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Setting the Time-of-Use Tariff Rates With NoSQL and Machine Learning to a Sustainable Environment

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ABSTRACT The electricity consumption will continue to increase despite the overall efforts and tendencies of changing the old appliances to less energy intensive ones. The advancements of Electric Vehicles (EV) and public mobility, electric heating, and the abundance of smart appliances that enhance the comfort of modern life lead to an increasing consumption trend. On the other hand, prosumers raising the quota of distributed generation and storage capacity will balance the electricity consumption trend. These changes at the consumption and generation level lead to the necessity to increase the awareness and incentive the consumers' behavior to flatten the consumption curve and improve the savings. Such objectives could be reached by properly setting the Time-of-Use (ToU) tariff rates to encourage the consumption at off-peak hours when the rates are lower and unstress the grid loading. In this paper, we propose a methodology for setting the Time-of-Use (ToU) tariff rates and peak/off-peak intervals using big data technologies and machine learning, and verify the assumptions considering the large volume of consumption data of over 4200 residential consumers recorded in a smart metering implementation trail period that took place in Ireland from January to December 2010. We calculate the contribution to the peak/off-peak of the total consumption and use it in setting the ToU tariff rates starting from the flat tariff. Then, the consumers' sensitivity to tariff change from flat to ToU is considered to identify the consumption change. The results show that using ToU instead of flat tariff, the peak is reduced in average by 5 to 7.5% and annual savings are around 4%. Also, by clustering the consumers a better allocation of the tariffs is possible. Thus, clustering is proposed considering the importance of the tariff allocation in Demand Side Management (DSM).

INDEX TERMS Time-of-use tariff rates, contribution to consumption peak/off-peak, big data, machine learning, tariff elasticity.

NOMENCLATURE

Symbol	Description
$C_{cluster}^{off}$	Consumption at off-peak hour for a cluster of consumers
$C_{cluster}^{peak}$	Consumption at peak hour for a cluster of consumers
$\Delta C\%$	Consumption variation in percentage
c^{off}	Contribution to consumption off-peak coefficient
c^{peak}	Contribution to consumption peak coefficient
C_h	Hourly consumption
C_i	Initial consumption
C_{mod}	Modified consumption
$h_{l+1} \div h_{k-1}$	Off-peak hours
$\alpha_h^{off/peak} \times FT_{rate}$	Off-peak/peak rate
$Payment_{FT}$	Payment with flat tariff
$Payment_{ToU}$	Payment with time of use tariff
$h_k \div h_l$	Peak hours
FT_{rate}	Rate of the flat tariff
E	Tariff elasticity
$\Delta T\%$	Tariff variation in percentage
C_{total}	Total consumption

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I. INTRODUCTION

The electricity tariff reforms are essential in the smart grid context, are analysed and depicted in [1] considering their impact on the society welfare and implications to the energy poverty and subsidy removal, since entire removal of subsidies might not be a viable option when differences in the elasticity of energy consumption among the various category of consumers exist [2]. Hence, tariffs can encourage energy efficiency and offer signals take advantages of opportunities and cope with challenges in the smart grid context. The progressive tariffs that penalise high consumption and electricity saving tariffs that incentive the consumption reduction are analysed using the price elasticity and incentive elasticity, indicating that progressive tariffs such as ToU tariffs are more efficient in terms of savings confirming the consumers' loss aversion [3]. Such tariffs could be further investigated from the consumption peak point of view considering that reduction of the peaks alleviates the stress on both generators and grid, avoiding onerous investment.

With its seven-hour night rate cheaper than the day rate, the first ToU tariff, known as Economy7, appeared in UK in 1978 and it is still implemented today. Since then, with the advancements in smart metering, suppliers are already offering new tariffs such as Interval Tariff in Spain, Offerte Biorarie in Italy, TIDE tariff and Agile Octopus that became the first 30-minute tariff in UK proving that consumers reduce consumption peak and shift electricity usage of EV owners out of the peak hours. ToU tariffs design varies and influences the effectiveness by several factors such as: the tariff ratio between peak and off-peak hours, the length of the peak period, the number of tariff periods [4]. ToU tariffs along with critical peak pricing tariffs [5] such as Tempo in France and real-time tariffs are significant instruments used in DSM. Designing the tariff rates is a tariff-based DSM stimulus and a sensitive issue as it may motivate or demotivate the consumers to behave accordingly [6].

The impact of ToU tariffs is investigated in [7] emphasizing their influence on load curves of residential consumers in grid areas with RES, heat pumps and storage facilities. The response of energy storage facilities to tariff system and their effect of peak shaving on the distribution grid is analysed using Monte Carlo method in the context of higher EV and heat pumps penetration. The operation of storage facilities showed that ToU tariffs have little effect on the consumption peak, requiring other measures to reward flexibility. There is a similarity between [7] and our approach in the sense that we both investigate the effect of the ToU tariffs on the consumption peak, but our methodology is aiming to set a tariff to respond to the consumers' actual contribution to the consumption peak/off-peak.

Also, a Monte Carlo method is applied [8] for simulating the residential demand considering tariff elasticity and PV generation. 1100 households' smart-metered consumption is used to identify the impact of constant and variable tariffs derived from the wholesale market and retailers' rules and RES availability. The results reveal useful insights in the future tariff design, discouraging purely sales-driven tariffs devised by retailers or variable tariffs totally driven by a wholesale market, since they proved not be suitable for grid critical situations. These results support our article focusing more on the demand side strategies and demand contribution to the peak/off-peak.

Shifting the consumption from peak to off-peak hours is essential to avoid grid congestion and infrastructural onerous investment that negatively impacts the environment. ToU tariffs and smart metering systems could incentive the consumers to change the consumption behavior scheduling the appliances' operation at lower rate intervals. Thus, designing the ToU peak/off-peak rates and setting the intervals are important steps in getting adequate demand response [9]. The major risk is to design a ToU tariff that leave the consumers indifferent. Offerte Biorarie tariff offered in Italy has two time slots, with a very narrow difference in rate between them that does little to incentivize consumers to change the consumption behavior and shift the electricity usage at night [10]. Since our approach is focused more on the consumers' contribution to the peak/off-peak consumption, comparing with other approaches that are more focused on market-driven prices [11], this risk is mitigated.

Usually, ToU tariffs are applied by the electricity suppliers. Also, innovative is the designing and testing of tariff rates or day-ahead/dynamic tariffs for distribution service even if the actual tariff is flat. This initiative is already analysed in other European countries [12] due to the benefits of ToU tariffs on sustainable development of the grid by avoiding peaks that rarely occur for only short time intervals and require onerous reinforcement of the grid [13]–[16]. For ToU tariff model, the contribution of each cluster of consumers on peak/off-peak proposed in this paper and tariff elasticity will be considered as they should be motivated by adequate rates to consume more/less at off-peak/peak. Implementing such tariffs will challenge and impact distribution system operators [10], [11], consumers and regulatory bodies.

By stimulating consumers to use the programmable appliances at off-peak hours, the difference between the peak and off-peak load is reduced, avoiding costly investment in grid capacity that would have been transferred in the electricity tariff. The consumption optimization process can be further improved from day-ahead to real-time that corrects to some extent the controllable appliances deviation from the day-ahead schedule [20]. On 24-hour data set, savings of up to 17.5% can be obtained for the entire community of 11 houses when a ToU tariff is applied. Evaluated for each house, the payment gain after optimization with the ToU tariff can reach up to 33.5%, but there are houses with small negative gains that underline that not any consumption curve can be optimized, the optimization requiring a certain level of flexibility. On a one-year dataset, the payment gains with the ToU tariff are of 6.65% [21] show a decrease of 29% of the average consumption peak after shifting for a single house. In terms of electricity payment, the savings for 2014-2016 are up to 20.5% in relation to the standard tariff. According to optimization algorithms proposed in [22], consumption peak decreases between 9.1% (at hour 22) and 33% (at hour 19), complemented by 6.12% savings with a ToU tariff. This way, the end consumers benefit from direct savings, peak reduction and improving activity of the grid operators that can better plan their resources [23].

Using a set of flat and ToU tariffs, [24] propose a model for calculating the Pareto-optimal shares of the capacity and energy for various sets of decision variables, underlining the impact of the tariff structure and stressing on the importance of the tariff design process. Also, using a quadratic transfer cost, [25] set the optimal ToU tariff from the consumers and producers point of view, emphasizing that the ToU tariff brings benefits for both producers and consumers. With a Gaussian Mixture Model clustering technique, [26] group the consumers into clusters and investigate the effects of ToU tariffs on the demand response, in terms of savings and peak reduction. [27] aim at setting the ToU tariff for domestic customers starting from flat rate. Implementing the ToU tariffs lead to peak reduction that varied from 4.2 to 9.5% and savings that also varied from 3.2 to 5.1% [27]. A review on the designing of ToU tariffs and the consumers' willingness to take advantage of such tariffs, providing four interesting conclusions, is presented in [28]. One of them is that comparing the real time pricing tariffs with ToU tariffs, the latter proved to be more popular.

[29] show that 93% of the analyzed electricity consumers are loss-averse caring more about avoiding losses than making savings; hypothesis also confirmed by [3]. Thus, the ToU tariffs analyses should also concentrate on evaluating the losses [30]. When setting the ToU tariffs, one of the most significant aspect is the tariff-elasticities of demand. [31] propose a quadratic programming and stochastic optimization techniques for setting the ToU tariff, addressing the tariff-elasticities of demand. Also, [32] show that the electricity generating companies require less capacity for base-load and peak-load under the TOU tariff than under the flat tariff. The reduction in the demand of the base-load and peak-load periods was not significant, although the demand during the peak hours decreased.

Zhou et al. propose a TOU tariff and a stepwise power tariff model combination to stimulate consumers to shift the flexible consumption in response to electricity tariff targeting at both energy conservation and peak load shaving [33]. The similarity with our approach consists in the analysis of residential demand response considering the tariff elasticity.

Starting from the assumption that flat tariffs do not reflect the real costs that consumers incurs to an electricity supplier, [34] investigate a prediction-of-use tariff that considers a baseline consumption and charges the actual consumption and deviations from the baseline consumption prediction. This approach, validated using a large data set of residential consumers in the U.K., demonstrated that joining consumers together when buying electricity using a polynomial time algorithm leads to efficient buyer groups. There are some similarities with our approach since we also assume that the flat tariff does not reflect the costs that consumers incurs to an electricity retailer and efficiently groups the consumers. While [34] charge the deviations from prediction, we stress the importance of charging the contribution to the consumption peak/off-peak and giving a signal to adjust this contribution to obtain a lower tariff rate.

Thus, special attention in this paper is focused on understanding the contribution of the consumers to peak/off-peak consumption so that to properly design the rates. Hence, the proposed methodology will consider the consumers' type, seasonal or monthly behaviour and electricity tariff elasticity to incentive the consumption at off-peak and discourage the consumption at peak hours.

To the best of our knowledge, the proposed methodology of setting the ToU tariffs represents a novel approach that focuses on the impact that groups of consumers has on the load curve or their contribution to the consumption peak and off-peak level. Therefore, we start from the flat tariff and compute the contribution for groups of consumers (clusters) and use this contribution to set the tariff rates that will be customized for each group; that is the group that has the highest contribution to the consumption peak will be charged more at peak hours. By keeping the payment with flat tariff and with ToU tariff equal, the peak and off-peak intervals can be set in the nearness of the peak/off-peak hours. Then, we test the impact of the ToU tariffs using the tariff elasticity with a large data set comprising more than 4,200 residential consumers and totalizing 157,992,996 records that require a NoSQL database and machine learning algorithms.

Thus, setting the ToU tariff as proposed in our methodology gives an economic signal to reward the consumption at off-peak hours and penalize the consumption at peak hours leading to valley-filling and peak shaving. The methodology also requires overlapping or matching the load curve pattern with off-peak and peak intervals and update or recalculate the tariffs to consider the changes that inherently appear during seasons or in consumers behavior.

The paper is organized as follows. We give the definition of the mathematical model of setting the ToU tariff rates and peak/off-peak intervals and the research methodology in section 2. Input data and process flow are described in section 3. Simulations, results and conclusion are given in section 4 and section 5, respectively.

II. RESEARCH METHODOLOGY

The methodology for setting the ToU tariff rates consists in 5 steps as in Figure 1. The electricity consumers from a specific area are classified into several categories: residential, industrial, small and medium enterprises and other categories. Due to the fact that consumers activities depend on their type and influence the load profile, the consumers are separated by categories.

Then, 24-hour profiles for each consumer are calculated and clustered grouping the consumers based on the similarities on the hourly load [35]. A data mining technique - clustering is the grouping of data into subsets based on similarities. In each group, the members are similar, but between groups, the members are different. It is an unsupervised machine learning algorithm for grouping data that

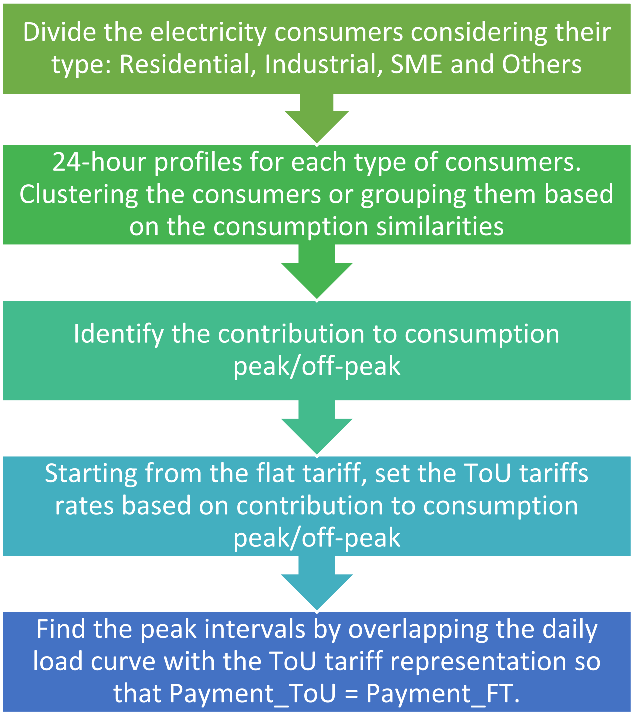

FIGURE 1. Methodology for setting the ToU tariff rates.

identifies commonalities or similarities in the data. Therefore, clustering is useful when analyzing large data sets. There are different clustering algorithms. When choosing the clustering algorithm, the type of variables is essential. Hence, there are algorithms intended strictly for numerical variables or categorical variables or a combination of the two types of variables. Clustering methods are known as hierarchical methods that build clusters gradually [36] and partitioning algorithms that learn clusters directly. The partitioning algorithms are computationally faster than hierarchical methods and tend to provide tighter clusters, leading to better results in terms of precision [37]. K-means is a relocation technique, a subdivision of the partitioning algorithms, that show clusters through centroids. K-means is more sensitive to outliers and perfectly suited for numerical variables, with a statistically meaningful representation. Therefore, k-means is very efficient for processing large data sets with numerical variables.

The contribution to the peak/off-peak of the total consumption or the cluster's consumption can be calculated and used as input data when setting the ToU tariff rates. Starting from the Flat Tariff (FT) in per unit (p.u.), red line, the algorithm sets the ToU tariffs rates (blue line from Figure 1) based on the contribution, increasing the FT at peak hours and consequently decreasing the FT at off-peak hours.

Then the peak intervals are identified by overlapping the daily load curve with the ToU tariff allure so that payment with ToU tariff equals payment with the Flat Tariff (FT). Sometimes the ToU tariff representation does not overlap the load profile that is not efficient in term of demand

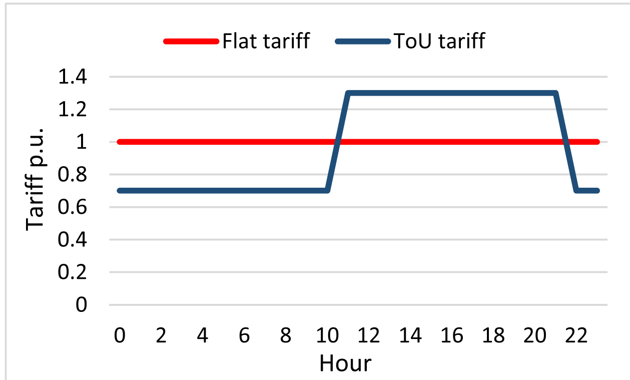

FIGURE 2. Flat tariff and ToU tariff graphical representation.

response. Usually, this is the consequence of the fact that the consumption evolved, and the tariff schema did not follow the consumption trend.

The mathematical model for setting the ToU tariff rates is defined in the following paragraphs. First, let's define the 24-hour electricity consumption payment considering the FT:

$$Payment_{FT} = \sum_{h=1}^{24} FT_{rate} \times C_h \tag{1}$$

$Payment_{FT}$ – electricity consumption payment in case of flat tariff implementation;

FT_{rate} – hourly flat tariff (constant);

C_h – hourly consumption.

Second, we will define the 24-hour electricity consumption payment considering the ToU tariff, including the contribution to consumption peak/off-peak:

$$Payment_{ToU} = \sum_{h=1}^{24} \alpha_h^{off/peak} \times FT_{rate} \times C_h \tag{2}$$

$$\alpha_h^{off} = 1 - c^{off} \tag{3}$$

$$\alpha_h^{peak} = 1 + c^{peak} \tag{4}$$

$Payment_{ToU}$ – electricity consumption payment in case of ToU tariff implementation;

$\alpha_i^{off/peak} \times FT_{rate}$ – off-peak/peak rate;

c^{off} – contribution to consumption off-peak coefficient;

c^{peak} – contribution to consumption peak coefficient.

The two contribution coefficients for a cluster of consumers are calculated as below:

$$c^{off} = \frac{C_{cluster}^{off}}{C_{total}} \times 100\% \tag{5}$$

$$c^{peak} = \frac{C_{cluster}^{peak}}{C_{total}} \times 100\% \tag{6}$$

$C_{cluster}^{off}$ – consumption at off-peak hour for a cluster of consumers;

$C_{cluster}^{peak}$ – consumption at peak hour for a cluster of consumers.

C_{total} – total consumption.

Following the load profile, the peak hours are identified when payment with FT equals payment with ToU tariff. Hence, we can set the intervals for lower/higher rates so that:

$$Payment_{FT} = Payment_{ToU} \tag{7}$$

Therefore, setting the intervals for lower and higher tariff rates is given below:

$$peak\ hours : h_k \div h_l \rightarrow Upper\ Rate \rightarrow \alpha_h^{peak} \tag{8}$$

$$off-peak\ hours : h_{l+1} \div h_{k-1} \rightarrow Lower\ Rate \rightarrow \alpha_h^{off} \tag{9}$$

As expected, the electricity consumption will diminish as the tariff increases. The consumer's sensitivity to tariff change can be measured by the tariff elasticity that is the percentage change in consumption divided by the percentage change in tariff.

$$E = \frac{\Delta C\%}{\Delta T\%} \tag{10}$$

$E-$ tariff elasticity;
$\Delta C\%$ - consumption variation in percentage;
$\Delta T\%$ - tariff variation in percentage.

Considering the tariff elasticity, the modified consumption when ToU is applied is calculated below:

$$\Delta C\% = \frac{C_{mod} - C_i}{C_i} \times 100\% \tag{11}$$

$$\Delta T\% = \frac{\alpha^{off/peak} \times FT_{rate} - FT_{rate}}{FT_{rate}} = \alpha - 1 \tag{12}$$

$$C_{mod} = \left[1 - E \times \left(\alpha^{off/peak} - 1\right)\right] \times C_i \tag{13}$$

$C_{mod}-$ modified consumption;
C_i- initial consumption.

The outcome of the algorithm consists in the evaluation of the consumption peak and savings for consumers as a consequence of using ToU tariff.

INPUT DATA AND PROCESS FLOW

The Irish Commission for Energy Regulation carried out a project aiming to identify the customers' behaviour in the context of smart metering implementation with a set of four ToU tariffs and one weekend ToU tariff, and other DSM stimuli. Their secondary objective was to identify a tipping point for ToU tariffs that would significantly bring change in the electricity usage. Hence, small and medium enterprises (SME), residential consumers and others were considered in a one-year trial period from January to December 2010.

In this paper, we preponderantly analysed the residential consumers, as they are more numerous and required a NoSQL data management solution. Also, we encountered more insufficient or incomplete data for SME and others. Thus, the consumption data consisted in 6 data files in.txt format, with 3 fields, such as: customer identifier, date and time, and consumption data for each 30 minutes. The data files consist in 157,992,996 records. The data files are correlated with auxiliary data, matrix allocation of ToU tariffs, data manifests, and so on.

The attempts to use several relational databases failed either in the import or when querying or updating data due to a very large amount of data. Hence, a NoSQL solution is used as an alternative. Thus, MongoDB is chosen as a data storage solution [38] and the Python language was selected as a solution for handling, manipulating and analyzing the data as in Figure 3. MongoDB provides faster reading speed and is better suited for rapid growth when the structure of the data sources is not clearly known from the beginning (compared with other NoSQL databases like CouchDB). On the other hand, CouchDB offers mobile support and more replication advantages, that are not provided by MongoDB. But CouchDB' advantages are not essential for our objective [39]. In terms of popularity, based on rankings [40], MongoDB is more popular, its rank is better than other competitors.

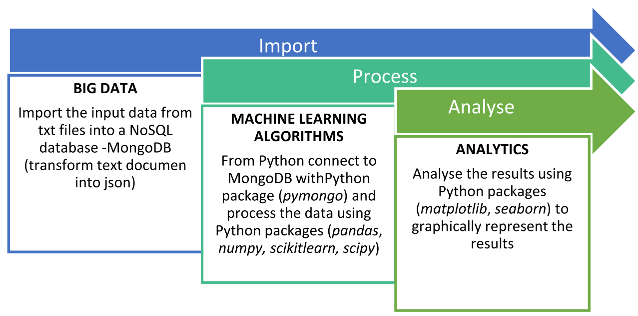

FIGURE 3. Data process flow.

Starting from the input consumption data of the residential consumers, we obtained 4 clusters (from 0 to 3). From the initial input data stored in a (4225×171) *dataframe* formed by 4225 rows and 171 columns (*meterID*, *residential_tariff_allocation*, *recommended* and 168 hourly consumption values for a week, *H0÷H167*), we compute a new (4225×26) *dataframe* formed by 4225 rows and 26 columns (*METERID*, *CLUSTER*, 24-hour consumption values, *H0÷H23*) as in Figure 4. Based on the consumption similarities, the consumers are grouped in 4 clusters with k-means. Then, the load profiles are calculated as average hourly consumption of each cluster.

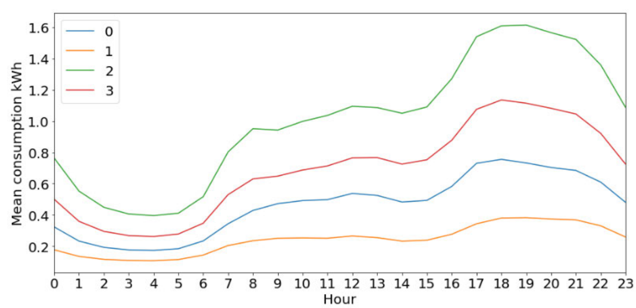

FIGURE 4. Load profile calculation by clusters.

The clusters are similar in shape, with clear morning, noon and evening peaks and afternoon and night off-peaks. However, their profiles significantly differ in amplitude. Cluster 2 (green) is the highest and with the most sinuous curve, whereas cluster 1 (orange) has a rather flat profile. We can also easily notice that on average the night off-peaks of clusters 2 (green) and 3 (red) are higher than the evening peak of cluster 1 (orange). Although, cluster 2 records the highest consumption, its members totalize 9.3% of the data sample as in Figure 5. The biggest number of members are in cluster 0 (blue) almost 35%, while the second biggest cluster has 25% of the total members. Also significant is cluster 1, with the lowest load profile, having more than 31% of the total members.

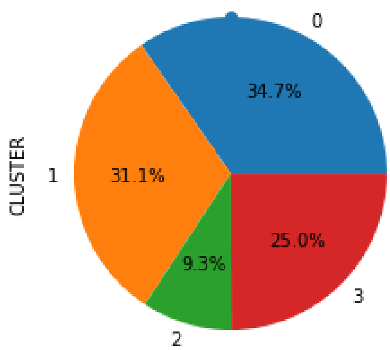

FIGURE 5. **Segmentation of members for each cluster.**

The variability of the consumption profiles at peak hour can be analysed by box plotting the consumption data for each cluster as in Figure 6. The highest variability of data belongs to cluster 2 while the lowest belong to cluster 1. Half of the data in case of cluster 2 is spread from 1.4 to 1.8, one whisker that goes up to 2.3 and the other one to 0.8, and biggest outlier to 3.4.

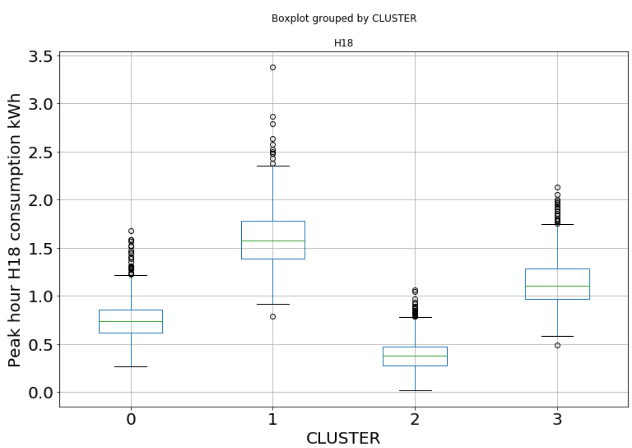

FIGURE 6. **Box plotting the consumption at peak hour for each cluster.**

Considering that each consumer contributes to certain extent to the consumption peak and off-peak, when designing the electricity tariffs, it is reasonable to incentive the consumers that consume more at off-peak hours by decreasing the tariff rate and discourage the consumers that consume more at peak hours by increasing the rate. Hence, starting from the regular tariff rates that would be applied to all consumers, the peak and off-peak rates could be adjusted to reflect the contribution of each group of consumers according to the particular level of consumption from the total consumption.

In Figure 7, the contribution to the evening consumption peak recorded at H18 of individual consumer is plotted as a Load Duration Curve (LDC), rearranging all the loads of the chronological curve in the order of descending magnitude. The corresponding contribution to the night off-peak recorded at H4 is also plotted for the same MeterIDs. We can easily notice that some members of cluster 2 majorly contributes to the total consumption peak. The MeterID's coefficient that has the highest contribution to the peak is almost 0.1.

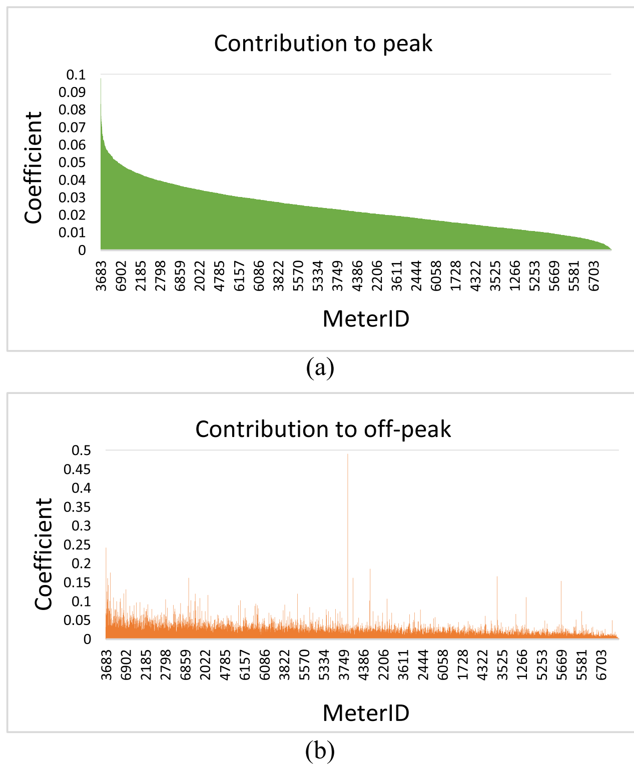

FIGURE 7. **Individual contribution to the consumption peak (a) plotted as a duration curve and off-peak (b).**

Similarly, in Figure 8, the contribution to the night consumption off-peak recorded at H4 of individual consumer is plotted as a LDC. The corresponding contribution to the evening peak is also plotted for the same MeterIDs. We can easily notice the consumers that significantly contribute to the total consumption off-peak belong to all clusters. The MeterID's coefficient that has the highest contribution to the off-peak is almost 0.5. However, the two contributions should be differently treated. Hence, the contribution to the

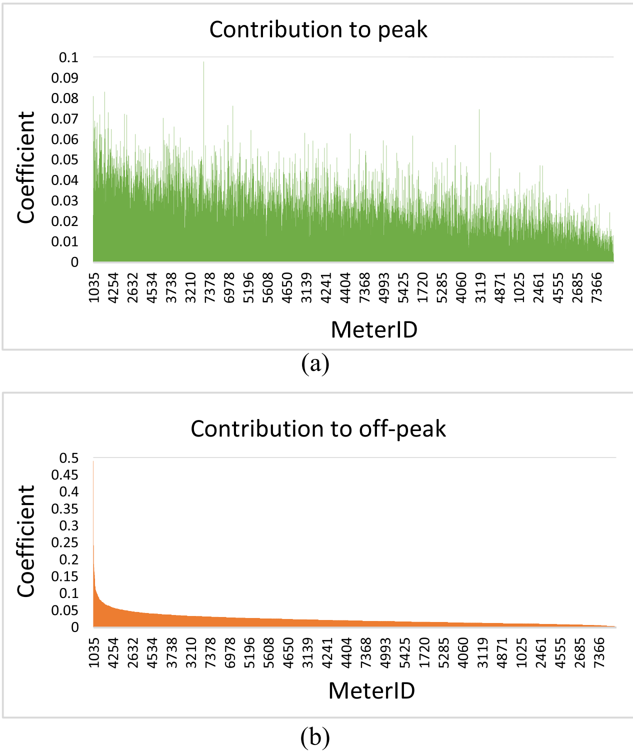

FIGURE 8. Individual contribution to the consumption peak (a) and off-peak plotted as a duration curve (b).

consumption peak should be discouraged imposing higher rates, whereas the contribution to the consumption off-peak should be encouraged with lower rates.

The data is further analyzed using the pivot table facilities. The total consumption of each cluster for peak and off-peak hours is depicted in Figure 9.

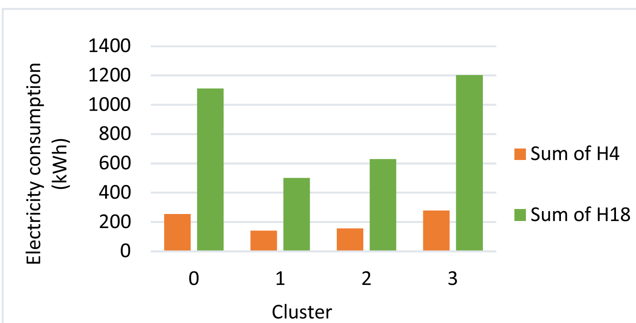

FIGURE 9. Total electricity consumption of each cluster at peak and off-peak hours.

Although, there are differences among clusters, interesting is to notice that the contribution of each cluster to the peak (left) and off-peak (right) is relatively similar (Figure 10).

The highest contribution to the peak and off-peak too belongs to cluster 3 (red), while the lower contribution belongs to cluster 2 (green) that has also the smallest number of members. Nonetheless, some members of cluster 2 majorly

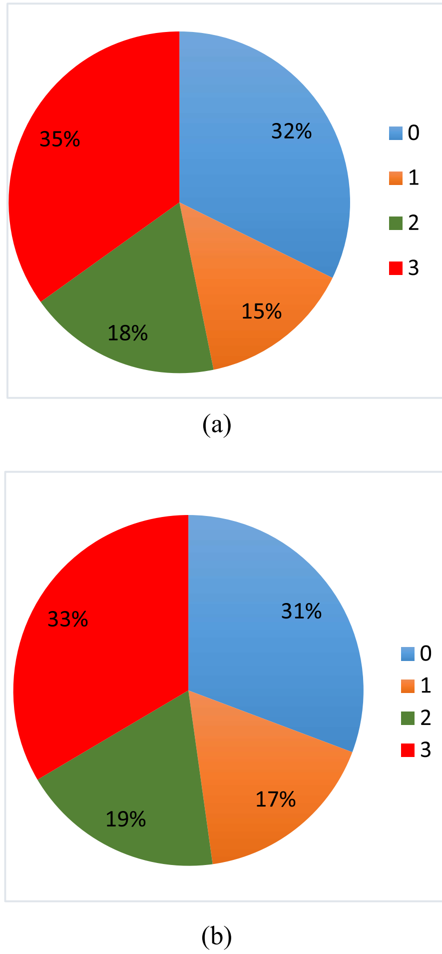

FIGURE 10. Contribution of each cluster to the peak (a) and off-peak (b).

contributed to the peak as shown in Figure 7. Starting from these contributions, it is obvious that members of cluster 3, for instance, should be charged with the highest rates at peak and lowest rates at off-peak hours such as tariff D from [41], as cluster 3 has the highest contribution to peak and off-peak hours.

III. SIMULATION AND RESULTS

For each cluster (from 0 to 3), starting from off-peak and peak hours, the contribution is calculated according to Table 1.

TABLE 1. Contribution coefficients to consumption peak/off-peak at the cluster level.

Cluster	H4 Load	H18 Load	Contribution coefficient to peak	Contribution coefficient to off-peak
0	254.8483	1111.494	30.73632022	32.27097706
1	141.4410	500.4338	17.05867822	14.52952955
2	155.1812	630.1684	18.71584337	18.29622952
3	277.6732	1202.157	33.48915818	34.90326387
Total	829.1437	3444.253	100.00000000	100.00000000

Then, the off-peak/peak rates are calculated in Table 2 according methodology described in section 2.

TABLE 2. Peak/off-peak rates at the cluster level.

Cluster	Off-peak rate	Peak rate
0	0.692636798	1.322709771
1	0.829413218	1.145295296
2	0.812841566	1.182962295
3	0.665108418	1.349032639
Average	0.75	1.25

Based on the peak/off-peak rates, four ToU tariffs are calculated and graphically represented in Figure 11, where tariff T0 is recommended for cluster 0 and so on.

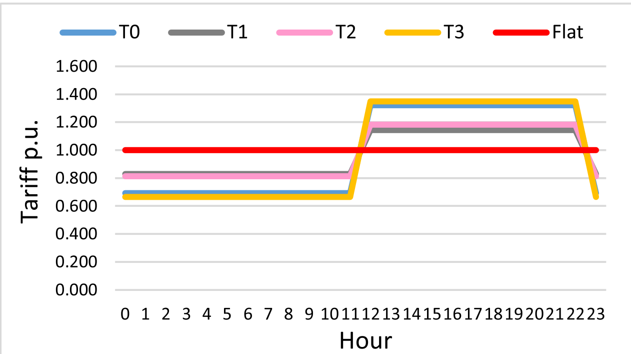

FIGURE 11. Calculated ToU tariffs.

Starting from the ToU tariffs, we calculated the electricity consumption payment with FT and ToU tariff as in Table 3 and Figure 12. The payment is calculated in three modes: as initial consumption (C_i) times flat tariff (FT), initial consumption times ToU tariff (ToU) and modified consumption (C_{mod}) times ToU tariff as demand response (DR). Due to different tariff rates and tariff elasticity effect on the consumers' behaviour, the electricity payment decreases when ToU tariff is implemented. Also, the consumption curve is modified according to Figure 13.

TABLE 3. Electricity consumption payment evaluation.

	Payment
C_i x FT	50837.97
C_i x ToU	49165.37
C_{mod} x ToU (DR)	48864.41

Considering only cluster 3, as the cluster with the highest contribution to consumption peak/off-peak, we notice a similar effect of ToU tariff on the consumption curves as in Figure 14.

Considering the calculated T3 tariff rates for cluster 3, we evaluate the electricity consumption payment as

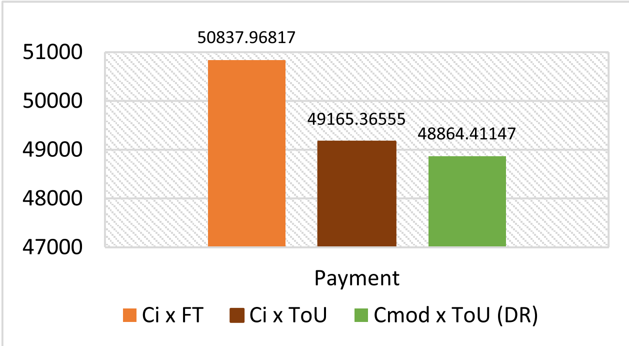

FIGURE 12. Electricity consumption payment.

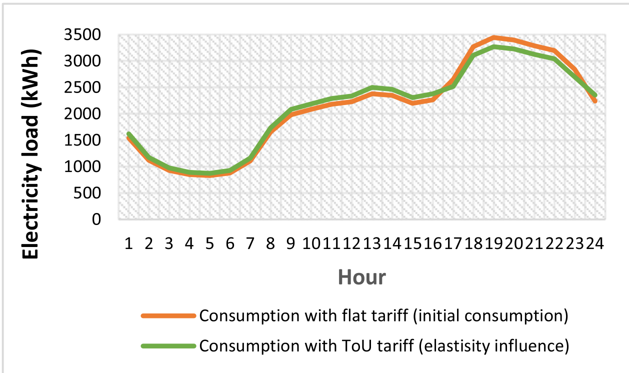

FIGURE 13. Daily load curve for entire data sample.

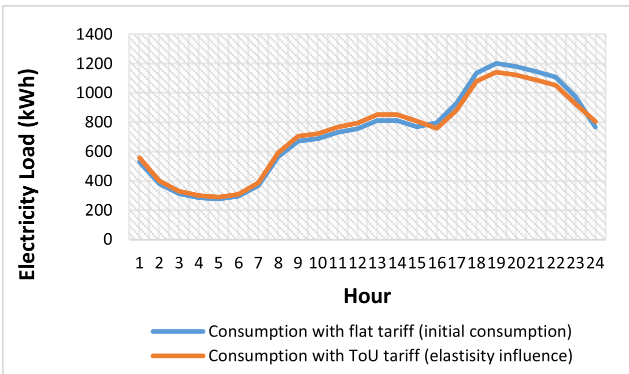

FIGURE 14. Daily load curve for cluster 3.

in Table 4 and Figure 15. The payment is also calculated in three modes: as initial consumption (C_i) times flat tariff (FT), initial consumption times ToU tariff (ToU) and modified consumption (C_{mod}) times ToU tariff as demand response (DR). We notice that the payment decreased as a consequence of changing the consumers' behaviour and different rates that encourage the consumption and night.

In both cases - entire data sample or cluster 3, the consumption peak decreased by 5% (when $E = 0.2$) or 7.5% (when $E = 0.3$). The savings varies from 4% for entire data sample to 2% for cluster 3. When assessing the payment for each month, we obtained the results presented in Table 5.

TABLE 4. Electricity consumption payment evaluation for cluster 3.

	Payment
Ci x FT	17472.32
Ci x ToU	17338.65
Cmod x ToU (DR)	17146.98

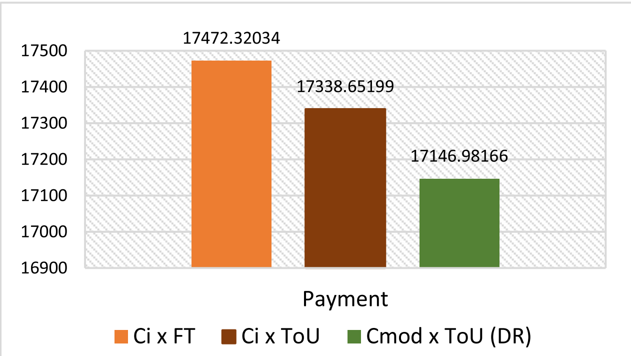

FIGURE 15. Electricity consumption payment.

TABLE 5. Monthly electricity payment assessment.

Months	Payment with ToU	Payment with FT	Difference %
January	3676566.17	3793945.26	-3.19
February	3044734.64	3143838.20	-3.25
March	3075033.10	3186434.12	-3.62
April	2672450.73	2798919.76	-4.73
May	2630912.22	2768512.36	-5.23
June	2426486.04	2569892.06	-5.91
July	2521729.00	2669953.74	-5.87
August	2574146.02	2718675.73	-5.61
September	2659290.28	2774982.84	-4.35
October	2910447.29	3022957.41	-3.86
November	3193365.00	3285826.58	-2.89
December	3827956.56	3936992.68	-2.84

For all months, the payment with ToU was lower than the payment with FT. The difference in percentage varied from almost 3 to 6%.

IV. CONCLUSION

In this paper, we proposed a methodology of calculation of ToU tariff rates and setting the intervals for applying the peak/off-peak rates, considering its significance of shaving the consumption peak to a sustainable environment and development of the power systems. The proposed methodology is based on the contribution of clustered consumers to the consumption peak and off-peak, considering the effect of the tariff elasticity on the consumers' behaviour. The results were proved by considering a large data set recorded by smart meters at 30 minutes from a 1-year trial period that took place in Ireland. The data set totalizing 157,992,996 records required big data solutions (NoSQL) and machine learning algorithms developed in Python that compute the ToU tariff rates at different intervals at the convenience of the electricity supplier. The main outcome has two components: peak shaving of about 5% when the tariff elasticity is 0.2 or 7.5% when the tariff elasticity is 0.3. Also, the savings were recorded, varying from 4% for entire data sample to 2% for cluster 3. At the month level, the payment with ToU tariff was always lower than the payment with FT, the difference in percentage varying from 3 to 6%.

The advantage of our approach in calculating the ToU tariff is that it relies on the real contribution of the consumers to the consumption peak/off-peak, easy to understand and transparent. One of the limitations of our approach is that it depends on the tariff elasticity that can vary and influence the results in terms of peak reduction and savings.

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