact that both the price of energy and the quality of the forecast depend on the precision of the prediction. An additional factor of growing interest in prediction methods is the increasing competitiveness of the electricity market, which forces its participants to look for alternative tools. The large-scale increase in the share of renewable energy sources does not make the pattern of energy consumption more random or orderly, but the prediction itself becomes increasingly complex [21]. Therefore, various prediction methods have been adapted, considering many input variables, such as energy price and energy demand, or other external factors, such as weather conditions. Prediction methods are based on econometric and statistical models using various analysis techniques to achieve the goal in a specific time period. In short-term forecasting for large data sets, artificial intelligence and machine learning methods are mainly used, such as support vector machines (SVM), logistic regression (LR), naive Bayes (NB), K-nearest neighbor (KNN), decision tree classifier (DTC) and neural networks (NNs); works [22–26] can be cited here.

For smaller data sets, statistical methods that use time series [27–29], exponential smoothing [30,31] and linear and dynamic regression models [32] are much better. The main advantage of statistical methods are simple predictive models and high computational efficiency [33]. In the research conducted, we have been dealing with time series.

One of the methods of improving the stability of the power system operation is demand side response (DSR) programs, whose undoubted advantage is the possibility of shaping energy prices during the day. Programs introduce appropriately selected tariffs for electricity prices [34,35]. Dynamic pricing in the local power grid aims to activate consumers and assess their behavior [36,37]. Since individual residential prosumers represent a significant percentage of the total local load, price flexibility creates significant opportunities for peak load management and demand response programs. Various methods have been developed to allow dynamic pricing based on a comparison of consumer and prosumer load profiles settled according to time tariffs of electricity [38,39]. The key role in the dynamic shaping of the local energy price plays in the determination of changes in energy consumption in individual short time intervals. An excellent tool is the statistical analysis of a prosumer load profiles, which quantifies their responses to price signals [40,41].

Buildings have a huge potential to reduce global carbon emissions. This leads to the need to analyze the efficiency of energy management. Energy management in buildings is primarily about forecasting demand and generation. The economic yield, which is the result of forecasting demand and matching the generation profile, depends on the accuracy of the forecast [42]. However, it should be remembered that in small buildings, the volume of energy consumption is relatively small. Therefore, the economic gain will also be relatively small. Therefore, the investment and operating cost of the energy management system must be adequate for the expected effects. In this case, it may turn out that the cost of investing in an energy management system (EMS) will not be balanced with the savings resulting from its use.

2. Problem Statement

The aim of this article is to justify a methodical approach to evaluating the effectiveness of implementing energy management in small- and medium-sized buildings using statistical methods and mathematical modeling tools. Energy management in buildings requires short-term forecasting of the electricity demand. The quality of the forecast depends on the available data on the basis of which the forecast will be made. Our goal was to check whether the available electricity demand profiles are useful and sufficient to be used to forecast electricity demand in small and medium-sized buildings. To this end, we performed a statistical analysis of the available electricity demand profiles of selected buildings, checked the participation of individual receivers in the building's energy consumption and determined the following indicators: relative standard deviation (RSD) and participation of random devices (PRD) in total energy demand in the building, described in Section 3. Industrial and service buildings were compared to residential buildings.

3. Materials and Methods

The data used for the analysis are the result of the implementation of several independent projects. One of the projects involved the development of energy management solutions in small and medium-sized buildings on the basis of available data from the distribution network operator (DNO), the other in the implementation of its own solutions along with measurements in selected facilities. In buildings where we conducted the measurements ourselves, the measurement system was a limitation and the challenge was the use of data collected by the measurement system, which is an integral part of a typical building automation system. For this reason, both the method of obtaining the data and the time interval and the time of acquisition are not the same. However, the same conditions are provided for the calculation of the RSD and PRD factors. Data from the DNO operator were used for statistical analyzes and calculation of the RSD indicator. Data from EMS systems were used to analyze the energy consumption of devices and PRD factor calculations. Results obtained for both periods are not compared with each other, the analyzes conducted are independent and do not affect each other.

In statistical methods, small power systems (micro installations) are also a limitation, where there are many devices that consume small volumes of energy. In these lists, there are usually dominant devices, characterized by much higher energy consumption compared to other devices. This affects the quality of the forecasts. However, the use of statistical methods is a cheap solution, where there is no need to use complex computing systems.

This paper discusses the possibility of using historical electricity demand profiles, which can be easily downloaded from DNO or local EMS systems. For this purpose, statistical analyzes of such profiles were conducted. The analysis includes 15 specific buildings according to the demand profile, including 8 medium-sized buildings (commercial buildings) and 7 residential buildings with different annual demand.

To determine the quality of available data for forecasting purposes, box plots were prepared and RSD values were calculated. To determine the possibility of using additional data in the form of electricity demand profiles of individual devices in buildings, the Pareto principle was checked for devices and consumed energy.

During data recording using the Fibaro distributed measurement system, technical limitations of this type of measurement systems were defined. This chapter shows these limitations.

3.1. Methods of Obtaining Measurement Data

The research conducted as part of two projects required the acquisition of electricity demand profiles of end users belonging to groups of small and medium buildings. Data acquisition was conducted in two ways:

- obtaining 15 min demand profiles from the DNO operator. Data obtained for 2017. Data used for statistical analysis and calculations of RSD coefficient;
- measurements of energy demand in buildings using a Fibaro distributed energy management system (EMS) Fibaro. Data registered in the period: April 2021–December 2022. Data used to analyze the energy consumption of buildings and devices.

3.1.1. Profiles Obtained from the DNO Operator

One of the ways to obtain data on the electricity demand profile is to obtain them from the DNO operator. Anonymous 15 min electricity demand profiles were obtained for selected groups of recipients from the SME (small–medium enterprises) sector. The profiles were aggregated to hourly profiles and used in this form in further statistical analysis of each element. To test the possibility of forecasting consumption in individual hours, data from selected characteristic commercial buildings were used. When selecting facilities, the opening hours, the type of service provided and the annual demand for electricity were considered. Objects selected for analysis were collected in Table 1.

Electricity demand profiles of residential buildings, single-family houses were also obtained. The method of heating was used as the selection criterion because electric heating, if it exists, is usually the device with the highest energy demand. The buildings selected for the analysis were gathered in Table 1.

For this set of buildings, the year 2017 was selected for the analysis, for which the authors have a rich database of profiles. This is very important from the point of view of statistical analysis because the data did not cover the period of the epidemic. During the COVID-19 epidemic, there was a significant change in the use of buildings and, consequently, a change in the demand profile. Example hourly profiles used of the analysis for a hospital and a home without electric heating are shown in Figures 1 and 2, respectively. Without an analysis, and only on the basis of a visual assessment, it can be concluded that the profile of a residential building will be much more difficult to predict. Periodic repetition of the shape of the demand profile is visible for the hospital.

Table 1. Characteristics of SME sector and residential buildings. Source: compiled on the basis of data obtained from the DNO operator. Anonymous data.

No.	Type	Annual Energy Consumption, (MWh)	Description
1	bank	30	open from 8 am to 5 pm
2	hotel	70	24-h reception
3	shopping center	300	open from 9 am to 9 pm, textile industry
4	kindergarten	40	with care from 6:30 to 16:00, with the largest group of children between 8:00 and 13:00
5	restaurant	35	open from 12:00 to 22:00, with high energy demand during the preparation phase 08:00–12:00
6	petrol station	120	open 24/7
7	hospital	3500	multi-specialty
8	house without electric heat	2.5	usable area of 190 m^2, 3 persons, gas heating
9	house with air-to-air heat pump	3.2	usable area of 70 m^2, 3 persons, heat pump as an additional source of heating
10	house with ground source heat pump	7.5	usable area of 200 m^2, 3 persons, heat pump as the main source of power, recuperator

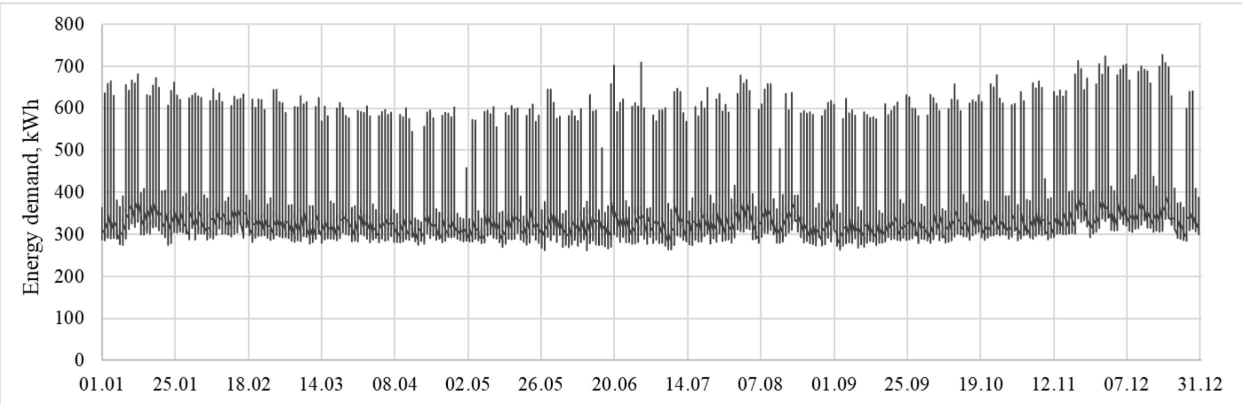

Figure 1. Hourly demand for electricity in building 7–hospital. Source: compiled on the basis of data obtained from the DNO operator. Anonymous data.

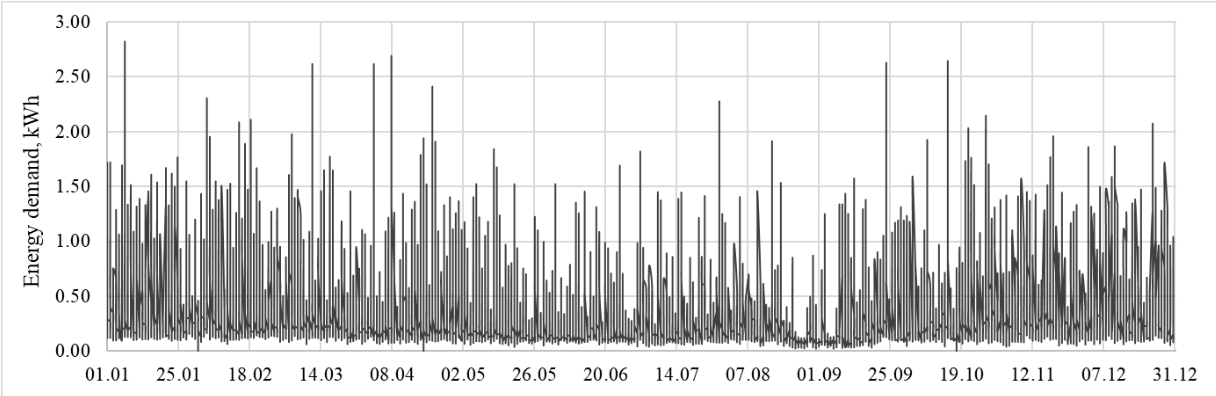

Figure 2. Hourly demand for electricity in building 8–house without electric heating. Source: compiled on the basis of data obtained from the DNO operator. Anonymous data.

3.1.2. Profiles Obtained from Fibaro Systems Installed in Buildings

Profiles obtained from DNO operators are characterized by data continuity, but their main limitation is the reading frequency, which is 15 min. The limitation is the inability to observe changes in the values of active power. Therefore, an alternative way to obtain measurement data (as part of one of the research projects) was to install our own measurement systems with full access to the measurement data. The Fibaro measurement and control system was selected [43,44]. This system enables monitoring and recording of electricity flow for the entire building and selected devices and photovoltaic source. Fibaro Wall-plug and Fibaro wall-switch measurement systems and AEOTEC meters communicated with the Fibaro control panel via the Z-wave interface [45,46]. The measurement system is shown in Figure 3. It should be noted that the Fibaro measurement systems were installed in other buildings than those described in Section 3.1.1.

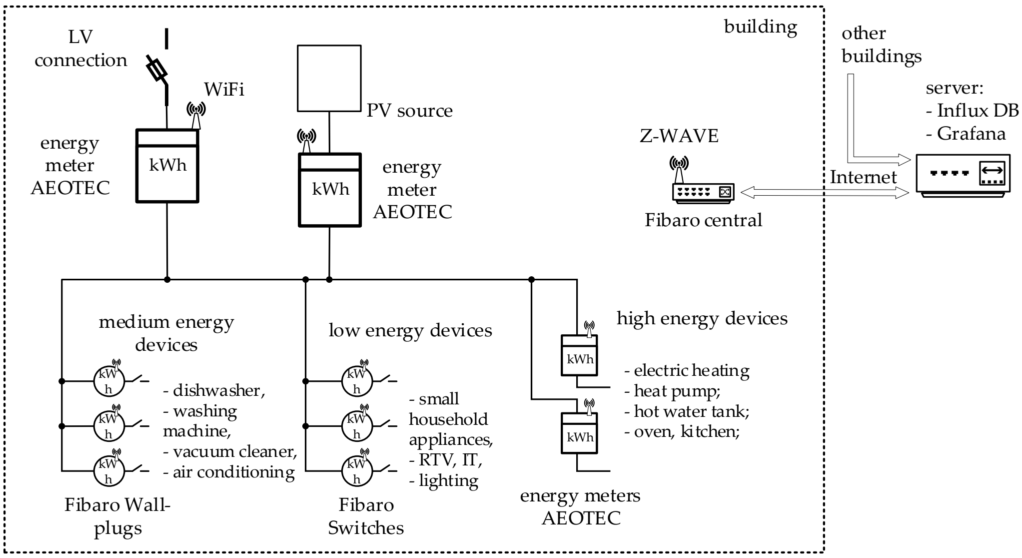

Figure 3. Scheme of the Fibaro measurement system in the building. Source: author's development.

The biggest problem with the measurements was the inability to synchronize the measurements for all devices in the building. Fibaro measurement systems and AEOTEC meters send data to the aggregator only when the power value or energy counter changes. For the AEOTEC meter, it is visible in the form of N/A in Table 2, there was no change in power in the specified time. For this reason, the data was recorded asynchronously, without a specific sampling period. This is a significant limitation in the case of the need to perform analyzes; additional data preparation is necessary. It also turned out that the

Fibaro power measurement systems (measuring power and energy for individual devices) sent a random "zero" value when the power value did not change. The data from the Fibaro control panels was read by periodic polling. Table 2 shows exemplary results of the active power consumed by the dishwasher: measurement with the Fibaro wall plug system (measures the energy consumed by the dishwasher) and the AEOTEC meter (measuring the energy consumed by the building). The waveforms of active power for both measurement systems are shown in Figure 4.

Table 2. Exemplary results of measuring the active power consumed by the dishwasher. Source: author's development.

AEOTEC		Fibaro Wall-Plug	
Time	**Power (W)**	**Time**	**Power (W)**
19:38:48	88	19:38:48	17
19:38:49	N/A	19:38:49	0
19:38:58	N/A	19:38:58	0
19:39:19	91	19:39:19	0
19:39:25	N/A	19:39:25	0
19:39:48	2258	19:39:48	2221
19:39:49	N/A	19:39:49	0
19:39:56	N/A	19:39:56	0
19:40:19	2239	19:40:19	2203
19:40:20	N/A	19:40:20	0
19:40:28	N/A	19:40:28	0
19:40:49	2246	19:40:49	2208
19:40:50	N/A	19:40:50	0
19:40:55	N/A	19:40:55	0
19:41:19	2254	19:41:19	2214

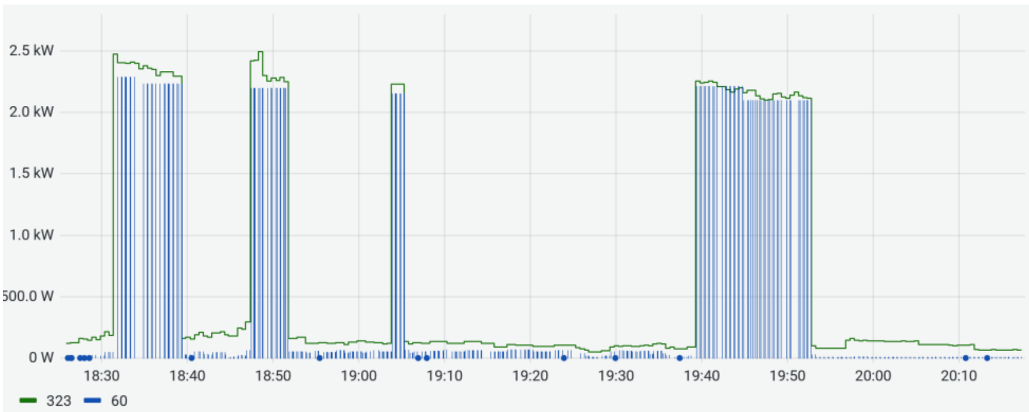

Figure 4. Comparison of registered dishwasher active power waveforms: 323–data logged with an AEOTEC meter (active power consumed by the whole building); 60–data logged using Fibaro wall-plug. Source: author's development.

The measured values of active power and energy were saved in the Influx DB database and supported by the Grafana application [47–49]. The Grafana system makes it possible to standardize recorded electricity waveforms to 15 min, 60 min and 24 h values [50]. In principle, the Grafana system made it possible to adjust the recorded electricity data to any chosen sampling period. Figure 5 shows an example graph of the Grafana application of 60 min energy waveform for a selected building, a flat used by 2 persons. Energy meters record and send to the database the increasing value of the counter. To obtain values, e.g., 60 min, it was necessary to use the differential recording function.

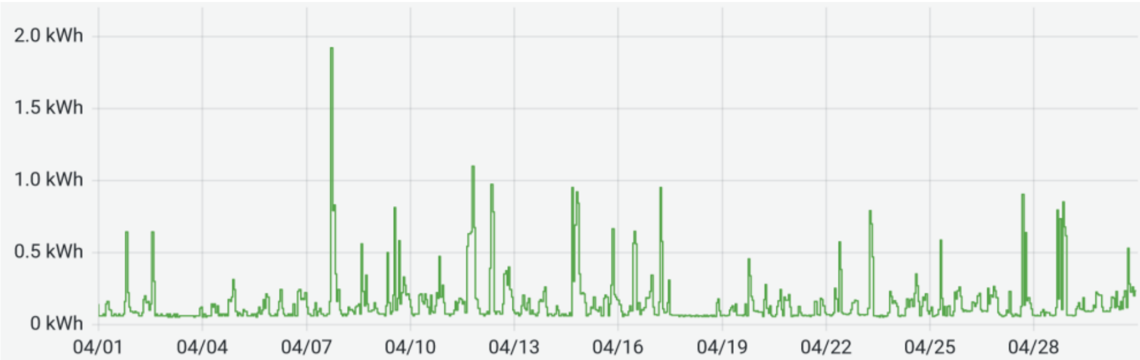

Figure 5. An example graph from the Grafana application of 60 min energy from 1–30 April 2022, for a flat used by 2 persons. Source: author's development.

The measurement data used in the article come from real buildings and were recorded from April 2021 to December 2022. As part of the project, in selected buildings, measurements of electricity demand for almost all devices connected to the network were conducted. Most of the devices were permanently connected to sockets through measuring devices located in mounting boxes. Example photos of installed measurement systems are shown in Figure 6.

(**a**) (**b**) (**c**) (**d**)

Figure 6. Photographs of sample installed measurement systems: (**a**) AEOTEC meter installed in the building's switchboard; (**b**) Fibaro switch in flush-mounted socket; (**c**) Fibaro wall-plug; (**d**) Fibaro switch in the housing of the ceiling lamp. Source: author's development.

The network of measurement points provided data to the Fibaro Home Center via a wireless Z-wave connection. Each element of the system, interconnected with other points of the MESH network [51], globally reduces electricity consumption due to its dispersed nature. Each of them is both a transmitter and receiver, enabling information transmission from further sensors. These devices do not emit as much radio power as standard networks, and therefore consume relatively little energy, with an extensive range. Smart-home systems use specialized networks, such as ZigBee [52] and Z-wave [53].

The measurement of global electricity and power is conducted using the AEOTEC ZW095 m, in which the current measurement is conducted using the attached measuring transformer with a maximum measuring range of 200 A. The measurement class of the device was in the range of 1%.

The influence of the measurement class on the results of the statistical analysis was also checked. The inaccuracy of the measurement affects the proposed indicators. In any case, this influence is below the accuracy of the measuring devices (Table 3). In any case, it should be used to obtain the best possible measurements, but this is not critical, especially since measuring devices are usually characterized by a class below 5%. Therefore, the influence of the device measurement class on the statistical analysis results is not considered in further analysis.

Table 3. Average Relative Standard Deviation (%) for measurement accuracy of the device.

Measurement Class	No Consideration	1%	5%	10%
Bank	15.29	15.28–15.31	15.54–15.68	16.32–16.58
House with air-to-air heat pump	111.56	111.50–111.58	111.44–111.95	111.32–112.24

The receiver profile was measured using Single Fibaro Switch (1 channel with a maximum current of 10 A) or Double Fibaro Switch (2 channels with a maximum current of 6 A). Their choice depended on the type of load, location and mounting possibilities. In cases where the measurements concerned non-stationary devices (for example, a vacuum cleaner) or when it was not technically possible to install the measuring devices in the boxes, the measurements were made with Fibaro Wall-Plug. The manufacturer has defined the measurement accuracy class of Fibaro Switch and Fibaro Wall-Plug at the level of 1% for the power consumption above 5 W.

Acquisition of measurement data in the Fibaro central was conducted by polling individual measurement systems. The aggregated information was transferred via JSON format to database servers. Buildings with installed the Fibaro system, listed in Table 4.

Table 4. Characteristics of buildings with installed the Fibaro system. Source: author's development.

No.	Type	Annual Energy Consumption, (MWh)	Description
11	apartment	1.2	inhabitants: 2 adults, district heating; number of measurement points: 65, number of monitored receivers: 61
12	single-family house	8.5	inhabitants: 2 adults + 1 child, electric heating and a stove wood; number of metering points: 85, number of monitored receivers: 81
13	apartment in a block of flats	1.5	inhabitants: 2 adults + 2 children, district heating; number of measurement points: 35, number of monitored receivers: 34
14	single-family house	5.5	inhabitants: 2 adults + 2 children, gas heating; number of measurement points: 121, number of monitored receivers: 77
15	commercial premises	2.0	number of employees: 5, gas heating; number of measurement points: 55, number of monitored receivers: 54

The shape of the profile of the electricity demand depends on the duty cycles of the installed equipment. It should be noted that the work schedule of some receivers is user-dependent and others are not. For example, devices, such as a refrigerator or a heat pump, work depending on the set temperature parameters and weather conditions. In residential buildings, household appliances are switched on depending on the user's request, such as an oven or dishwasher. Some receivers, depending on the type of building, are always used at a certain time, and others, depending on the user's request. An example is a computer that will be turned on in the office during working hours and at home as needed.

To assess the share of user-controlled receivers in energy consumption, the participation of random devices (*PRD*) indicator was introduced:

$$PRD = \frac{E_b}{E_{rd}} \quad (1)$$

where: E_b is the annual energy consumed by all devices in the building; E_{rd} is the annual energy consumed by randomly switched-on devices.

3.2. Method of Statistical Analysis of Electricity Demand Profiles in Buildings

The statistical method is a low-cost method to forecast electricity demand, but depending on the type of the analyzed building, it can be characterized by low forecast accuracy. The reason for the inaccuracy of forecasting based on statistical data is the behavior of people and, especially for residential buildings, the power of individual household appliances in relation to the connection power of buildings. Therefore, for example, random (resulting from behavior) switching on of an electric kettle significantly affects forecasting. The purpose of statistical analysis is to identify the limitations of such a method.

Building load profiles 1–10 were used as input for statistical analysis. Due to the need to compare buildings of different character, it was assumed that the statistical analysis would use data only for working days (without Saturdays, Sundays and holidays). Tukey's box plot [54] was used to visualize the statistical analysis, which allows for a detailed presentation of statistical data.

The graphs were presented for each hour and calculated based on the demand for individual hours in 2017. First, statistical analysis was performed for each month separately. Box plots were created based on about 20 measurement samples. This is a representative number of samples that does not require correction factors when calculating the standard deviation. Monthly analysis in the general case allows for more accurate forecasting. There are short-term forecast methods described in the introduction; however, statistical analysis for the whole year is used in further analysis to assess the limitations resulting from the use of statistical forecasting methods.

In the case of an analysis conducted for the whole year, the box plot was made on the basis of approximately 250 samples per hour. To determine the accuracy of forecasting based on statistical analysis, the percentage Relative Standard Deviation coefficient was adopted.

$$RSD = \frac{\sigma}{\overline{x}} \cdot 100\% \quad (2)$$

where: σ is the standard deviation and $\overline{x}$ is the average value.

This coefficient allows for normalization and comparison of buildings with different annual energy consumption. An average factor $\overline{RSD}$, defined as the arithmetic mean of the *RSD* factors for each hour, was also introduced. For the shopping center (Table 5), the factor $\overline{RSD} = 33\%$. This suggests that the use of forecasting based on statistical data in this case is burdened with relatively high uncertainty.

Table 5. Relative Standard Deviation (%) for shopping center each hour on a business day in 2017. Source: built on the basis of author's calculations and data from DNO operator.

Hour of the Day	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**
January	5	5	5	5	5	5	5	10	17	14	15	15	15	16	16	17	18	19	13	6	6	6	5	5
February	2	2	2	2	3	3	8	4	16	6	4	5	4	5	5	5	6	9	4	3	4	2	2	2
March	1	2	2	1	2	9	6	2	15	4	3	4	6	4	6	6	7	7	10	15	3	2	2	2
April	2	2	2	2	2	16	5	13	28	9	4	4	5	4	7	6	7	7	6	5	13	3	3	2
May	34	30	27	21	17	25	23	26	27	29	34	32	35	27	32	36	37	39	48	59	59	44	37	39
June	30	26	26	22	26	27	30	26	29	20	22	25	22	20	20	22	26	25	27	36	36	33	29	26
July	22	22	16	16	20	21	21	21	19	18	18	22	18	19	18	17	17	16	22	19	25	22	26	23
August	34	26	28	28	23	27	26	30	35	23	24	22	21	22	22	19	24	25	25	29	31	28	26	29
September	27	26	25	21	25	16	26	34	43	15	15	19	17	18	21	26	25	31	31	34	20	21	27	20
October	7	6	6	6	7	6	13	14	16	5	5	7	7	7	6	9	8	10	14	16	22	22	22	22
November	3	3	3	3	4	4	7	3	10	7	15	17	17	15	16	17	22	20	20	5	3	3	3	3
December	7	6	6	6	6	6	6	11	15	14	12	6	5	5	5	4	4	4	9	21	9	7	7	7
Year	36	31	30	28	26	23	29	37	43	24	25	28	28	28	29	29	34	36	38	47	45	40	42	39

4. Results

The described methodology of statistical research allows to assess the possibility of using historical energy demand profiles for forecasting purposes. The presentation of the results in the form of a box plot allows of a rough comparison for the accuracy of the forecasting. The presence of outliner data is also very important. The more there are, the more the forecast can increase the error. The reason may lie in a very high dependence of energy demand on a random factor, e.g., the presence of people in the hotel. The methods described in Section 3 were used to calculate the values of the comparative indicators RSD and PRD.

4.1. Statistical Analysis of the Electricity Demand for Individual Months of the Year

Examples of box plots for a shopping center in selected months are shown in Figure 7. It can be seen that better forecasting in this case, a smaller interquartile range (IQR), occurs for months of "stable" sales, while high IQR for summer months in which air-conditioning plays an important role.

From Table 5 it can also be seen that the annual hourly *RSD* is at a high level in individual months. This is an additional argument in favor of using annual data in comparative analyses.

Based on the analysis of data from Table 5, it can be seen that there is a possibility of better forecasting, considering the forecasts for each month, but the annual value of the coefficient is sufficient to compare different types of buildings. The average ratio $\overline{RSD}$ for shopping centers is presented in Table 6.

It can be seen that the annual value of the ratio (Table 6) is comparable to that of the month with the highest volatility (May). Therefore, in the next part of the article, annual modeling was adopted for statistical analyses and the determination of the possibility of using statistical methods for analysis based on *RSD* and $\overline{RSD}$ coefficients for the analyzed buildings. Since the ratio $\overline{RSD}$ takes values close to the worst from the monthly analysis, this approach can be treated as an example of worst-case analysis.

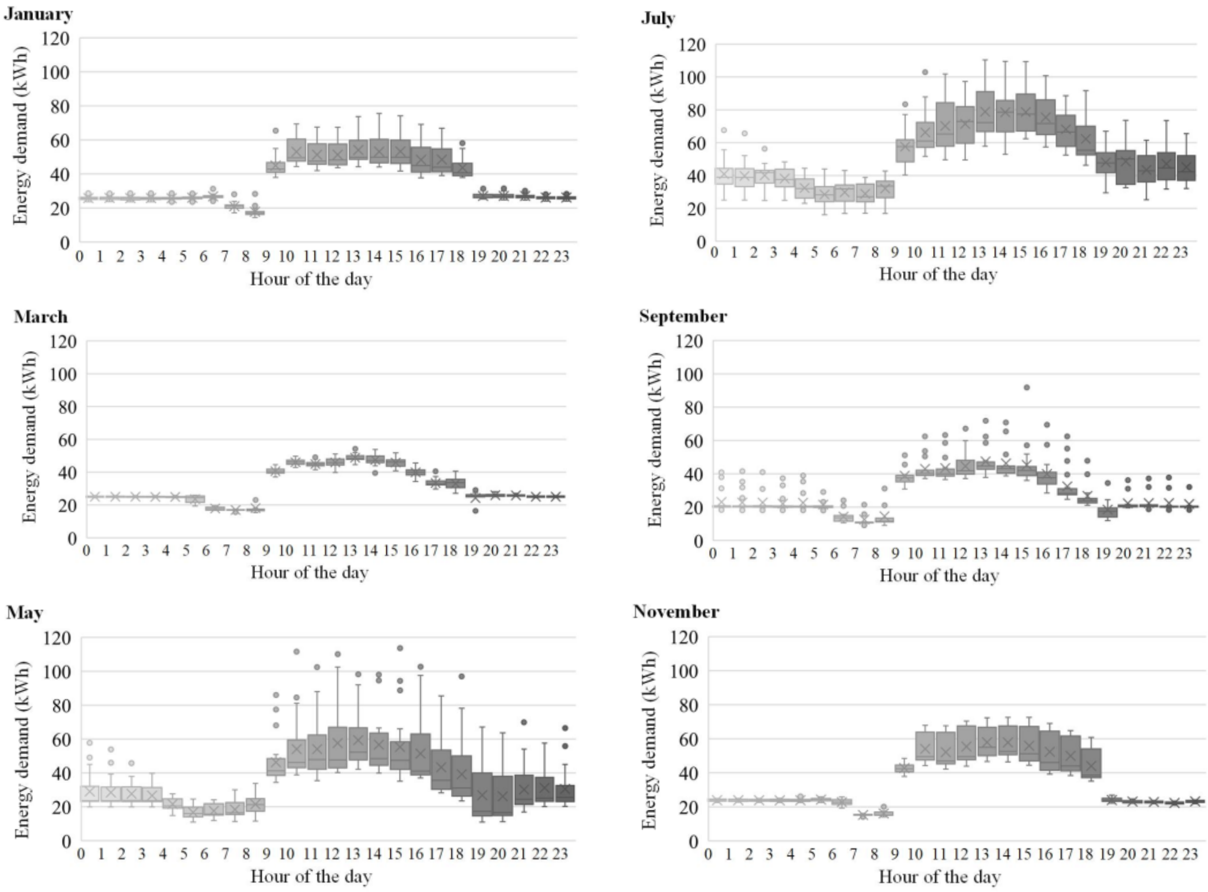

Figure 7. Month's box plots of data for shopping center in day in 2017. Source: built on the basis of author's calculations and data from DNO operator.

Table 6. Monthly average Relative Standard Deviation (%) for shopping center on a business day in 2017. Source: built on the basis of author's calculations and data from DNO operator.

Month	$\overline{RSD}$
January	10
February	4
March	5
April	6
May	34
June	26
July	20
August	26
September	24
October	11
November	9
December	8
Year	33

4.2. Statistical Analysis of the Electricity Demand Profiles of Selected Buildings

The results of the statistical analysis presented using the box plot for the buildings, described in Section 3.1.1, are shown in Figure 8. For each analysis building, there are outline values that indicate the occurrence of situations that strongly deviate from the forecast value. One can also see in Figure 8, based on the data in Table 1 the higher the annual consumption, the lower the uncertainty in the forecasting. This means that the IQR is smaller (the size of the boxes is smaller) and there are no outline values.

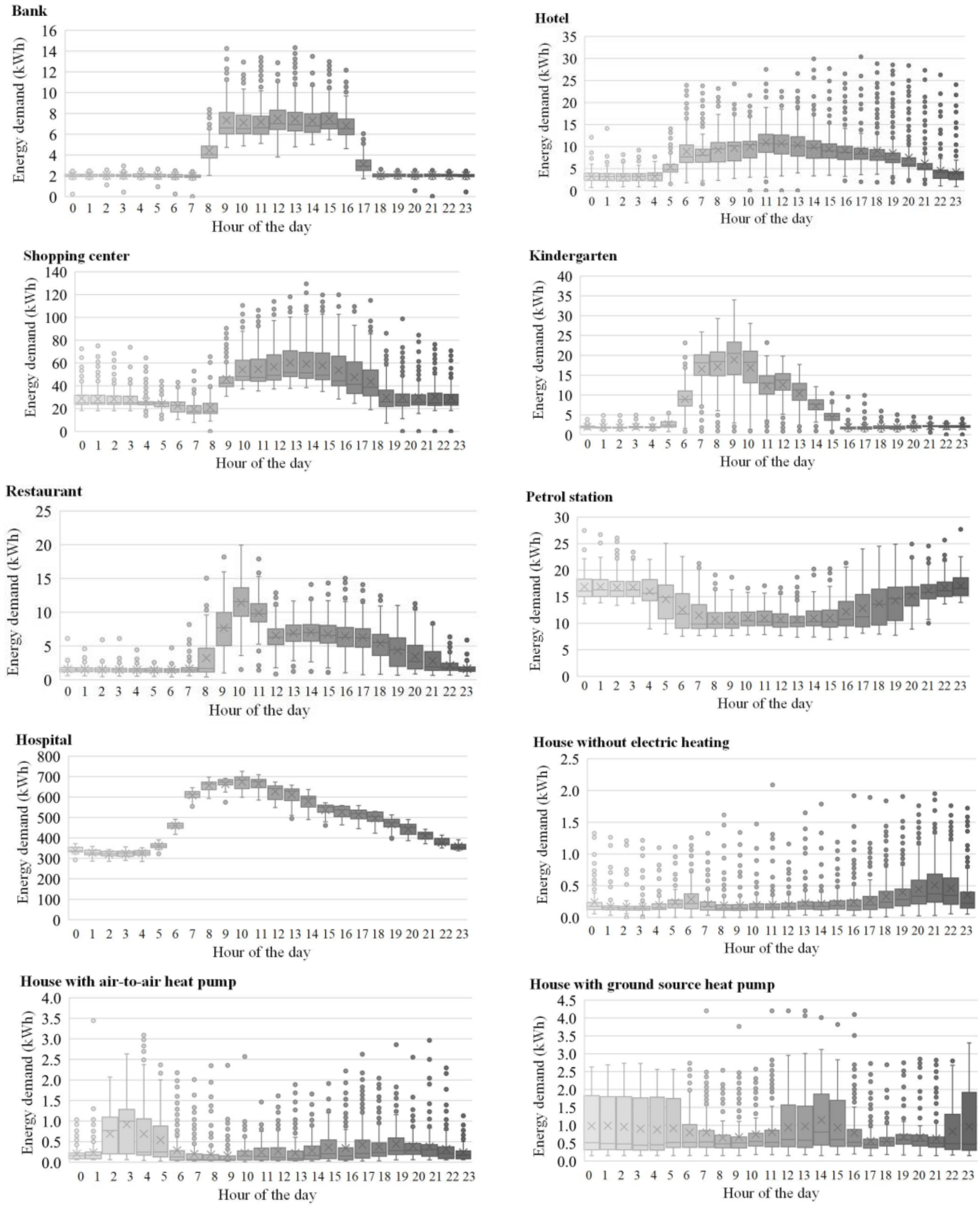

Figure 8. Box plot of data for selected characteristic buildings each hour on a business day in 2017. Source: built on the basis of author's calculations and data from DNO operator.

Based on the statistical analysis of the selected buildings, it is possible to determine the hourly profile of the variability of energy demand for selected buildings. This profile strongly depends on the functionality of the building. One can see that forecasting can be performed with different accuracy. For example, the Bank has a repetitive demand profile and forecasting in residential buildings is subject to high uncertainty. The forecast quality was determined numerically using the *RSD* coefficient (Table 7).

Table 7. Relative Standard Deviation (%) for different types of buildings each hour on a business day in 2017. Source: built on the basis of author's calculations and data from DNO operator.

Hour of the Day	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**
Bank	11	10	10	10	10	10	12	12	24	26	22	23	21	22	22	20	18	26	10	10	11	11	9	10
Hotel	40	41	37	37	38	45	43	40	38	36	34	35	34	37	40	40	40	43	48	52	57	59	75	74
Shopping center	36	31	30	28	26	23	29	37	43	24	25	28	28	28	29	29	34	36	38	47	45	40	42	39
Kindergarten	20	21	19	19	20	40	45	36	33	36	35	32	33	35	34	36	54	47	34	31	25	18	18	20
Restaurant	36	36	35	37	34	30	34	51	89	46	29	23	30	25	27	30	35	36	43	56	63	66	54	37
Petrol station	14	14	14	13	19	27	30	30	21	21	19	18	19	19	19	22	28	33	31	27	21	15	13	13
Hospital	5	5	5	5	5	6	7	9	8	7	7	7	6	7	7	8	9	10	10	10	9	6	5	5
House without electric heating	88	82	89	81	74	63	74	74	92	89	87	98	70	87	90	67	94	90	88	88	77	75	75	94
House with air-to-air heat pump	88	123	66	66	112	102	138	145	176	153	116	104	122	140	105	102	130	117	98	91	84	98	108	92
House with ground source heat pump	82	81	84	86	84	79	78	80	75	78	74	84	80	82	70	75	79	65	47	60	69	76	80	88

The annual $\overline{RSD}$ factor was used for comparison (Table 8). This factor determines the possibility of using the measurement data obtained from DNO operators as an input to the forecasting. It can be seen that the accuracy of forecasting (based on measurements and statistical analysis) is the greater the smaller the influence of the human factor. Therefore, the hospital is the best predictor. This is due to the constant number of patients resulting from the need to comply with admission limits, the repetitiveness of the activities performed and the highest annual energy consumption.

Table 8. Annual Relative Standard Deviation (%) for different types of buildings on a business day in 2017. Source: built on the basis of author's calculations and data from DNO operator.

Building	$\overline{RSD}$
Bank	15
Hotel	44
Shopping center	33
Kindergarten	31
Restaurant	25
Petrol station	21
Hospital	7
House without electric heating	83
House with air-to-air heat pump	112
House with ground source heat pump	77

A bank, in which customer service does not require the participation of devices that consume a large amount of energy, has good forecasting as does a 24 h gas station and a restaurant. An interesting example is the hotel, which has a very large share of outliers. This is due to the strong dependence of energy consumption on the number of guests. It is also the most difficult to predict building, apart from residential buildings. Kindergartens and shopping centers can be predicted with average accuracy, where energy consumption is strongly dependent on the presence and number of people.

Residential buildings have the greatest forecast uncertainties, especially when a high-power device occasionally operates, such as in a house with an air-to-air heat pump.

4.3. Energy Consumption Analysis of Electrical Devices in Buildings

Based on the energy demand measurements of the receivers, described in Section 3.1.2, an analysis of the energy consumption of individual receivers and their impact on the annual energy demand was conducted. An aspect of the research was the estimation of the impact of individual receivers on annual energy consumption. An analysis was also conducted using the Pareto principle [55]. Tables 9 and 10 show the percentage share in building electricity consumption of 20% of the receivers that consume the most energy. Devices have been sorted according to the largest share of consumption. The energy consumed by these receivers is in the range of 80–95% of the building's annual energy. Other devices have a negligible impact on energy consumption and the shape of the demand profile.

The analysis confirmed the Pareto principle, that is, 20% of devices account for at least 80% of the demand.

Table 9. Percentage of annual electricity consumption, 20% of consumers using the most energy, part 1. Source: built on the basis of author's calculations.

Building 11		Building 12		Building 13	
Device	**Percentage**	**Device**	**Percentage**	**Device**	**Percentage**
fridge	21.5%	**desk: computer + lamp**	18.8%	electric boiler	35.7%
locker with rtv + audio + lamp	16.8%	**bathroom lighting**	13.3%	bathroom radiator 1	17.3%
dishwasher	11.6%	const lighting	9.2%	tank hot water heater	13.4%
router + Fibaro control panel	7.4%	**rtv**	9.0%	bathroom radiator 2	9.9%
system audio	5.0%	kitchen lighting	8.5%	fridge 1	3.1%
desk: computer + audio + printer	4.2%	**wash machine**	7.6%	**desk: computer + printer**	2.3%
microwave	4.1%	router wifi	3.8%	**dishwasher**	2.1%
air conditioner	3.8%	**desk socket**	3.8%	**electric cooker**	2.0%
coffee machine	3.0%	**rtv lighting**	3.3%	fridge 2	1.9%
phone	1.8%	**hood**	2.9%	**locker with rtv**	1.6%
iron	1.6%	**sum**	80%	**desk: computer**	1.5%
wardrobe lighting	1.4%			**vac**	1.3%
main lighting	1.3%			router + Fibaro control panel	0.9%
sum	**84%**			**wash machine**	0.9%
				rekuperator	0.8%
				kitchen sockets	0.7%
				sum	**95%**

Table 10. Percentage share in annual electricity consumption, 20% of receivers consuming the most energy, part 2. Source: built on the basis of author's calculations.

Building 14		Building 15	
Device	**Percentage**	**Device**	**Percentage**
fridge 2	13.7%	server	22.8%
locker with rtv + audio	12.0%	fridge	12.0%
dishwasher	11.8%	desk: computer	11.8%
fridge 1	7.7%	**dishwasher**	10.5%
dryer	7.2%	lighting	8.4%
hot water tank with heater	4.2%	gas boiler	7.6%
rtv-kitchen	3.7%	desk: computer + lamp	4.1%
kettle	3.4%	office computer equipment	2.8%
desk: computer	2.8%	**kettle**	2.8%
central heating boiler	2.7%	office lighting	2.6%
alarm	2.6%	hall lighting	2.2%
router	2.5%	**microwave**	1.2%
desk: computer + lamp	2.3%	**sum**	**89%**
solar panels	2.2%		
garage lighting	2.1%		
terrarium	1.9%		
sum	**83%**		

In Tables 9 and 10, in bold, are receivers whose activation time depends only on the human, causing stochastic changes in the shape of the electricity demand profile. One can see that in residential buildings (buildings 11–14) at least 50% are such receivers. In the service building (building 15), the same receivers depend not only on the user, but also on tasks performed during the day, conditioned by working hours. An example is a computer that is turned on at home as needed and in the office, it is turned on during work hours. An exception is building 13, where the largest share in electricity consumption is attributed to heating devices, the operation of which depends on the season and weather conditions. Four heating devices consume approximately 75% of the annual energy.

The values of the *PRD* indicator for particular buildings are presented in Table 11. The higher value of the *PRD* indicator, the greater the share of receivers controlled freely by the user in the building's energy consumption. The difference is clearly visible for building 13, where 20% of the devices consume 95% of the energy. However, if we do not take heating devices into account, then the *PRD* indicator increases from 0.12 to 0.6.

Table 11. The *PRD* factor for buildings. Source: built on the basis of author's calculations.

	PRD
building 11	0.45
building 12	0.5
building 13	0.12/0.6 [1]
building 14	0.45
building 15	0.15

[1] In the case of building 13, if the energy for heating purposes is not considered, the PRD indicator will be approximately 0.6.

5. Discussion

The use of statistical methods to forecast the energy demand profile undoubtedly has limitations, as indicated in the text of the article. However, by using the proposed method, some dependencies can be found. The accuracy of the forecast (Tables 7 and 8) turns out to be inversely proportional to the ability to control the building's energy demand profile. This is due to the human factor, which is minimized in public buildings in favor of operating schemes, which at the same time translates into fixed power supply schemes.

By design, its reconfigurability is limited. In contrast to public buildings, the greatest volatility of electricity is revealed in residential buildings. This is due to the randomness of the procedure; even if the activities are repeated every day, they result from habits, employment method and age of residents. This is because how energy is used is affected by a number of random variables, such as weather and even well-being. In addition, an important aspect determining the nature of the profile is the analyzed day, which can be a working day, Saturday, Sunday or holiday.

The relatively simple method allows for the use of data to control the demand profile. For industrial and service buildings, the control of the demand profile is limited by the operating scheme. However, the profile of this type of object is relatively well predictable. This is in part due to the repetitive shape for the energy demand profiles of commercial and industrial buildings, which are highly dependent on the building process. The energy consumption of individual receivers was analyzed (e.g., building 15), which allowed to put forward such a thesis. For this reason, it is possible to adjust the operation of the energy source that cooperates with the storage.

The proposed ratio $R\bar{S}D$ is a determinant that allows to calculate that with a probability of 68.3% (σ) the demand will be within $\pm R\bar{S}D$. The following levels of the possibility of using statistical methods for forecasting are assumed, depending on $R\bar{S}D$:

- very good: <10%
- good: 10–30%
- average: 30–50%
- bad: >50%.

The assumptions adopted in this way result from the analysis of the possibility of using energy storage, i.e., for the average projection of the forecasts, the level of battery charge in the EMS system should be predicted, allowing the use of 50% more energy than a forecast. If we want to ensure a probability of more than 95% (2σ), additional available capacity should be foreseen to provide the average forecast twice the available energy for a given hour. For example, for a demand forecast of 1 kWh in a given hour, for a very good forecast, the available capacity should be 1.1 kWh for a 68% probability or 1.2 kW for a 95% probability. For an average forecast, it will be 1.5 kWh and 2 kWh, respectively.

For residential buildings, the accuracy of the forecast is low, while controlling the demand profile is much easier compared to industrial and service buildings. The accuracy of the forecast can be improved by planning the profile by controlling the selected receivers. The results of measuring the energy consumption of household appliances have shown that appliances with a significant impact on energy consumption are usually controlled by users. Some of them could work according to a fixed schedule, e.g., washing machine, dishwasher or hot water tank. These are devices with medium or high energy consumption.

Forecasting and controlling the operation of devices requires measuring the power consumed in order to determine the activation time and energy consumption. The greater the number of measured devices, the better the building profile is reproduced. At the same time, it should be remembered that each measuring system consumes electricity. Each single Fibaro measurement point continuously consumes approximately 1 W of active power. In one of the buildings, 85 metering points were installed, resulting in an additional annual energy consumption of more than 700 kWh. In this case, the additional energy consumption will not be compensated by the savings resulting from the load control.

When the measurement data, especially the annual energy consumption of individual devices, the Pareto principle is confirmed. 20% of the devices in the building consume energy in the range of 80% to 95% of the annual energy of all devices. For building 13, excluding four heating devices, this share is in the range of 80–89%. In these 20% of devices there are controllable devices that can work according to a given schedule. Therefore, it makes no sense to conduct the measurement for all devices, but to limit the measurements only to controllable devices and the total measurement.

This article presents measurement systems implemented with the use of standard smart home devices. They enable the measurement of power and energy of individual receivers and the implementation of their control. It should be considered that the use of such systems does not guarantee high measurement accuracy. In many cases, the manufacturer does not specify it. This may be the result of reducing the costs associated with checking the devices during release for production, and then the finished products.

An important aspect of measuring is to estimate the accuracy required to correct the results. In many cases, the aim is to ensure that the instrument accuracy is high enough to obtain a reliable result. In the case described, the reference point is the accuracy of the forecast of electricity demand, which is usually tens of percent. Therefore, it can be assumed that the measuring devices of the worst accuracy are still sufficient for the purposes provided.

An additional inconvenience with the use of these devices is the asynchronous transmission of data to the aggregate. The result is unsynchronized device profiles, often distortions. This leads to errors in the forecasting of electricity consumption by assigning the energy count to a different time interval. The result is incompatibility with the main electricity meter. Fibaro wall-plug additionally sends "zero" values randomly. For this reason, the interpretation of this waveform is difficult, because it is not known whether the zero value is true (the device does not consume power) or if it is a false value. This is a significant limitation of using the Fibaro wall-plug to record active power waveforms.

The limitation of the statistical method Is the need to access historical data on energy consumption, preferably at least an annual electricity demand profile. The advantage is that a 15 min profile is sufficient. It is also possible to forecast based on incomplete data, but in this case an additional random factor resulting from the variable demand for energy in different months can be expected, which is observable in Table 6. At the same time, very high volatility in successive periods is important. For example, a good consumption forecast in April for a shopping center ($R\bar{S}D$ = 6%), and a very strong deterioration of the forecast in May ($R\bar{S}D$ = 34%) make forecasting unreliable.

Further research will be conducted to determine the impact of selected factors on the accuracy of the forecasts. However, the assumption will be that they must be easily accessible and do not require large computational effort and costly data acquisition. Initially, it is assumed to take into account the current temperature, the possibility of determining the type of day (working, Saturday, Sunday, holidays, night work, etc.), e.g., by introducing a schedule and using a moving average taking into account local conditions in the long-term forecast. Correlations between the proposed indicators and additional data and those achievable in real EMS systems will be analyzed to determine which of these data and indicators are useful for forecasting. It is planned to increase the analyzed buildings, including the study of the same type of buildings.

The forecast results obtained using statistical methods may be sufficient to implement demand profile control algorithms to achieve a set profile or reduce daily energy consumption. The statistical method can determine the probable daily energy consumption. Additional information on the consumption of electricity by selected controllable can determine the probability of turning the device on a specific day and the impact of these devices on daily consumption. In this way, it is possible to prepare an energy guard algorithm, considering probable daily energy consumption and the impact of connected devices on the total demand profile.

6. Conclusions

For effective operation of EMS systems, a forecast of the energy consumption profile is needed. The quality of the forecast depends, among other things, on the available data based on which the forecast will be implemented.

There are many forecasting methods [22–39], but many of them require complex and efficient data analysis systems, often using artificial intelligence to determine the behavior of energy consumers.

The proposed relative standard deviation (RSD) and participation from random devices (PRD) coefficient to determine the feasibility of using measurement data obtained from the DNO operator or own measurements (e.g., Fibaro) allows to determine the possibility of using a forecast based on simply statistical analysis, dedicated to low-cost solutions that can be implemented in small and medium-sized buildings with relatively low energy consumption.

The obtained results made it possible to compare the quality of the forecast in selected, characteristic buildings from the SME sector and residential buildings, and to introduce forecast quality levels. The good quality of the forecast is for the annual average coefficient $\bar{RSD}$ that is less than 30%, which allows for the calculation of hourly energy demand with a probability of 68.3% with uncertainty $\pm$ 30%, which is sufficient to reduce the requirement for large energy storage systems controlled by EMS.

The presented method allows to easily disclose limitations in the quality of data used for forecasting. Based on the results obtained, it can be concluded that industrial and service buildings can be effectively predicted using statistical methods. The situation is even worse with residential buildings. However, it should be emphasized that the method of obtaining data for analysis and forecasting is problematic because they come from devices from different manufacturers and their quality is not fully known. We only know Fibaro and AEOTEC solutions. Data obtained from the DNO are standardized. The proposed method can be used with any EMS system where energy consumption measurement data is available. Including profiles downloaded free of charge from the DNO operator, without the need to install your own measuring devices.

Author Contributions: Conceptualization, M.K. and M.F.; methodology, K.B. and M.F.; validation, A.P. (Anna Piaskowy); formal analysis, K.B.; investigation, K.B., M.F. and A.P. (Adam Pilśniak); resources, A.P. (Adam Pilśniak); data curation, K.B. and M.F.; writing—original draft preparation, M.F., K.B. and A.P. (Anna Piaskowy); writing—review and editing, M.K.; visualization, K.B., M.F. and A.P. (Adam Pilśniak); supervision, M.K.; project administration, M.F. All authors have read and agreed to the published version of the manuscript.

Funding: This research was partly financed by the EU funding for 2014–2020 within the Smart Growth Operational Program.

Data Availability Statement: Data can only be made available on the basis of an individual request to the authors of the article. The data are not publicly available.

Conflicts of Interest: The authors declare no conflict of interest.

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