Response of socioeconomic groups to dynamic and static tariffs of electricity

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***Abstract*—Electricity consumption of a home depends on various socio-economic and dwelling factors, such as area of the house, income, age-groups of the family members, size of the house, number of bed rooms, etc. To cope with the high demand, electricity companies use different pricing strategies that help them regulate electricity consumption. This paper explores how consumers respond to static (fixed) and dynamic pricing strategies. In particular, we analyze a large number of factors (826 socio-economic and dwelling factors), called geo-demographic factors, of consumers and study how these factors influence their response to a pricing strategy. Our study can help electricity companies better understand consumer behaviour when it comes to pricing strategies, and can help these companies plan and manage electricity production.**

I. Introduction

Electricity is the backbone of an economy and its demand rose by almost 323% from 1974 to 2018 [1]. It is forecasted that this demand will even further rise by 79% by 2050 [2]. According to International Energy Agency [1], 66.3% of the total electricity is produced by burning fossil fuels (e.g. coal and natural gas). So the increase in electricity demand will also increase the carbon emissions, hence will further aggravate the problem of climate change.

There are various efforts that are being taken to regulate consumer behaviour when it comes to consuming electricity. Demand Response (DR) [3] is one of such methods. Under this scheme, consumers are encouraged to shift their electricity consumption from peak hours to off-peak hours by entitling them to an incentive [4, 3]. Different pricing policies can be applied to shift a consumer's electricity usage. Currently, there are two common policies, static or dynamic pricing. In static pricing, the user pays a flat tariff (price) irrespective of the time or amount of consumption. In dynamic pricing, the tariff depends upon the time of consumption. There are several dynamic tariff structures. One example is the Time of Use (ToU) [5] pricing, which follows 3 pricing structures: high, medium and low. Another scheme is RTP (Real Time Pricing) where the tariff fluctuates on hourly basis, based on the price in the wholesale market [6].

Electricity consumption within a house depends on various factors such as weather conditions [7], dwelling conditions (area of the house, age of the buildings, number of bedrooms etc) [8, 9], family (number of family members, family structure), socio-economic status (education qualification, nature of employment, etc.) [10] and appliance factors (e.g. air conditioning, number of TV sets, etc) [11, 10]. In the past, researchers have mainly focused on dwelling-related factors. They did not explore the influence of socio-economic factors in detail. The socio-economic factors that have been explored are limited to number of occupants, family composition, age, employment status, education and household income [10].

Socio-economic factors are very important. Ultimately, the high socio-economic status of a person will permit them to own a big house, buy more home appliances or afford them high electricity bills. Sometimes this high socio-economic status also gives people the liberty to have a careless attitude towards their electricity consumption, because they are almost unaffected by any increase in their electricity bills.

Companies over decades have tried to reduce the consumer demand to meet the demand supply balance. They have employed different techniques such as ToU and RTP mentioned earlier, but they have not studied how different socio-economic groups respond to different tariff structures. In this paper, we try to bridge this gap and present a study of how the different *geodemographic* groups respond to static and dynamic pricing. Geodemography is an enhanced consumer categorisation which segments the population based on 826 factors [12]. These factors range over 15 different categories, e.g. social, economic, dwelling, family structure, health, education, finance, occupation, transport, digital behavior and leisure-time preferences.

In this paper, we are addressing the following research question:

RQ: How do the different geodemographic groups respond to the pricing strategy of an electricity company?

To answer this question, we analyze the geodemographic factors of 4917 homes in the City of London and study how they respond to static vs dynamic pricing strategies. We find that high income people change their consumption when dynamic pricing is used, while those who are financially struggling consume higher electricity when static strategy is used (especially in early hours of the day).

We expect this study to be useful for the electricity companies. Knowing how different geodemographic groups respond to the pricing strategies can help design better energy management programs and tariff structures. Companies can achieve better demand reductions, hence, optimize their operating costs. Consumers will also have better understanding of their response to a particular pricing strategy. The rest of this paper is organized as follows. Section II discussed related work. Section III provides an overview of the dataset used in our study. Section IV discussed the methodology. Section V discussed the results and Section VI concludes the paper.

II. Literature Review

Researchers studied the impact of different pricing strategies on electricity consumption. Arun et al. [13] discovered that Demand Response programs are most successful in urban areas which witness a high industrial infrastructure and a large population density.

Kessels et al. [14] propose that dynamic tariff structure should be very simple to understand. They also suggest that a Demand Response program which leads to a noticeable difference within the electricity bills posses a higher chance of success. Yang et al. [15] also supported Kessel's observations. They also propose that the utilities should design easy to understand energy management programs.

Gyamfi et al. [16] discovers that higher income groups do not change their electricity consumption in respond to price changes. Loi et al. [17] also make a similar observation. They find that a significant number of wealthy people either are not interested in saving electricity or they do not want to change their lifestyle (i.e. energy consumption behaviour) by reducing consumption. We also noticed similar patterns in our analysis.

Faruqui et al. [18] observes that dynamic pricing leads to a reduction of 3%-6% during peak hours. Du et al. [19] finds a strong correlation between the price of energy, income and demographics with consumption. Mohamed et al. [20] studies the impact of economic and demographic variables on power consumption in New Zealand from 1965 to 1999. They developed multiple linear regression models to predict the total consumption of New Zealand using *GDP (Gross Domestic Product)*, *the average price of electricity*, and *population*. They rely only on two social-economic variables *GDP* and *the price of electricity*, whereas we use 826 demographic factors.

This paper contributes to existing research by studying the impact of a large number of gedemographic factors on the consumer's response to a pricing strategy. It also explores how different socio-economic groups change their consumption when the pricing strategy changes from static to dynamic pricing.

III. Dataset

This study uses London Smart Meter data [21], which consists of smart meter readings of 4917 homes in London. These readings are recorded at a frequency of half an hour. Out of these 4917 houses, 3888 houses are put on static (flat) tariff of £0.14/kWh. The remaining 1029 houses are charged using ToU (Time of Use) pricing, which has 3 levels: high (£0.67/kWh), low (£0.03/kWh) and medium (£0.11/kWh).

TABLE I: Metadata of the London Smart meter data

Feature Name	Description
Home Id	Unique Identifier for a household
Pricing	Type of pricing (fixed or dynamic)
Consumption	Power Consumption (in kWh)
Timestamp	Timings of the consumption
ACORN label	Geodemographic label for the home

Each house in the dataset is assigned a geodemographic group, also known as ACORN (A classification of residential neighborhood used in the UK) group [22]. This ACORN classification has been developed by CACI (California Analysis Center, Inc.) [23] using 826 factors [24]. These factors come from various categories like housing, finance, education, family, transport, etc.

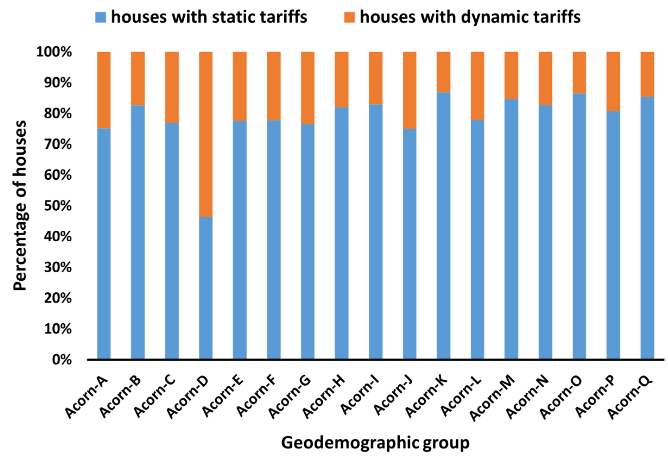

Fig. 1: Percentage of houses of each ACORN group belonging to static pricing and dynamic pricing

TABLE II: The complete geodemographic classification system of UK

	Geodemographic Category	ACORN group
1	Affluent Achievers	a) **ACORN-A** (*Lavish Lifestyle*) b) **ACORN-B** (*Executive wealth*) c) **ACORN-C** (*Mature Money*)
2	Rising Prosperity	a) **ACORN-D** (*City Sophisticates*) b) **ACORN-E** (*Career Climbers*)
3	Comfortable Communities	a) **ACORN-F** (*Countryside Communities*) b) **ACORN-G** (*Successful Suburbs*) c) **ACORN-H** (*Steady Neighborhoods*) d) **ACORN-I** (*Comfortable Seniors*) e) **ACORN-J** (*Starting Out*)
4	Financially Stretched	a) **ACORN-K** (*Student Life*) b) **ACORN-L** (*Modest Means*) c) **ACORN-M** (*Striving Families*) d) **ACORN-N** (*Poor Pensioners*)
5	Urban Adversity	a) **ACORN-O** (*Young Hardships*) b) **ACORN-P** (*Struggling Estates*) c) **ACORN-Q** (*Difficult Circumstances*)

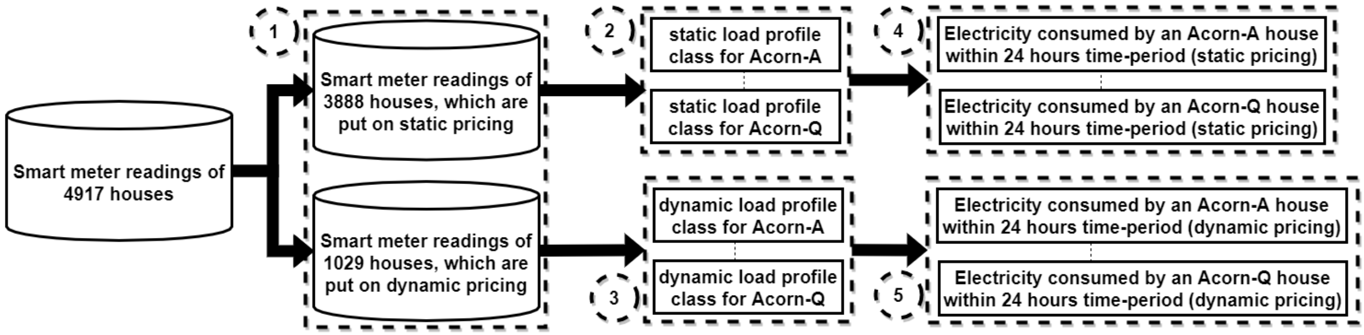

Fig. 2: Steps involved in generating the load profile class for each ACORN group

We analysed our dataset and identified 17 different ACORN groups within it. The number of houses in each ACORN group are shown in the Figure 1. This stacked bar chart also shows the number of houses that use the static and dynamic pricing. Acorn-E contains the maximum number of houses, while Acorn-B contains the least number of houses.

ACORN is a geodemographic classification system used in the United Kingdom. ACORN classification has five major categories and 17 groups, which are listed in the Table II. In the remaining of this section, we present an overview of the five categories.

A. *Category 1: Affluent Achievers*

This category contains middle-aged and old people who live in prosperous suburbs and rural areas. They have high level of education and live in large, expensive detached homes. They are either large business owners or work for high-end jobs. They own multiple cars and they belong to top strata of the society.

B. *Category 2: Rising Prosperity*

This category is populated with young adults who live in cities. They are corporate employees and earn high salaries. They mostly prefer living in flats at prime locations. They have an active social life and enjoy visiting pubs and restaurants.

C. *Category 3: Comfortable Communities*

This category contains the middle class who live in small suburbs and towns. It contains people belonging to all age-groups. They usually own a detached or semi-detached home and work in professional, clerical or skilled jobs.

D. *Category 4: Financially Stretched*

This category involves lower-income people who live mostly in terraced or semi-detached homes. They lack higher education and work in small manual or semi-skilled jobs.

E. *Category 5: Urban Adversity*

This category includes poor people who live in cities. They barely earn enough money to meet their day to day needs have to depend on social welfare schemes for survival. They live in small homes and prefer social housing. This category also experiences high unemployment.

IV. Methodology

Our methodology consists of the following steps:

Step 1: Grouping houses based on their tariff structures (static and dynamic). We have 3888 houses with static pricing and 1029 houses with dynamic pricing.

Step 2: Forming load profile class for each ACORN in static pricing scheme, i.e. we aggregate the consumption of all the houses within such particular ACORN group, then we calculate the average consumption for a house in that ACORN group. This profile class will give us the average electricity consumption of any house in that ACORN for the whole year.

Step 3: Forming of load profile class for each ACORN dynamic pricing scheme: We calculate the average the consumption of all the houses that use a particular pricing strategy within that ACORN group.

Step 4: Calculating the total 24-hour consumption for each ACORN for houses that use static pricing.

Step 5: Calculating the total 24-hour consumption for each ACORN for houses that use dynamic pricing.

TABLE III: Percentage change in the electricity consumption of ACORN labels

ACORN	Percentage change in consumption
ACORN-A	**19.45%**
ACORN-B	**32.98%**
ACORN-C	6.55%
ACORN-D	6.27%
ACORN-E	12.41%
ACORN-F	7.63%
ACORN-G	**15.79%**
ACORN-H	7.62%
ACORN-I	0.2%
ACORN-J	**45.23%**
ACORN-K	0.31%
ACORN-L	13.35%
ACORN-M	10.82%
ACORN-N	0.13%
ACORN-O	7.6%
ACORN-P	**49.02%**
ACORN-Q	6.2%

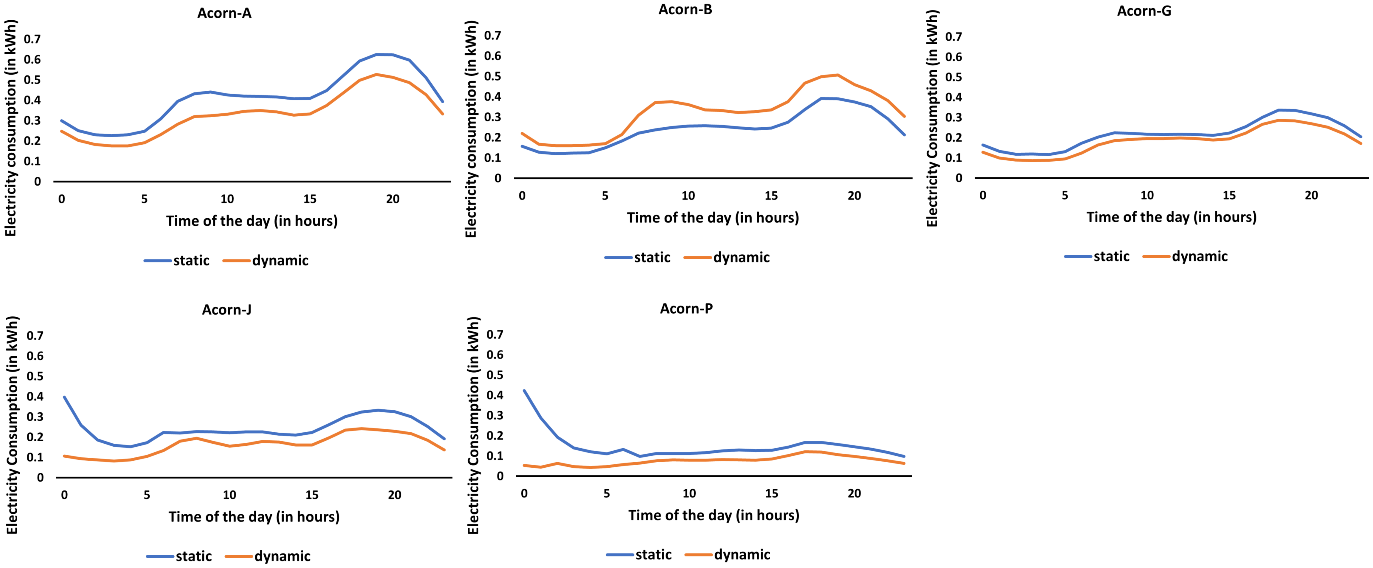

Fig. 3: Electricity consumption of ACORNs throughout the day (24 hours)

V. Results

Table III summarizes our results. Most geodemographic groups do not show a large difference in electricity consumption when there is a change in the pricing strategy. However, we notice that a few ACORN groups are sensitive to price changes, namely, ACORN-A, ACORN-B, ACORN-G, ACORN-J and ACORN-P. There change in consumption for these ACRONs is greater than 15%. These ACORN groups could be potential candidates for Demand Response (DR) programs. We discuss these ACORNs in the remaining of this section.

Figure 3 shows the results for the five ACORNs. We show the average electricity consumption of a home belonging to an ACORN group over a period of 24 hours. We depict the change in behavior of the home when the pricing scheme is switched from static to dynamic. The x-axis represents the hour of the day and the y-axis represents the consumption in kWh (Kilowatt-hour).

A. Acorn-A (Lavish Lifestyle)

We observe that Acorn-A has over 19% reduction when dynamic strategy is used. Since this group is the biggest consumers of electricity overall, they also have the potential to deliver the highest reductions for the Demand Response programs. This group consists of the most affluent people. Their annual incomes are higher than £100,000. They have high level of education levels and either work in top management jobs or own big businesses. Most of them own detached houses and have at least 5 bedrooms. Their house value is at least £1 million. Although they can very easily afford for their high electricity consumption, they still reduce their consumption when switched to dynamic tariffs. This maybe due to the fact that they have concern for the environment.

B. Acorn-B (Executive Wealth)

This group mainly contains middle aged people living in detached houses, which are around £750k to £1 million in value. Majority of them have 4 or 5 bedrooms and work in top administrative and management positions. They are mostly graduates and their salaries fall within the range £80k-£90k. They mainly work from home, which may explain their high electricity bills. As shown in figure 3, dynamic pricing does not result in reduction in consumption (their consumption is higher when dynamic pricing is used). This could be because the consumer may underestimate how much electricity they use (e.g. how much electricity a particular appliance consumes), and end up consuming higher electricity when dynamic pricing is used (because they do not check their usage/underestimate how much they use). Utility companies can use energy management programs that consider their work schedule. Utility companies can also design campaigns to reduce consumption targeting this particular group of consumers.

C. Acorn-G (Successful Suburbs)

The difference in for this group consumption is 15.79% when the pricing strategy is changed for this group. As we see from Figure 3, this group reduce their consumption when dynamic pricing is being used. This group involves people living in suburbs and semi-rural areas. Their houses normally contain 3 or 4 bedrooms and are valued around \$150k - \$250k. A significant proportion of people work in public sector jobs. This group include minorities, i.e. Asian families, and there is also a high proportion of Hindu, Sikh, Muslim families.

D. Acorn-J (Starting Out)

This group includes young couples who live in their very first homes. Some of them who have not yet bought a house are planning to buy a new home in the near future. They are still at the start of their careers. They usually spend a large amount of time over the internet and have an active social life.

Overall, this ACORN is sensitive to pricing strategies as people reduce their consumption on dynamic pricing. Therefore, it is a potential group for DR programs. Fig. 3 shows that dynamic pricing results in significant reduction in electricity consumption during the early hours of the day (after midnight till early hours of the morning).

E. Acorn-P (Struggling Estates)

This group includes low-income families in urban areas. These families have many children, and since the house sizes are small, there is overcrowding in the house. Most of these people work in factory jobs or in retail stores. This group also include unemployed people and they rely on social benefits. Social renting is high among this group.

As with ACORN-J, this group also achieve the highest reduction with dynamic pricing during the early hours of the day. Both ACORN-J and ACORN-P groups consume overall less electricity then more affluent groups, e.g. ACORN-A.

VI. Conclusion

This paper explores the impact of static and dynamic pricing strategies on the consumption behaviour of different geodemographic groups. We have found significant changes in the electricity consumption for various geodemographic groups. We believe that these findings can help implement static and dynamic tariffs more effectively, since we now know how the different geodemographic respond to the various price signals. Using this information, electricity companies can achieve greater demand reductions. In future, we plan to expand our study to understand whether consumers' response towards pricing strategies change over days of the week (i.e. whether their response is different on weekends vs. weekdays). We also plan to study seasonal effects on their response (e.g. whether there is difference between summer and winter months).

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