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Changing Electricity Tariff—An Empirical Analysis Based on Commercial Customers' Data from Poland

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Abstract: Nearly 60% of commercial customers are connected to a low-voltage network in Poland with a contractual capacity of more than 40 kW and are assigned a fixed tariff with flat prices for the whole year, no matter the usage volume. With smart meters, more data about how businesses use energy are becoming available to both energy providers and customers. This enables innovation in the structure and type of tariffs on offer in the energy market. Customers can explore their usage patterns to choose the most suitable tariff to benefit from lower prices and thus generate savings. In this paper, we analyzed whether customers' electricity usage matched their optimal tariff and further investigated which of them could benefit or lose from switching the tariff based on the real dataset with the hourly energy readings of 1212 commercial entities in Poland recorded between 2016 and 2019. Three modelling approaches, i.e., the k-nearest neighbors, classification tree and random forest, were tested for optimal tariff classification, while for the benchmark, we used a simple approach, in which the tariff was proposed based on the customers' previous electricity usage. The main findings from the research are threefold: (1) out of all the analyzed entities, on average, 76% of them could have benefited from the tariff switching, which suggests that customers may not be aware of the tariff change benefits, or they had chosen a tariff plan that was not tailored to them; (2) a random forest model offers a viable approach to accurate tariff classification; (3) the policy implication from the research is the need to increase the customers' awareness about the tariffs and propose reliable tools for selecting the optimal tariff.

Keywords: energy consumption; energy efficiency; commercial customers; changing electricity tariff; k-nearest neighbors; classification tree; random forest

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1. Introduction

The liberalization of the electricity market supports worldwide efforts aimed to enable innovation in the structure and type of tariffs offered in the energy market. The availability of high-frequency data is crucial for the development of the demand-side management (DSM) and demand-side response (DSR) programs for creating new tariffs and efficient use of the electricity [1,2]. These programs are also used to support policy makers in creating new strategies to influence the behavior of energy users, with the goal of moving the demand from on-peak to off-peak periods. The energy market liberalization in Poland is progressing rather slowly in comparison to other European countries. The Polish market has an oligopoly structure with a vast majority of state-owned companies, and therefore customers do not benefit fully from liberalization. For instance, until 2022, no more than 5% of electricity users changed the electricity supplier in Poland, mainly due to the fact that benefits due to switching are not significant, in terms of the monetary value, for a typical household or a small business.

From the demand-side perspective, the electricity market in Poland is divided into several tariff groups. As of 2021, there were approximately 17.2 million end users, of which 90.1% (15.5 million) are customers who belong to the G tariff group (mainly households). The remaining end users are assigned to A (large factories connected to high-voltage grids), B (big clients connected to medium-voltage grids) or C (small- and medium-sized enterprises supplied from the low-voltage grid) tariff groups. The A, B, C groups use electricity to maintain their business activity, and they are referred to as commercial customers [3].

One of the most important challenges of the Polish electricity market, since the transformation in the late 1990s, is related to the availability of data and detailed information about electricity consumption by commercial customers assigned tariffs A, B and C, supplied from various voltage levels. The knowledge of usage characteristics based on hourly data could become the prerequisite for designing innovative tariff strategies including static tariffs (fixed-price or time-of-use) and also dynamic tariffs for this group of customers.

For the commercial customers connected to low-voltage networks, utility providers created tariff C, which is divided into several subtariffs depending on the contractual power level [4]. Tariff C is dedicated to small- and medium-sized enterprises, including shops, retail and service outlets and farms, which use electricity for production purposes, e.g., to supply greenhouses, piggeries or cold stores. The recipients of this tariff can be divided into two main groups: (1) C1x with the contractual power below 40 kW; (2) C2x with the contractual power exceeding 40 kW.

Within the C2x tariff group, there are four subtariffs:

- C21, which is a single-zone tariff with a flat rate for the electricity throughout the day;
- C22, which is a two-zone tariff, in which the price depends on the hours during the day, and sometimes even on the day and the month; it is available in several variants, e.g., C22a, C22b, C22c, C22w;
- C23, which is a three-zone tariff, in which the day is divided into the morning peak, the afternoon peak and other hours of the day; in this tariff, the rate for electricity depends on the hours of the day and the month;
- C24, which is a four-zone tariff, in which the day is divided into the morning peak, the afternoon peak, the night off-peak and other hours of the day; it is rarely offered to customers.

This paper seeks to answer the following research questions: (1) whether commercial customers are charged the optimal tariffs that match their usage characteristics and allow them to optimize their expenses; (2) whether there is some simple and reliable approach to recommend the most suitable tariffs to customers based on their previous electricity usage; (3) whether selected classification techniques, i.e., k-nearest neighbors (k-NN), decision tree or random forest, can predict the optimal tariff based on the customer's previous electricity usage with high accuracy. We believe that our research can help to explain how commercial customers use their tariffs and further investigate possible improvement of the tariffs they use. Moreover, we hope that this research can fill the gap related to the fact that only few works use commercial data because the availability of such data for scientific purposes is very limited.

Therefore, based on the dataset with 1212 commercial customers assigned to tariff group C2x, i.e., C21, C22a, C22b and C23, we are going to investigate if the electricity usage of those customers matched their tariffs and further analyze if there was, potentially, room for improvement if some of those customers changed the tariff in the subsequent period based on some simple but reliable approach (treated as a benchmark) or based on the classification models.

The rest of the article is structured as follows. Section 2 contains a description of related works. Then, we describe the dataset used in this study in Section 3 and characterize the tariffs in Section 4, which is a necessary pre-processing step to perform the experiments. Finally, we apply three classification methods for tariff selection that we investigate in Section 5. The last section summarizes the conclusions from our analysis and gives some ideas for future work.

2. Literature Review

Based on the ARE reports [5], there are 106,100 customers in the Polish market who are assigned the C2x tariffs, and nearly 60% of them are assigned the C21 flat-rate tariff despite the fact that two-zone and three-zone tariffs are available to the customers throughout the country. This observation is important for both the customers and electricity providers. It may suggest that customers are not aware of other tariffs offered by providers, or they do not see the benefits from switching the tariff. The literature provides two potential explanations for the fact that consumers stick to the default tariff plans. The first possibility is that consumers have information frictions when making a tariff choice, and they are not fully informed about the characteristics of available tariffs, which could be a main obstacle that prevents customers from switching to more economically attractive plans [6]. The second possibility is related to multiple switching costs, which may include the explicit cost of switching such as a penalty fee for early termination or significant logistics and/or organizational efforts related to the handling of the matter. For instance, in [7], the authors show that most residential electricity customers are not interested in switching to a new provider even though the information on alternative tariffs was easily available, and the switching costs were low. This implies that there could be other factors which may play a key role in the decision process such as availability of information about the expected savings from the tariff switching.

With this article, our intention was to verify to what extent customers can benefit from tariff switching. Consequently, if customers are well matched to the tariff plans, then the electricity providers can better balance the demand with less instability in the network, which would help to manage the overall costs of the system better. Obviously, when a vast majority of the customers are assigned just one tariff, with a lot of volatility inside the tariff, it creates a number of issues, including inaccurate load forecasting to meet the DSR and also impacting the stability of the whole network [6]. In this context, there is a need for a reliable approach not only to maintain but also to improve the efficiency and effectiveness of the grid management and related operations through splitting the mass of customers into smaller groups of users who have similar behavior patterns and who are matched to the corresponding tariffs accordingly [8,9].

Based on the literature review, there is a clear research trend focused on the tariff selection problem for new customers and tariff switching for existing customers, including the choice between static tariffs (fixed-price or time-of-use) and dynamic tariffs (e.g., with half-hourly pricing). For instance, the authors of [10] analyzed consumers' willingness to switch to smart-time-of-use electricity tariffs, indicating that a major challenge is to encourage consumers to switch from flat-rate electricity tariffs to more tailored plans. In [11], the authors studied how to predict which businesses save or lose money when they change from a static-price electricity tariff to a dynamic one. Another study [12] based on South African data, raised a general question if the electricity tariff model is conducive to an energy efficient economy and indicating that efficiency programs, residential energy conservation efforts and subsequent savings can suffer when the utility providers are not supportive.

The most frequent studies investigate tariff changes from a flat-price tariff to a time-of-use tariff [13,14], and some researchers analyzed the change from static to dynamic tariffs [15,16]. The majority of studies are usually performed using residential data [10–12,17,18] with only few works using commercial data [13,15], as the availability of such data for scientific purposes is very limited. Specifically, in [13,15], the authors analyzed the results of a time-of-use (TOU) rate experiment, which demonstrated that offering a time-of-use option can be profitable for both the customers and the utility provider, even despite free-riders, i.e., customers who have relatively low on-peak consumption and obtain bill savings without changing their consumption behavior. Moreover, the analysis in [15] suggests that the adoption of real-time pricing may not be successful without support programs which compensate those customers who lose due to the change.

As far as critical-peak pricing or real-time pricing programs are concerned, only zonal TOU electricity tariffs are available to consumers in Poland, and they are organized by electricity suppliers and distribution system operators [19,20]. Basically, the need of new electricity tariffs for residential customers is quite often highlighted in the literature, which is due to the fact that well designed tariffs have significant impact on energy bills and generation profiles through fostering peak shavings [21,22]. Currently, with smart meters and advanced electricity tariff mechanisms, real time tariffs and peak pricing tariffs enable significant electricity consumption optimization for the customers. Therefore, customers play a substantial role in shifting their consumption and changing their behavior dynamically depending on the price and investing in generation or storage devices (including wind turbines and photovoltaic panels). In the future, the current load profiles for customers may become obsolete, and electricity suppliers will be required to calculate load profiles dynamically and to use advanced methods for consumption forecasting as outlined in [23–26].

Therefore, with our article, we aimed to fill the gap for the empirical analysis of commercial customers supported by a significant collection of data that characterize customers in tariff group C2x in Poland. The key contribution of our research is the benchmark established to assess financial savings for the customers before costly energy efficiency measures are implemented and the tools proposed for tariff prediction based on previous electricity usage.

3. Dataset Characteristics

This study was prepared based on a historical dataset which comprises hourly electricity usage observed between 2016 and 2019 for 1212 different Poland-based businesses. The data were purchased from electricity-distributing companies, which no longer operate on the market. There are some limitations related to the dataset. Firstly, the sample consists of 1212 commercial customers, which is 1.6% of the total population of the customers assigned the C2x tariffs. Secondly, the tariffs' structure in our dataset differs from the structure observed for the market (based on [5]) as indicated in Table 1. Unfortunately, no other data were available, so the experiments were conducted bearing in mind those limitations.

Table 1. Dataset characteristics in terms of the tariff structure and electricity volume.

Tariff	No. of Customers	% of Customers	Min (kWh)	Q1 (kWh)	Mean (kWh)	Q3 (kWh)	Max (kWh)	Std (kWh)
C21	451	37	0	4.47	25.56	31.58	38,593.80	44.53
C22a	249	21	0	5.53	26.89	36.43	766.94	33.74
C22b	301	25	0	5.36	25.88	33.52	813.00	36.26
C23	211	17	0	17.68	47.54	58.66	1025.50	61.54

Initially, there were more customers in the dataset; however, it was necessary to perform a pre-processing of data to ensure sufficient quality of the dataset, i.e., all the readings whose values were negative or had a repeated time stamp were removed, and the customers with less than ten different values in their readings were removed. Within those 1212 businesses, we can distinguish entities that are assigned the C21, C22a, C22b and C23 tariffs.

The structure of the dataset as well as some basic statistics, which describe the volume, are given in Table 1. The structure of our dataset is different from the structure of the Polish market, since based on the ARE reports [5], nearly 60% of the customers are assigned the C21 tariff, 27% are assigned the C22 tariff, and 13% are assigned the C23 tariff.

As shown in Figures 1 and 2, a number of seasonal cycles were observed for the analyzed entities including annual, weekly and daily cycles. For instance, the load curves for corresponding tariffs have different shapes and volume depending on the season, as presented in Figure 1. Figure 2 presents weekly profiles with significantly lower consumption during the night and a few peaks in the middle of the day. Finally, we can observe that consumption is much lower during the weekend days as compared to working days, except for C23, where Saturdays are quite busy, i.e., with the volumes only slightly lower than those for working days.

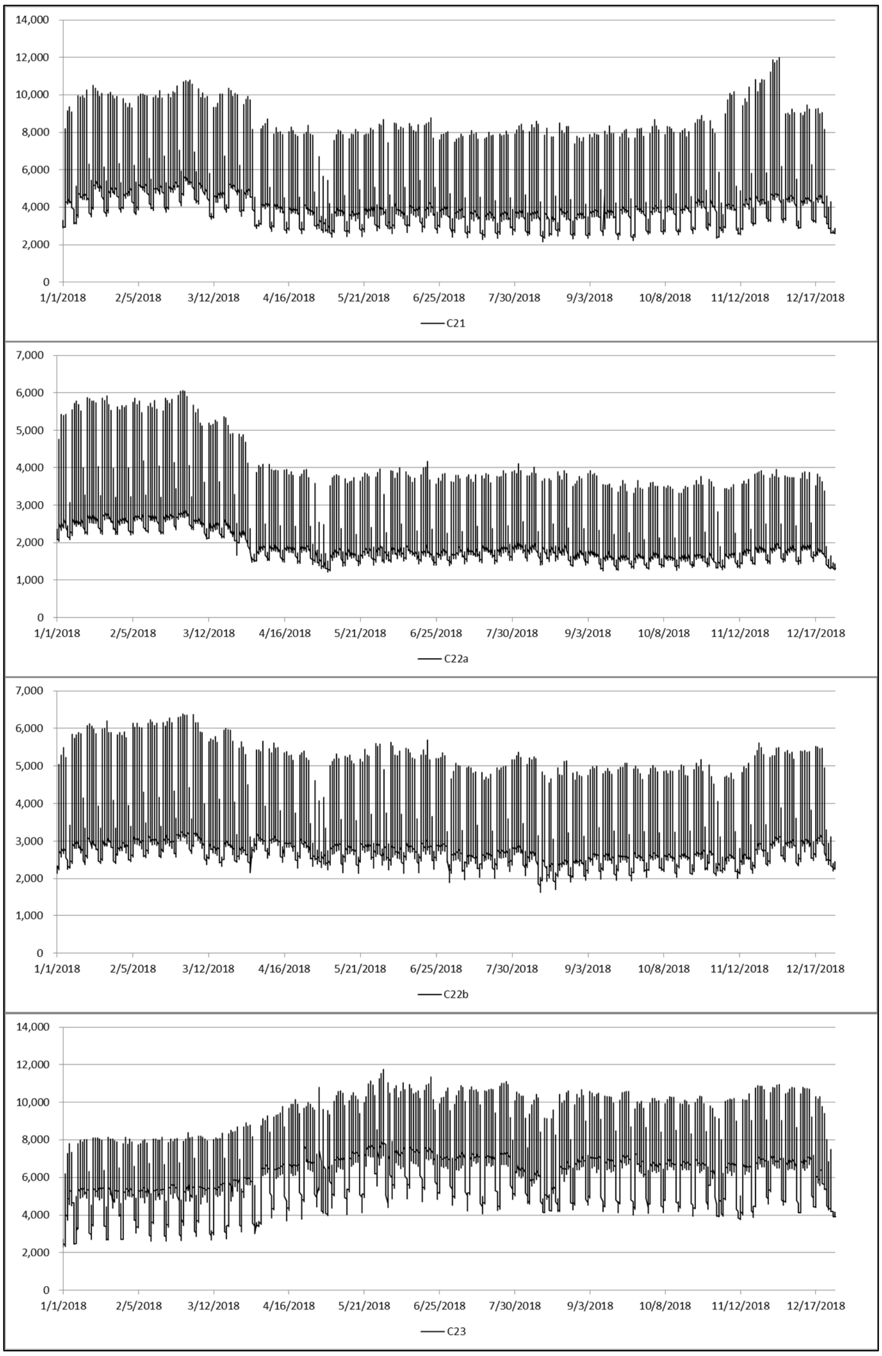

Figure 1. Hourly load data for customers with C21, C22a, C22b and C23 tariffs observed in 2018.

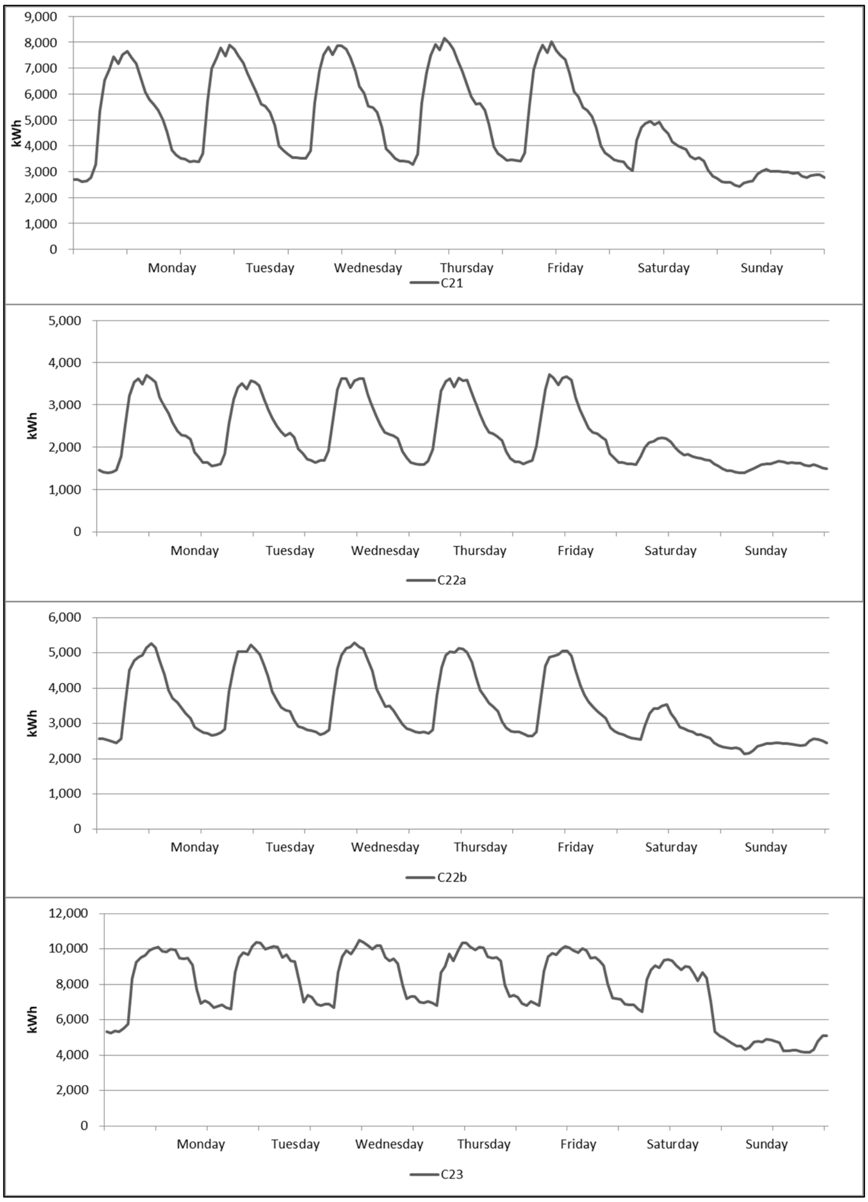

Figure 2. Daily characteristics for each tariff (C21, C22a, C22b and C23) observed between 14 May (Monday) and 20 May (Sunday) 2018.

4. Tariff Plans and Prices

Tariff design is a key component of the electric power system. Properly designed tariffs ensure that the power system is used to the best advantage in the short and medium terms. For the customers, tariffs are key enablers of demand response through incentivizing them to shift their electricity consumption from high- to low-demand periods, which supports their energy savings (thus reducing costs) and delivers benefits to the power system.

With the C2x tariffs, the customers are charged less per kWh if the usage falls between certain time zones and times of the year. Table 2 lists the prices in PLN/kWh (1 PLN is ~EUR 0.22) for the C21, C22a, C22b and C23 tariffs depending on the zone in 2019.

The C21 tariff has the fixed price of 0.5140 PLN/kWh during all the periods of the day, for all days. C22a has two zones with the prices as follows:

- 0.6947 PLN/kWh for the following peak periods: between 8 and 11 AM; between 4 and 9 PM in November, December, January and February; between 6 and 9 PM in March and October; between 7 and 9 PM in April and September; between 8 and 9 PM in May, June, July and August;

- 0.4604 PLN/kWh for the off-peak periods.

Table 2. Average variable electricity price for the C2x tariff groups in PLN/kWh in 2019.

Zones	Tariffs			
	C21	C22a	C22b	C23
I	0.5140	0.6947	0.5759	0.5554
II	-	0.4604	0.3820	0.7514
III	-	-	-	0.3817

C22b has two zones with the prices as follows:

- 0.5759 PLN/kWh for the peak period, which is during the day, i.e., between 6 AM and 9 PM, regardless of the month;
- 0.3820 PLN/kWh for the off-peak period, which is during the night, i.e., between 9 PM and 6 AM.

Finally, C23 has three zones with the prices as follows:

- 0.5554 PLN/kWh for the morning peak period between 7 AM and 1 PM for working days (Monday–Friday) regardless of the month;
- 0.7514 PLN/kWh for the afternoon peak: between 4 and 9 PM during the winter, i.e., between October and March; between 7 and 10 PM during the summer, i.e., between April and September;
- 0.3817 PLN/kWh for the off-peak periods.

Examples of these four tariffs showing the price variability for two days with 1 h resolution and prices in PLN/kWh are given in Figure 3.

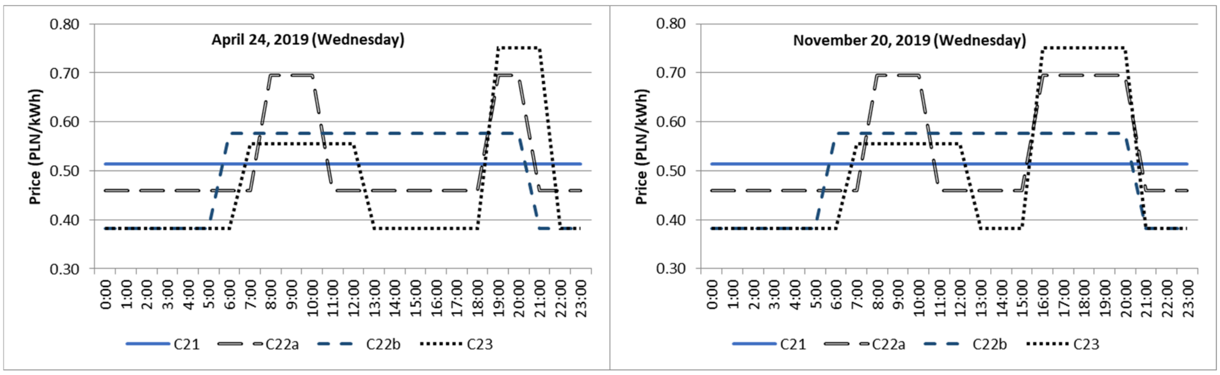

Figure 3. Examples of C21, C22a, C22b and C23 prices in PLN (1 PLN is ~EUR 0.22) for 24 April (on the **left**) and 20 November 2019 (on the **right**).

Based on these data, we could easily identify the entities who are assigned the C21 flat-price tariff while their actual usage pattern fits two or three zones. For instance, Figure 4 presents average usage observed for a customer assigned the C21 tariff, who, in fact, fits the characteristics of the C22b tariff since the electricity usage is observed during the nights, between 10 PM and 6 AM, regardless of the weekday, and, additionally, with significantly lower consumption during the days.

In Figure 5, there is another example of a C21 customer whose load characteristics are matching the C23 tariff group. The customer reduces the usage during the peak hours, i.e., during the morning and afternoon peaks, and increases the usage volume in the off-peak periods (between 1 PM and 4 PM and after 9 PM).

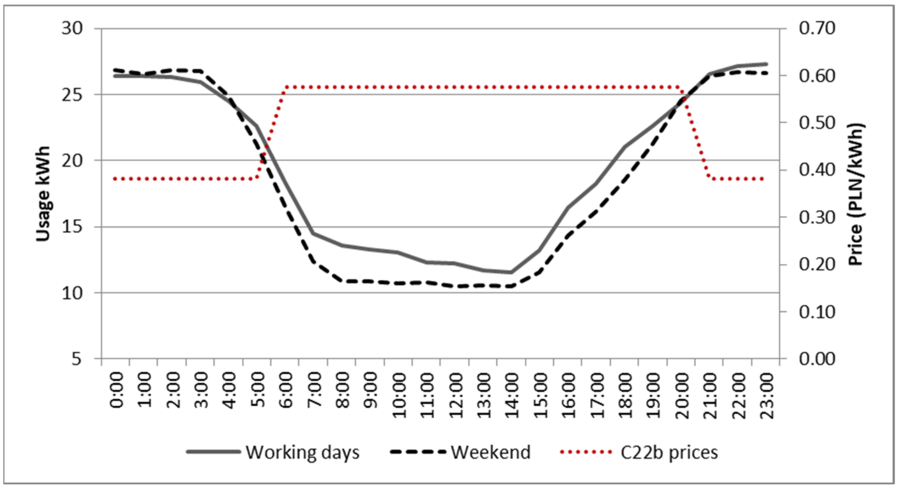

Figure 4. C21 customer with usage profile matching C22b characteristics.

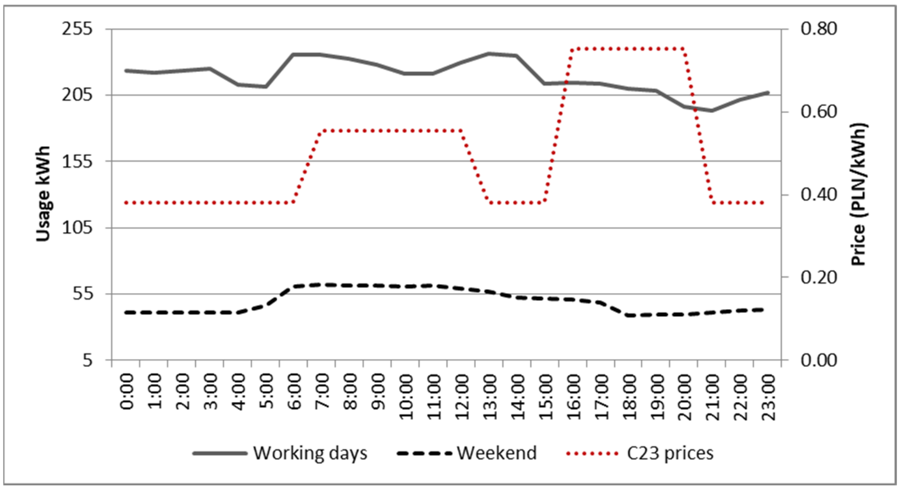

Figure 5. C21 customer with usage profile matching C23 characteristics.

5. Simulation Study

5.1. Evaluation of Customers' Electricity Usage Matching Optimal Tariff

The goal of this analysis was to investigate whether the current tariffs paid by customers match the actual electricity usage. Therefore, for each customer, we calculated the cost of paying the actual tariff and compared it with the costs of paying three other tariffs and selected the optimal one. For instance, if a customer was charged the C21 tariff, we compared the costs associated with the C22a, C22b and C23 tariffs and assigned that customer the optimal tariff, i.e., the tariff with which the savings would be the biggest due to the tariff change. The evaluation was prepared for each year separately as shown in Table 3. In the calculations, we used only the total variable electricity price, as provided in Table 2. The fixed costs and the capacity fee were not taken into account in the calculations, as these are comparable for each tariff.

Table 3. Evaluation of actual and optimal tariffs based on 2016–2019 data.

2016		**No. of Customers Paying Actual Tariffs in 2016**				**Total Savings (in PLN) if Customers Would Have Paid Optimal Tariffs Instead of Actual Tariffs in 2016**				**Average Savings (in PLN) if Customers Would Have Paid Optimal Tariffs Instead of Actual Tariffs in 2016**			
		C21	**C22a**	**C22b**	**C23**	**C21**	**C22a**	**C22b**	**C23**	**C21**	**C22a**	**C22b**	**C23**
Optimal Tariffs for 2016	C21	13	11	6	4	0	38,392	45,476	17,403	0	3490	7579	4351
	C22a	0	0	0	0	0	0	0	0	0	0	0	0
	C22b	5	2	4	1	11,907	1719	0	19	2381	859	0	19
	C23	177	107	122	55	870,587	878,649	671,424	0	4919	8212	5503	0
2017		**No. of Customers Paying Actual Tariffs in 2017**				**Total Savings (in PLN) if Customers Would Have Paid Optimal Tariffs Instead of Actual Tariffs in 2017**				**Average Savings (in PLN) if Customers Would Have Paid Optimal Tariffs Instead of Actual Tariffs in 2017**			
		C21	**C22a**	**C22b**	**C23**	**C21**	**C22a**	**C22b**	**C23**	**C21**	**C22a**	**C22b**	**C23**
Optimal Tariffs for 2017	C21	23	10	21	5	0	58,453	82,987	12,343	0	5845	3952	2469
	C22a	0	0	0	0	0	0	0	0	0	0	0	0
	C22b	8	7	19	12	9529	10,523	0	1159	1191	1503	0	97
	C23	273	131	172	105	1,073,443	964,355	1,039,658	0	3932	7361	6045	0
2018		**No. of Customers Paying Actual Tariffs in 2018**				**Total Savings (in PLN) if Customers Would Have Paid Optimal Tariffs Instead of Actual Tariffs in 2018**				**Average Savings (in PLN) if Customers Would Have Paid Optimal Tariffs Instead of Actual Tariffs in 2018**			
		C21	**C22a**	**C22b**	**C23**	**C21**	**C22a**	**C22b**	**C23**	**C21**	**C22a**	**C22b**	**C23**
Optimal Tariffs for 2018	C21	39	39	38	20	0	145,393	117,706	55,363	0	3728	3098	2768
	C22a	0	0	0	0	0	0	0	0	0	0	0	0
	C22b	2	3	7	1	9463	2734	0	2	4732	911	0	2
	C23	200	78	140	154	626,208	520,138	629,147	0	3131	6668	4494	0
2019		**No. of Customers Paying Actual Tariffs in 2019**				**Total Savings (in PLN) if Customers Would Have Paid Optimal Tariffs Instead of Actual Tariffs in 2019**				**Average Savings (in PLN) if Customers Would Have Paid Optimal Tariffs Instead of Actual Tariffs in 2019**			
		C21	**C22a**	**C22b**	**C23**	**C21**	**C22a**	**C22b**	**C23**	**C21**	**C22a**	**C22b**	**C23**
Optimal Tariffs for 2019	C21	12	6	3	11	0	9571	14,494	1440	0	1595	4831	131
	C22a	0	0	0	0	0	0	0	0	0	0	0	0
	C22b	15	8	28	27	2426	8353	0	3684	162	1044	0	136
	C23	90	26	60	114	402,446	88,666	382,142	0	4472	3410	6369	0

Specifically, Table 3 shows the number of customers paying the actual tariff vs. the optimal tariff as well as the total and average monetary savings if the customers would have paid the optimal tariff instead of the actual one. For instance, for 2016, thirteen is the number of the C21 tariff users for whom C21 is the optimal tariff; eleven is the number of the C22a tariff users for whom C21 is the optimal tariff; six is the number of the C22b tariff users for whom C21 is the optimal tariff; four is the number of the C23 tariff users for whom C21 is the optimal tariff; and so on. In a similar way, total and average savings are presented in the table. For example, the savings for the C21 tariff users are equal to zero, because those customers pay the optimal tariff; 38,392 PLN is the total amount of savings (while the average savings are 3490 PLN) for the C22a tariff users if they would have paid the C21 tariff; 45,476 PLN is the total amount of savings (while the average savings are 7579 PLN) for the C22b tariff users if they would have paid the C21 tariff; 17,403 PLN is the total amount of savings (while the average savings are 4351 PLN) for the C23 tariff users if they would have paid the C21 tariff; and so on.

Based on the data presented in the table, in 2016, only 72 customers out of 507 (14%) were assigned proper tariffs, which ensured that they incurred the lowest cost of the usage. In particular, there were thirteen customers paying the C21 tariff, four customers paying the C22b tariff and fifty-five customers paying the C23 tariff. All the other customers' electricity usage did not match their tariffs, so the cost of that mismatch was equal to 2,535,577 PLN. In other words, this is the total amount that the customers could have saved if they would have changed their tariffs to the optimal ones.

Based on the 2017 data, there were 147 customers out of 786 (19%) whose electricity usage matched their tariffs: 23 customers paying the C21 tariff, 19 customers paying the C22b tariff and 105 customers paying the C23 tariff. In total, the amount that the customers could have saved if they would have changed their tariffs to the optimal ones equals 3,252,450 PLN.

In 2018, the percentage of the customers whose electricity usage matched their tariffs increased to 28%, which is 200 customers out of 721. In total, the amount that the customers could have saved if they would have changed their tariff to the optimal one equals 2,106,152 PLN.

Finally, in 2019, there were 154 customers out of 400 (39%) whose electricity usage profile matched the proper tariff. The usage profiles of all the other customers did not match their tariffs, so they could have saved 913,222 PLN by changing the tariff.

Additionally, Table 3 contains information about average savings (in PLN) for the customers when switching the tariff plan is provided. The highest average savings are observed when switching from tariff C22a to C23, and those are 8212 PLN, 7361 PLN, 6668 PLN for 2016, 2017 and 2018, respectively. While for 2019, the highest average savings, i.e., 6369 PLN, are observed when switching from tariff C22b to tariff C23.

In Table 4, we prepared a summary of costs and savings for the optimal and actual tariffs assigned to the customers in a given year. The savings due to the tariff change vary from 4.64% in 2016 to 1.81% in 2019. The amount of savings is decreasing, which stems from the fact that, starting from 2017, more and more customers are paying tariff C23, which is the optimal tariff for them; thus, they realize their savings.

Table 4. Costs and savings associated with both actual and optimal tariffs (in PLN).

Costs and Savings	2016	2017	2018	2019
No. of customers	507	786	721	400
Electricity cost when paying actual tariffs	54,697,953	88,498, 793	90,094,951	50,347,221
Electricity cost when paying optimal tariffs	52,162,376	85,246,343	87,988,799	49,433,999
Customers' savings due to tariff switch	2,535,577	3,252,450	2,106,152	913,222
Customers' savings due to tariff switch (in %)	4.64	3.68	2.34	1.81

Finally, Table 5 shows the distribution of savings in PLN observed for each year due to the optimal tariff selection. For instance, the average amount of savings in PLN for the customers when switching from their actual tariff to the optimal tariff is 4986.73 PLN, 4134.79 PLN, 2944.03 PLN and 2271.53 PLN for 2016, 2017, 2018 and 2019, respectively.

Table 5. Distribution of savings (in PLN) for the customers when switching to the optimal tariff.

Year	Min	Q1	Median	Mean	Q3	Max
2016	0	768.92	2516.91	4986.73	6229.27	102,250.90
2017	0	217.92	2073.82	4134.79	5773.92	42,833.00
2018	0	0	1359.01	2944.03	3781.62	71,918.90
2019	0	0	133.37	2271.53	2300.74	42,307.97

This analysis reveals that only 14% of the customers were charged the optimal tariff, i.e., in line with their usage profile, in 2016, 19% in 2017, 28% in 2018 and 39% in 2019. If the remaining customers would have paid the optimal tariffs instead of the current ones, they could have saved on average 4986.73 PLN, 4134.79 PLN, 2944.03 PLN and 2271.53 PLN for 2016, 2017, 2018 and 2019, respectively.

5.2. Fitting Optimal Tariff Based on Usage from the Previous Year (Benchmark)

The goal of this analysis was to propose a simple and reasonable tool for the customers so they could map their electricity usage to the proper tariff that would bring savings to them. As mentioned earlier in this work, based on the ARE reports [5], nearly 60% of customers are assigned the C21 flat-tariff plan. Therefore, the key question is why do consumers stick to the default tariff plans when there is an obvious economic benefit from switching to an alternative tariff, as analyzed in the previous section? We believe that the key factor here is related to the availability of information about the expected savings from the tariff switching.

Importantly, the approach to estimating savings needs to be simple, understandable and precise. Therefore, we tested the approach for matching the optimal tariffs to the customers based on their previous usage. Specifically, based on the electricity consumption observed in 2016, we assigned the best tariff for each customer and then assumed that the tariff would be applicable to 2017. Finally, we verified the outcome, i.e., whether, indeed, the proposed tariff was the optimal tariff based on the previous year. If so, we noted the correct classification. The same analysis was performed for 2018 based on the 2017 data and for 2019 based on the 2018 data, and the results are presented in Table 6. The accuracy for 2017 was 84.81%, i.e., for 268 customers (out of 316 customers) the predicted tariff was optimal based on the 2016 data. For 2018 and 2019, the accuracy was 75.81% and 75.84%, respectively, which is considered significant.

Table 6. Accuracy of optimal tariff prediction based on previous year.

Item	2017	2018	2019
Total no. of customers	316	525	356
No. of customers with optimal tariff prediction based on previous year	268	398	270
No. of customers with nonoptimal tariff prediction	48	127	86
Percentage of customers with correct prediction	84.81	75.81	75.84
Loss (in PLN) due to nonoptimal tariff prediction (see Table 6 for details)	15,875	183,597	22,759
Savings (in PLN) if all customers are assigned optimal tariffs (see Table 4)	3,252,450	2,106,152	913,222
Actual savings (in PLN) for the customers with correct predictions	3,236,575	1,922,555	890,461

Additionally, in Table 7, we provide a detailed distribution of the customers who were assigned the predicted tariffs accordingly and the calculation of losses due to the wrong tariff prediction. The total loss for 2017 is 15,875 PLN, for 2018, it is equal to 183,597 PLN, and for 2019, it is equal to 22,759 PLN. The loss for 2018 seems to be relatively high, but it needs to be compared with the overall savings which are presented in Table 7. To sum up, the total savings for all of the customers in 2018 would equal 2,106,152 PLN if all the customers were correctly assigned the optimal tariffs. Since our approach to tariff prediction based on the previous usage is not fully accurate, the actual savings for the customers in 2018 are equal to 1,922,555 (which is 2,106,152 PLN—183,597 PLN).

Table 7. Evaluation of predicted and optimal tariffs based on the usage from previous year.

2017		**No. of Customers with Tariffs Predicted for 2017 Based on 2016**				**Loss (in PLN) Due to Wrong Tariff Prediction for 2017 Based on 2016**			
		C21	**C22a**	**C22b**	**C23**	**C21**	**C22a**	**C22b**	**C23**
Optimal Tariffs for 2017	C21	12	0	0	5	0	0	0	−4346
	C22a	0	0	0	0	0	0	0	0
	C22b	0	0	2	39	0	0	0	−4953
	C23	2	0	2	254	−2631	0	−3945	0
2018		**No. of Customers with Tariffs Predicted for 2018 Based on 2017**				**Loss (in PLN) Due to Wrong Tariff Prediction for 2018 Based on 2017**			
		C21	**C22a**	**C22b**	**C23**	**C21**	**C22a**	**C22b**	**C23**
Optimal Tariffs for 2018	C21	26	0	0	86	0	0	0	−112,990
	C22a	0	0	0	0	0	0	0	0
	C22b	1	0	2	2	0	0	0	−173
	C23	8	0	30	370	−16,946	0	−53,488	0
2019		**No. of Customers with Tariffs Predicted for 2019 Based on 2018**				**Loss (in PLN) Due to Wrong Tariff Prediction for 2019 Based on 2018**			
		C21	**C22a**	**C22b**	**C23**	**C21**	**C22a**	**C22b**	**C23**
Optimal Tariffs for 2019	C21	16	0	0	10	0	0	0	−1337
	C22a	0	0	0	0	0	0	0	0
	C22b	1	0	2	68	1	0	0	−7833
	C23	6	0	1	252	−8426	0	−5164	0

The results allowed us to conclude that high classification accuracy (which is between 75.81% and 84.81%) and the actual saving for the customers with correctly predicted optimal tariffs are significant in terms of their monetary value, which makes the proposed approach to predicting the optimal tariffs based on the usage from the previous year a very appealing tool for the end users and can be assumed as the benchmark for further analysis.

5.3. Classification Models to Predict Optimal Tariff Based on Usage from the Previous Year

The goal of this analysis was to test the selected modelling techniques for the optimal tariff classification. For this purpose, the k-nearest neighbors, decision tree and random forest models were used.

In the data analysis, the k-nearest neighbors algorithm is a supervised, nonparametric and lazy learning technique which can be applied to both classification and regression problems [27]. Moreover, the k-NN algorithm is simple and very efficient in terms of training and very fast for solving the problems. It belongs to distance-based algorithms, which concentrate on measuring the similarity between the testing and the training samples to conclude the output, based on a specific similarity measure, e.g., Euclidean or Manhattan distance.

It is well known that the performance of the k-NN classifier heavily depends on the number of neighbors (k) and the optimal choice of a k-value is highly data-dependent. In general, a larger k value reduces the effects of noise but makes the boundaries between the classes less distinct resulting with lower accuracy.

The k-NN model was prepared using the knn function with Euclidean distance and through testing the k-value between 5 and 100 to find the optimal one, i.e., resulting with the highest accuracy.

Decision tree is a very popular method used for classification and regression problems, mainly due the tree rules, which are easily interpretable. The method has a structure of a tree graph, in which the top node is the tree root, leaves represent the final outcomes (e.g., classification), and branches are created due to the tests performed on a single attribute, with one branch and subtree for each possible outcome of the test. When the new case is to be classified or predicted, the variables of that case are tested against the decision tree. Finally, a path is followed from the root to the final leaf node that gives the class prediction for this new case.

The decision tree model was prepared using the rpart library which enables the construction of recursive partitioning and regression trees (RPART) which originate from the classification and regression trees (CART) by Breiman et al. [28]. The tree was allowed to grow to its maximum size with just one stopping rule, i.e., the complexity parameter (cp) of minimum 0.01 to avoid the leaves with only few observations inside. The complexity parameter controls the minimum improvement of the model required at each node. It is based on the complexity of the model where a misclassification error at each node is considered.

The random forest algorithm, proposed originally by Breiman in 2001, is currently a very popular technique for general-purpose classification and regression problems. The approach applies several randomized decision trees and combines their outcomes by averaging or voting. Due to its versatility it can be applied to various problems, including large datasets (in terms of the number of observations) or datasets where the number of input variables is much larger than the number of observations [29].

The training of the forest was prepared using the randomForest library, based on the n-element samples having 63% of the original population, which were drawn with replacement, and these were used to build the CART trees. Each tree could grow to its maximum size with just one stopping rule to avoid the leaves with five or less observations inside. The algorithm could freely use available variables on each tree level and the number of variables (mtry parameter) used in the forests varied from five to fourteen for the models depending on the year for which the classification was applied. The total number of trees in the forest was 500, and the final prediction was assessed based on majority voting.

The reason to use the decision tree and random forest models stems from the fact that often, based on the literature review, the classification results show that the random forest algorithm gives better results for the same number of attributes and large datasets, i.e., with a greater number of instances, while a single decision tree is handy with small datasets (less number of instances). In our case, we had 1212 observations available, which can be considered both a small dataset and a sufficiently large dataset, at the same time. Therefore, we wanted to test the performance of these techniques and to confirm the applicability of a dataset of this size. Finally, the k-NN choice was mainly because it is one of the simplest supervised learning.

For the modeling, for each year, we prepared 20 features based on the hourly electricity usage observed for each customer. These were the median value of the usage, the average value of the usage, standard deviation, the values of the first and third quartiles calculated for four time windows over the whole year. The time windows were as follows: (1) the morning peak, i.e., the period between 7 AM and 1 PM for working days (Monday–Friday); (2) the afternoon peak between 4 and 9 PM during the winter, i.e., between October and March; (3) the afternoon peak between 7 and 10 PM during the summer, i.e., between April and September; (4) the off-peak period.

Such feature design was used for predicting the optimal tariff for the customers based on their previous usage. Specifically, based on the 2016 data, we modelled the best 2017 tariff for each customer to benefit from lower prices. The same analysis was performed for 2018 based on the 2017 data and for 2019 based on the 2018 data, and the results are presented in Table 8.

The results allowed us to conclude that among the modelling techniques which were used, only the random forest models resulted in 100% accuracy classification for all the analyzed years. The accuracy of the k-NN models was between 77.52% and 83.99%, while the accuracy of the decision tree models was between 77.52% and 81.33% depending on the year. Importantly, no overfitting was observed for the tested models. The results for the k-NN and decision tree models were similar in terms of accuracy to those of the benchmark, which were the assigned tariffs based on the usage from the previous year. As expected, the random forest model demonstrated to be an outstanding algorithm as an ensemble technique which combines the predictions of many classifiers and utilizes the random subspace and bagging to prevent overfitting and to give better accuracy.

Table 8. Evaluation of predicted tariffs based on the k-NN, decision tree and random forest models.

2017		**No. of Customers with Tariffs Predicted for 2017 Based on 2016**											
		k-NN Accuracy = 81.33%				**Decision Tree Accuracy = 81.33%**				**Random Forest Accuracy = 100%**			
		C21	**C22a**	**C22b**	**C23**	**C21**	**C22a**	**C22b**	**C23**	**C21**	**C22a**	**C22b**	**C23**
Optimal Tariffs for 2017	C21	0	0	0	17	0	0	0	17	17	0	0	0
	C22a	0	0	0	0	0	0	0	0	0	0	0	0
	C22b	0	0	0	42	0	0	0	42	0	0	42	0
	C23	0	0	0	257	0	0	0	257	0	0	0	257
2018		**No. of Customers with Tariffs Predicted for 2018 Based on 2017**											
		k-NN Accuracy = 77.52%				**Decision tree Accuracy = 77.52%**				**Random forest Accuracy = 100%**			
		C21	**C22a**	**C22b**	**C23**	**C21**	**C22a**	**C22b**	**C23**	**C21**	**C22a**	**C22b**	**C23**
Optimal Tariffs for 2018	C21	16	0	0	96	37	0	0	75	112	0	0	0
	C22a	0	0	0	0	0	0	0	0	0	0	0	0
	C22b	0	0	0	5	1	0	0	4	0	0	5	0
	C23	17	0	0	391	34	0	4	370	0	0	0	408
2019		**No. of Customers with Tariffs Predicted for 2019 Based on 2018**											
		k-NN Accuracy = 83.99%				**Decision tree Accuracy = 78.93%**				**Random forest Accuracy = 100%**			
		C21	**C22a**	**C22b**	**C23**	**C21**	**C22a**	**C22b**	**C23**	**C21**	**C22a**	**C22b**	**C23**
Optimal Tariffs for 2019	C21	0	0	3	23	5	0	5	16	26	0	0	0
	C22a	0	0	0	0	0	0	0	0	0	0	0	0
	C22b	0	0	57	14	0	0	41	30	0	0	71	0
	C23	0	0	17	242	10	0	14	235	0	0	0	259

6. Conclusions

In this paper we analyzed commercial customers in Poland based on a real dataset with the hourly power consumption records of 1212 businesses spread throughout 2016–2019. These customers were assigned to the C2x tariff group, including the C21, C22a, C22b and C23 tariffs, and the main research goals were to answer the following questions: (1) did the electricity usage of those customers really matched their tariffs? (2) is there a possibility to build a simple and reliable method for the customers to match their electricity usage to the optimal tariff that would bring them savings? (3) whether the use of the classification techniques can help to predict the optimal tariffs based on the customers' previous electricity usage.

Based on our results, the contributions of our study are as follows. Firstly, for the majority of the customers in each year, their actual tariffs were far from optimal, i.e., not matching the characteristics of their electricity usage, and therefore they incurred higher electricity costs. Specifically, 86% of the customers from our dataset paid nonoptimal tariffs in 2016, 81% in 2017, 72% in 2018 and 61% in 2019. The decreasing trend, which is observed in the analyzed population, suggests that, from year to year, customers became more aware of their usage and the tariffs. Nevertheless, the savings, if all customers are assigned the optimal tariffs, could be significant, representing between 1.81% and 4.64% of their total electricity costs, depending on the year.

As far as the second goal of our work is concerned, we proposed a simple and reliable method (treated as a benchmark) for the customers so they could map their electricity usage to a proper tariff based on their usage from the past. The simulations revealed that the actual benefits for those customers with correctly predicted optimal tariffs can be significant in terms of their monetary value. Specifically, the accuracy of the optimal tariff classification for 2017 was 84.81%, 75.81% for 2018 and 75.84% for 2019. This translates to customers' savings of 3,236,574 PLN, 1,922,555 PLN and 890,461 PLN for 2017, 2018 and 2019, respectively.

Finally, when it comes to the application of the machine learning models to the prediction of the optimal tariffs, it was observed that the random forest models were able to classify the tariffs with 100% accuracy, which translates to maximal customers' savings of 3,252,450 PLN, 2,106,152 PLN and 913,222 PLN for 2017, 2018 and 2019, respectively. The other two techniques, i.e., the k-NN and decision tree, resulted in similar accuracy compared to the benchmark.

This research fits into a broad and popular stream focused on the overall improvements of energy efficiency programs [30]. Those efforts are expanding, and thanks to them customers become more aware of the benefits offered by energy efficiency programs. Clearly, such observation is important for both the customers and the electricity providers. The first group may benefit from lower prices while the providers can better manage the overall demand with less instability in the system. The greater the discrepancy between the tariffs and the actual electricity usage, the greater the problem with balancing the system, since the demand-side management which is organized based on tariffs should stabilize the system and ensure the effective use of power. Therefore, well-designed tariff plans should enable the improvement of the load profiles of commercial customers.

Bearing in mind that electricity tariffs play a critical role in the electricity market and are the key factors for the decision-making of the end users, the policy implications from the research would be to promote the tariffs, so that the customers' awareness about the tariffs and the benefits associated with those tariffs increases. It is especially necessary because, based on the results of our study, it seems that for the majority of customers, their actual tariffs are far from optimal.

Although our study was conducted using a sample of commercial customers from Poland (which can be considered a limitation), we believe that the conclusions made can be applicable to any other country where customers can choose between the flat-rate tariffs and zonal tariffs, e.g., two-, three-zone tariffs.

With respect to future work, we believe that some additional customers' features can be explored, especially those related to the identification of the triggers in the actual electricity usage, which may suggest a tariff change to benefit from lower prices much earlier. Proper identification of such key changes in the energy consumption could prompt customers to consider a tariff change going forward.

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