Smart Home Appliance Scheduling

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Abstract

This research aims to address the absence of a method to estimate potential cost savings for households in the UK that have the flexibility to shift their appliance usage based on dynamic electricity pricing. The study leverages a large dataset containing appliance usage data from over 39 homes to develop an optimized electricity consumption method. By analyzing the data for different appliance types, the research quantifies the potential cost savings that can be achieved by strategically adjusting appliance usage patterns in response to fluctuating electricity prices. We find that households can save up to £200 per year. The findings of this research can provide valuable insights for consumers in maximizing their bill savings while efficiently utilizing electricity resources.

Research Ethics Approval

This project was planned in accordance with the Informatics Research Ethics policy. It did not involve any aspects that required approval from the Informatics Research Ethics committee.

Declaration

I declare that this thesis was composed by myself, that the work contained herein is my own except where explicitly stated otherwise in the text, and that this work has not been submitted for any other degree or professional qualification except as specified.

(*Yue Sun*)

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Chapter 1

Introduction

Reducing energy cost in existing residential properties through modifications in occupant behavior is of paramount importance in addressing the financial difficulties faced by numerous households struggling to cover their energy expenses. Retail tariffs, most notably Octopus Agile, sets the price for the customers in the evening for each half-hour of next day. Theoretically, consumers can optimize their utilization of energy-intensive appliances like electric heaters, tumble dryers, and microwaves by operating them during periods of lower cost. However, the absence of a reliable method to estimate potential savings and the need for appliance-specific strategies to minimize expenses present intriguing areas for further investigation. This project aims to tackle these challenges by leveraging the extensive IDEAL datasets [1], which contain detailed information on appliance usage in 39 homes. Additionally, valuable tariff data from Octopus will be obtained through energy-stats.uk. The primary objective of the project is to develop simulations that demonstrate the potential cost savings achieved by shifting appliance usage to more economical timeframes.

The estimated cost savings would be significant as they can be applied in several realistic problems. For the households, the smart home appliance scheduling could help them save a lot of money on the use of electric appliances. Pedro et al. states that despite the individual size of each household being relatively small, their collective contribution to overall energy demand, especially during peak periods, is significant [2]. Running appliances at peak times means much more financial cost. People might have been aware of the higher cost on special times but they do not have an understanding of how much that value is. A precise data with good visualization could help customers make decisions better. In Scotland, 25% of households in 2019 were in fuel poverty. Current (2023) energy price increases are likely to further increase this proportion, particularly among low-income families [3]. Saving more money on electrical appliances might help the poor family mitigate their fuel poverty. For the appliance manufacturers, the estimated savings can also have some meanings. E.g., a washing machine cycle is complex and not all the washing machines remember where it was up to and resume. Would it be worth for manufacturers to include the remember function in their appliances? This function would provide the customers with more flexibility to schedule their appliances smartly. If the saving is high, then it would be worth for the manufacturers to include this function. What's more, shifting appliances to off-peak periods has benefits on energy systems. By decreasing the demand during peak periods, there is a potential to enhance the efficiency of the energy system in the near term and mitigate the requirement for additional generation and transmission infrastructure, particularly the expansion of fossil fuel-powered plants, in the long term [4]. This would benefit our environment as well.

This project mainly uses 2 datasets. One is the IDEAL dataset created by Goddard et al. [5]. This dataset consists of the energy cost data collected by sensors in 39 uk homes. Also, the data was collected in south Scotland, which suits our working place - Edinburgh well. Therefore the research result will be much realistic here. The other dataset is the agile tariff data in south Scotland, which stores the price data every 30 minutes.

The remainder of the paper is structured as follows. In chapter 2 we introduce the background of this project. In chapter 3 we describe the method which is used, and explore how the result is reached. In chapter 4, we analyze our result and make a visualization for it. In the end, we will summarize the report and give out a brief conclusion.

Chapter 2

Background

The primary objective of the project is to estimate the cost savings of electric appliances when they are moved to cheapest times. We are going to know how much the households will benefit from running appliances on off-peak times. On the other hand, how this operation would benefit other fields is also an interesting question. The power sector has long been striving to decrease peak electricity usage as a means to avoid the costly construction and operation of additional capacity[6] . However, beyond its financial benefits, this objective holds significant potential in terms of reducing carbon dioxide emissions [7] and enhancing the dependability of renewable energy systems [8].

Some research has been done on smart home appliance scheduling in the past ten years. Chen et al. proposed a smart energy scheduling method which took dynamic pricing models into their consideration [9]. This paper has focused on designing the scheduling algorithm itself, and the scope of its application is all the real-time pricing environments. Sai et al. proposed a secure appliance scheduling for flexible and efficient energy consumption scheme called SAFE, which effectively lowers electricity cost while preserving users' privacy [10]. In 2020, Alimi et al. stated that home energy management systems (HEMS) offer a promising approach to achieve cost-effective electricity consumption without sacrificing household needs. These schemes empower consumers to monitor, control, and optimize the energy usage of various household appliances, responding to Demand Response (DR) programs [11]. Through strategic scheduling of major appliances, residents can significantly reduce their electricity bills while maintaining a high level of efficiency in managing energy consumption [12].

However, these previous research have a drawback that they are not focused on some specified areas, and the situation of each different area would differ a lot. The pricing policy can be much different with the location changing. In this case, a regionally appropriate approach is quite needed for Edinburgh's residents. Moreover, some methods proposed by previous researchers were too complex that few households could really apply them in reality. If residents can derive sufficient benefits from merely shifting the timing of their appliance usage, it would result in not only cost savings for them but also yield advantages for the power sector in that region.

This project will be established in the household appliance use data in Edinburgh. Since the cost savings are computed based on the local tariff information, the results will be more referential for the residents in Edinburgh. As the result, the residents here can use this data as the basis for managing their own household electricity consumption directly. At the same time, this method could be used to estimate savings in other regions where dynamic tariff information is available as well.

Chapter 3

Methods

The main part of the project is implemented in python, and the rule-based methods are the optimization methods I use. This chapter will be divided in to the following parts: dataset analysis, rule-based optimization process and obstacles I met.

3.1 Dataset Analysis

The project starts with the analysis of the datasets we use. The first dataset is the IDEAL household energy dataset, which comprises electricity, gas and contextual data from 255 UK homes over a 23-month period ending in June 2018, with a mean participation duration of 286 days. Pullinger et al. mention that ”In addition, 39 homes formed an ‘enhanced group’, having additional sensors to measure real power electricity use for the whole home, selected sub-circuits, and a selection of high power and user-controllable electrical appliances [1] .” The data I need is the data from these 39 enhanced homes, whose sensors have measured the power electricity precisely.

To read the ideal data, I have used the ideal data interface example code provided by Goddard *et al* which is attached to the dataset [1]. The api can read the data from the dataset and each data object has the structure shown in table 3.1. One data object consists of the id of the home, the id of home, the type of the room, the electric category, the appliance type, the sensor id and the detailed readings. The data type of the readings is a dataframe, which has a structure like that in table 3.2.

Explicitly, there is a sensor for each electric appliance in the households that were recorded. The timestamp refer to the time that the sensors have recorded, and the correspond values refer to the real-time power at that time, and which continues unchanged until the time of the next reading. When appliances are running, the recording

homeid	roomid	roomtype	category	subtype	sensorid	readings
106	1085	kitchen	appliance	microwave	5211	...
136	1294	kitchen	appliance	dishwasher	9475	...
...	...	...	...	...	...	...

Table 3.1: The example of some data's structure read from the interface

Timestamp	**Power**
2017-05-17 18:46:01	0
2017-05-17 18:46:02	0
2017-05-17 18:47:53	133
2017-05-17 18:47:54	23
2017-05-17 18:47:55	246
...	
2018-06-14 07:28:06	0
2018-06-14 08:28:06	0
2018-06-14 09:28:06	0
2018-06-14 10:28:06	0
2018-06-14 11:28:06	0

Table 3.2: Example of the readings from one sensor

frequency would be higher. There are 219 tables of data we need to read in total.

The second data is the tariff data which is collected from https://energy-stats.uk/. The Agile tariff offered by Octopus Energy operates by monitoring the daily wholesale energy prices and releasing pricing information, typically between 4pm. and 8 pm., for the following day from midnight to midnight. This pricing model accounts for price fluctuations in electricity, which can vary every 30 minutes. The data I use is the agile tariff data in Southern Scotland. The structure of the tariff data is shown below as in table 4.1.

The tariff price changes every 30 minutes so the electricity price can be elastic in a day. This has brought the residents the possibility to save electricity costs by choosing off-peak times. With the energy consumed and the price data, the savings can be gotten by abundant computations. We will compute and present the detailed savings in the result part.

Figure 3.1 has shown one example distribution of tariff data on a specified date.

	time	Time	N	Region	Price
0	2018-02-21 00:30:00	00:30	N	Southern Scotland	10.5735
1	2018-02-21 01:00:00	01:00	N	Southern Scotland	10.6680
2	2018-02-21 01:30:00	01:30	N	Southern Scotland	10.1850
3	2018-02-21 02:00:00	02:00	N	Southern Scotland	10.1430
4	2018-02-21 02:30:00	02:30	N	Southern Scotland	10.1955
...					
92582	2023-06-03 19:30:00	20:30	N	Southern Scotland	16.3380
92583	2023-06-03 20:00:00	21:00	N	Southern Scotland	16.4010
92584	2023-06-03 20:30:00	21:30	N	Southern Scotland	16.0965
92585	2023-06-03 21:00:00	22:00	N	Southern Scotland	18.1230
92586	2023-06-03 21:30:00	22:30	N	Southern Scotland	16.5375

Table 3.3: Tariff data

Obviously, the tariff is highest between 15:00 and 18:00. This figure can reflect the overall distribution of tariff price, but we need more accurate calculation for the specified dates.

3.2 Rule-based Optimization

3.2.1 Overall rules

Since our project is greatly based on reality, we have constructed some hypothesis first that might be appropriate for normal households. Although the residents could save electricity cost by shifting their appliance use to cheapest times, not all electrical appliances are suitable for flexible adjustment of time. Based on this assumption, we created the following rules which limit the appliances' time shifting:

- can not be shifted: microwave, fridge freezer, electric heater, freezer, toaster, fridge, grill, electric oven, appliance, other
- can be shifted to anytime of that day: kettle, washing machine, dehumidifier, washing machine tumble drier, tumble drier
- whose data is not easy to record and not valid for modeling: vacuum cleaner

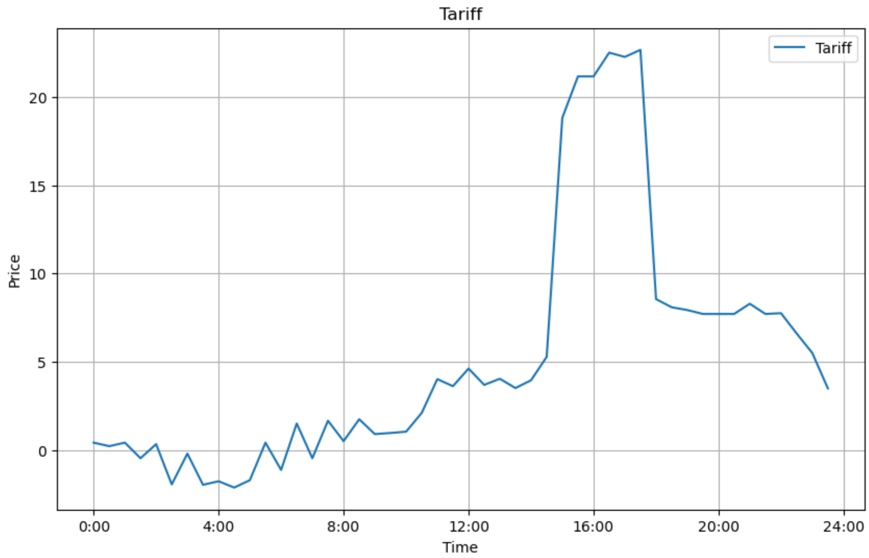

Figure 3.1: Example tariff of one day

Some appliances can not be shifted easily because people usually use them at relatively fixed times, such as the appliances for cooking. Fridge freezer is an example of appliance that should be run all day so it could not be moved to other time either. People usually can decide when to wash their clothes tomorrow in advance, and the appliances related to washing clothes are also energy-intensive. Dishwasher is a type of appliance that needs to be used before 4pm since people have to use the plates during the dinner.

3.2.2 Running time partitions

To make the cost saving optimization, the first thing to do is to divide the sensor readings in ideal data into pieces of working durations. A simple reason for this is that the running time of electric appliances can be much different. Some small appliances, such as dishwashers, usually run within half an hour. However, large appliances such as washing machines can run consecutively for longer than 2 hours. Considering the tariff data changes every 30 minutes, we have to move the appliance to ”cheapest period” but not ”cheapest time” when the running time is more than 30 minutes.

An appliance activation is defined as the time period when it is performing its main function. For example, the microwave is considered activated only when it is cooking food. If the microwave door is left open and the internal light is on, it does not count as activation, even though it may still consume energy during that time.

In order to calculate the activations of appliances, we have obtained some rules from Dr Goddard's lab's codebase. Thresholds are used to define when an appliance is considered to be activated. These define the minimum and maximum time duration of an activation, the minimum amount of time permitted between consecutive activations, and the minimum amount of power used at any point during an activation. For example, we define the "on_power_threshold" of microwave as 200. This means when the power is above 200 then the microwave is defined as open.

This method would help us partition the data of sensor readings and tell us when an appliance's use starts or ends.

3.2.3 Find the cheapest period and lowest cost

After partition divisions, we have been able to get the length of the running time of one appliance. However, in order to get the cost saving value, we still need to know the lowest price on that date. There will be different cases when the length of running time differs. If the appliance terminates in half an hour, we can just move it to the cheapest time of that day. But things are going to be more complex if it keeps running for longer than 30 minutes. For example, a washing machine runs for 2 hours. In this case, we have to find the "cheapest two hours" from the tariff data.

We can directly calculate the lowest average price of that activation's length on a given date. However, this method can be inaccurate. Because in fact the appliances do not use energy uniformly in most cases. For example, appliances like dishwashers and washing machinges use much more energy when heating water than when rotating the drum or pumping water, which are specific periods in their operation. So we have come up with a more accurate way, which is to convolve the appliance power demand curve with the tariff curve, starting at each half hour, and get the minimum of that.

The algorithm is shown in algorithm 1. The inputs include a demand list, a tariff list and the time range of the appliance which is k. First we calculate the intervals of these two lists and resample the demand list, then the two time series demand and tariff are aligned so that they have the same time intervals and can be effectively compared or convolved together. After that we set a small threshold to filter out the small values in the convolution result. This can help improve the accuracy and interpretability of the results by focusing on the most significant shifts in the demand pattern that lead to substantial cost savings or increases. At last we find the minimum of the convolution result and get the minimum cost.

Algorithm 1 Find Cheapest Period

Require: demand: List, tariff: List, k: Int

$demand\_interval \leftarrow \frac{k}{\text{length of demand}}$

$tariff\_interval \leftarrow \frac{48}{\text{length of tariff}}$

$resampled\_demand \leftarrow \text{repeat}(demand, \text{int}\left(\frac{\text{length of tariff} \times tariff\_interval}{demand\_interval}\right))$

$convolution\_result \leftarrow \text{convolve}(\text{abs}(resampled\_demand), \text{abs}(tariff), \text{mode} =' valid')$

$threshold \leftarrow 0.001$

$convolution\_result\_filtered \leftarrow []$

for x in $convolution\_result$ **do**

    if $x >$ threshold **then**

        $convolution\_result\_filtered.\text{append}(x)$

    end if

end for

if length of $convolution\_result\_filtered > 0$ **then**

    $cheapest\_period\_index \leftarrow \text{argmin}(convolution\_result\_filtered)$

    $cheapest\_period\_value \leftarrow convolution\_result[cheapest\_period\_index]$

end if=0

3.2.4 Savings Calculation

The core part of the programming part is the savings calculation. With the time partitions divided and the lowest cost computed, we have had the foundation for this calculation.

The algorithm 2 shows the steps inside the savings calculation process. In order to make the best use of every useful information we have, we have used an algorithm with 3 layers of for-loops. The outside loop is to iterate through every appliance in the dataset. Since we calculate the savings for each appliance once, so we can get the saving of one appliance each time we go over the outer loop. After that the algorithm goes into the second loop. This loop is to iterate through the each activation of this appliance. In this loop, we calculate k, which refers to the number of 30 minutes this workload have taken up. The inner loop is where we do the saving calculations, Here we go over each timestamp which is recorded by sensors in the data, and accumulate the total original price according to the tariff data. Because the readings of the sensors are in units of power instead of energy, we compute the gap between current timestamp and next one first, then multiply it by the power. As stated above, we could calculate the lowest cost by implementing convolution on the list 'tariff' and 'demand'. By subtracting the lowest cost from the original price, then the savings are calculated successfully.

3.3 Obstacles

3.3.1 Tariff lost before 2018

The data in the ideal dataset was collected from 2016 to 2018. This has brought me the first challenge: There is no tariff information before 2018. The tariff data from https://energy-stats.uk/ has stored price data since 2018. This means our cost saving can not be applied on their real using time.

To handle this problem, we decide to calculate the cost savings based on one same year, the year 2022, which is recorded in tariff data. This change means we assume that all electricity is charged based on the same year's price, as if all the dates in the timestamps DD-MM-YYYY are DD-MM-2022. This operation has the following meanings:

- Electricity charged based on the same year's price makes it easier for us to compare the cost savings of different types of appliances. The savings computed based on one year's price can be more referential if we are going to analyze the

Algorithm 2 Calculate Savings

```
for each table in data do
    Initialize total saving
    Initialize 'timestamps' and 'values' using the current appliance id
    for each activation in the current table do
        Calculate the running time length 'k' based on the activation partitions
        Initialize the demand and price
        for each timestamp in the current activation do
            Calculate the next timestamp using the timestamp records
            Calculate the number of hours between the current timestamp and next timestamp
            Transfer the year in the current timestamp to 2020
            if hours < 1 then
                Append the energy demand on current timestamp to list 'demand'
                Add the original cost of current time to 'price'
            end if
        end for
        Filter the tariff data on the activation's date and get the list 'tariff'
        Implement convolution on 'tariff' and 'demand' and get the lowest cost
        Substract the lowest cost from the original price and get the saving
        Add the saving of current activation to the total saving
    end for
    Store the saving of the current table into file
end for=0
```

results integrally.

- We did not change the residential electricity consumption data itself, we just unified the standard of pricing. This solves the problem of not having price data from before 2018.

3.3.2 Running Speed

Due to the huge size of the dataset used, we encountered this predictable difficulty. For some appliances, there are more than one million pieces of records in one file. Iterating through so many lines of data would cost us too much time without efficiency optimization.

To conquer this problem, we have taken several methods to optimize the running speed. The first one is saving the interim results in a file before the main program so that we will not have to compute these results every time we go over the loop. This is to avoid the repeated calculations.

Another method we have tried is parallel programming. Considering the independence of iterations, parallel programming might be a efficient method for improving the running speed of the program. But after we practised using that, we found that the concurrent running could not improve the speed sufficiently.

3.3.3 Distinguished Values

The program has produced some distinguished values in the process of calculating. Some are greater than one million and some are less than minus one million. These values are obviously wrong. After analyzing the data and the program, we have found these reasons:

- We have included the last timeframe in the inner iteration of calculation. This has led to the missing of next timeframe, then the next timestamp would be set to default value, which is very old such as 1954. Thus the time gap computed would be very strange.

- Sometimes there were huge intervals between the adjacent readings of a sensor. This might cause the time used by the appliance to be estimated very high, however that is always not true. To avoid this kind of error we included a condition clause to forbid the similar situations.

3.3.4 Rules designing for activation calculation

The activation of the electric appliances are in fact much more complex than what it seems to be. It's hard for us to define a uniform standard, because the detailed attributes differ a lot for the different kinds of appliances. For example, a washing machine could only be classified as activated on a high power demand, when for a kettle the things could be exact opposite. If we define a public threshold for both of them, neither of their accuracy could be satisfactory.

At first we just defined a public rule to calculate the activation of the appliances. However, the result was poor. After implementing a new rule which respectively contains a rule for each appliance type, we run the program again and got a much better result.

Appliance	**min_on_duration**	**max_on_duration**	**on_power_threshold**
dishwasher	600	15000	50
kettle	10	600	1000
washingmachine	1200	30000	50
tumbledrier	1200	30000	50
washingmachinetumbledrier	600	30000	50
dehumidifier	10	100000	100

Table 3.4: Thresholds

Some of the thresholds are shown in table 3.4. From the table we could see that the minimum threshold for kettle's duration is much lower than that of washing machine's. This also reflects the power demand difference between these appliances. As a result, in order to get over the difficulties of activation judgement, an individual rule is necessary for each appliance type. These values were obtained from Dr. Goddard's lab's codebase.

Chapter 4

Result

We have implemented the calculation of cost savings for these six appliance types based on the rules stated previously: washing machine, washing machine tumble drier, dehumidifier, tumble drier, dish washer and kettle. We have chosen these appliances as their using time are relatively more flexible.

The result part is divided into two subsections: one is the result analysis for 2022, the other refers to the result comparison between 2022 and 2020.

4.1 Result Analysis for 2022

We choose the tariff data from 2022 since this is the most recent year in the data, which could mean more reference. First we visualized the average savings per used time of different appliance types. The result is shown below in figure 4.1. The figure has told us that residents can save most one time when a dish washer or a washing machine tumble drier is shifted to the cheapest time, followed closely by the washing machine. The saving of a dishwasher or a washing machine tumble drier are around 30 pence a time. This is easy to understand as dish washers and washing machine tumble driers are large electrical apparatus. Washing machines are large appliances as well. They usually cost more electricity and took more running time. Small appliances like kettles would cost less in a time. The estimated saving on using kettle a time is 0.9 pence, which is a very small number.

The previous analysis approach has certain limitations. As stated above, some appliances have a much longer running time compared to other types, which can lead them to save more in a time. What's more, the using frequency of appliances differ a lot as well. Thus, we visualized the average saving per year this time in figure 4.2.

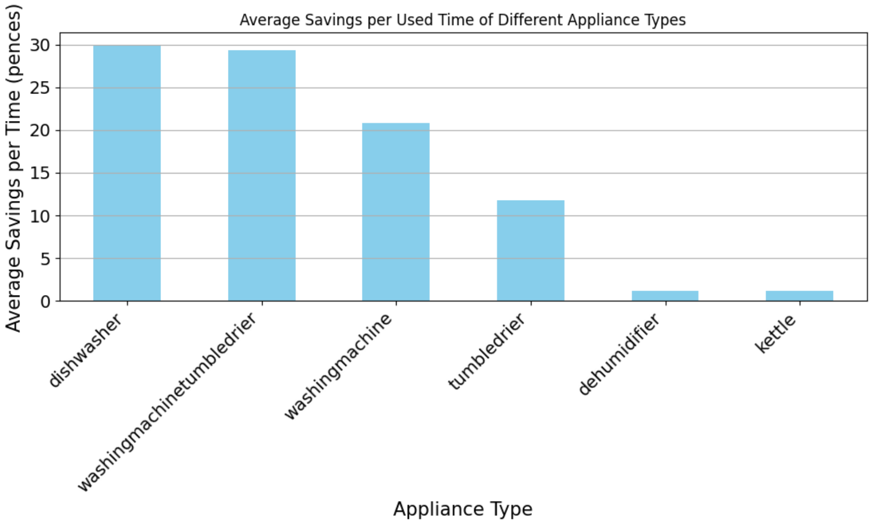

Figure 4.1: Average savings per used time

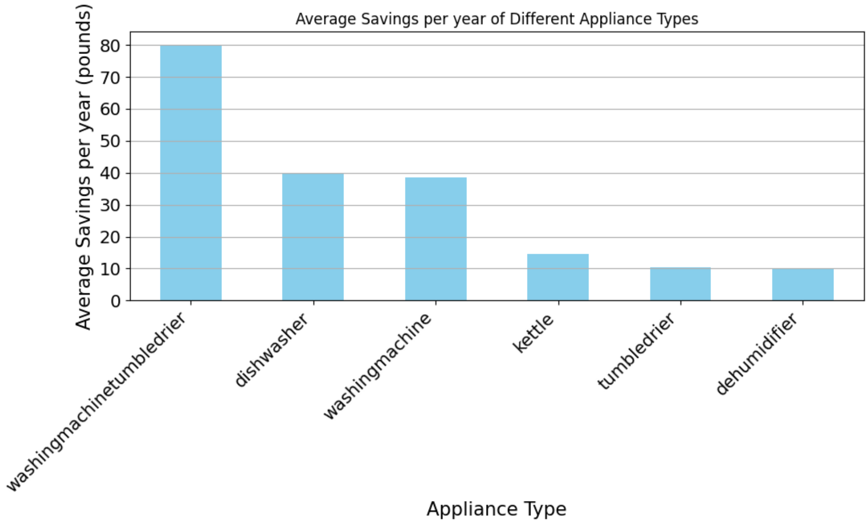

Figure 4.2: Average savings per year

We can observe from figure 4.2 that shifting washing machine tumble driers can lead to the most savings per year, which is estimated to be near £80. When applying our appliance scheduling rule, residents could save around £40 a year for a washing machine or a dish washer. Even for the relatively small appliances, people could save around £15 a year. The saved money would be considerable if these numbers are added up. From a certain point of view, this figure is more referential for residents to compare the savings of different appliances since it could reflect directly the cost savings of these appliances through the years.

Other than comparing the cost savings of different kinds of electric appliances, we have also analyzed the distribution of savings within one appliance type. This is also critical since the average value could not represent the reality perfectly and we should also pay attention to what most cases are like. The figure 4.3 has shown the distribution of 4 types of appliances. Dehumidifier and tumble driers are not included because they have only two or three samples in the data. Small samples are not referential for this graph.

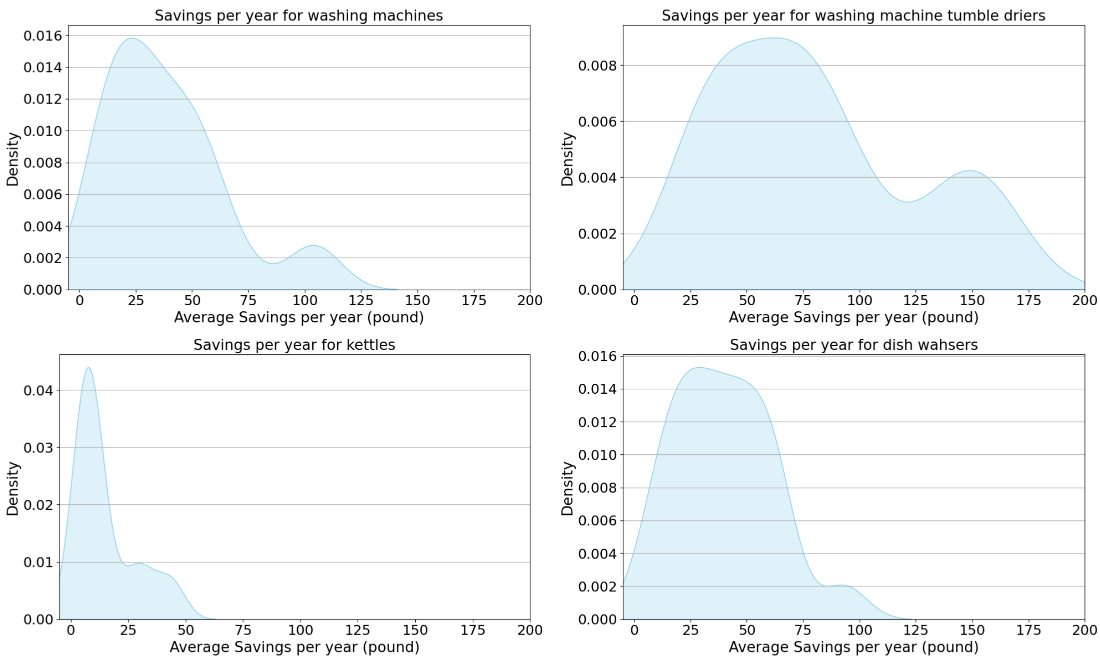

Figure 4.3: Distribution of savings per year for appliances in 2022

From the distribution of washing machines, we observe that most household could save around £25 to £40 a year on their washing machines, which matches the average value. This means this number is a relatively referential result. Also, we have observed that other than the highest peak around 25 pounds, there is also another lower peak which is more than 100 pounds. A plausible explanation for this is that most households don't wash clothes so frequently. They only wash their clothes 2 or 3 times a week, because they often gather enough clothes to wash together. However, some people take cleanness so seriously that they have to wash their clothes immediately every time they change. This has led to some households using washing machines much more than the normal ones.

The distribution of washing machine tumble driers is different from the previous one. There are two peaks in the graph as well, one is around £75 when the other is more than £150. This can be explained by the fact that most people do not use tumble driers every time after they wash the clothes since the clothes can be dried in the sun and the cost of tumble driers is high. But some people don't care it ana just use the washing machine tumble drier to dry the wet clothes every time.

When analyzing the distribution graph of dish washers and kettles, we may find that their peak values are both close to their average saving data. This has reflected that the saving per year of these two kinds of appliances have a relatively normal distribution. £10 a year for kettles and £25 a year for dish washers are referential enough.

The result above could provide the households some ideas on how to save money on their electric appliances. Moving their washing machines, dish washers and washing machine tumble driers could save them around 160 pounds a year in total. That is a considerable number. I think this can answer two questions for the households in need:

- Is it worthy for me to move my appliances to off-peak times?
- What appliances should I choose to shift their using times?

When shifting the using time of one large electric appliance could save more than 40 pounds a year, the earnings from shifting a small appliance could be from 10 pounds to 20 pounds. People could make decisions considering whether this earning is attractive enough for them. Also, they can choose what appliances to move based on the savings of shifting these appliances.

Appliances to shift	**Average savings a year in pounds**
Dish Washer	80.02
washingmachine+its tumbledrier+dishwasher	158.78
all 6 types of appliances	193.45

Table 4.1: Savings based on chosen appliances for reference

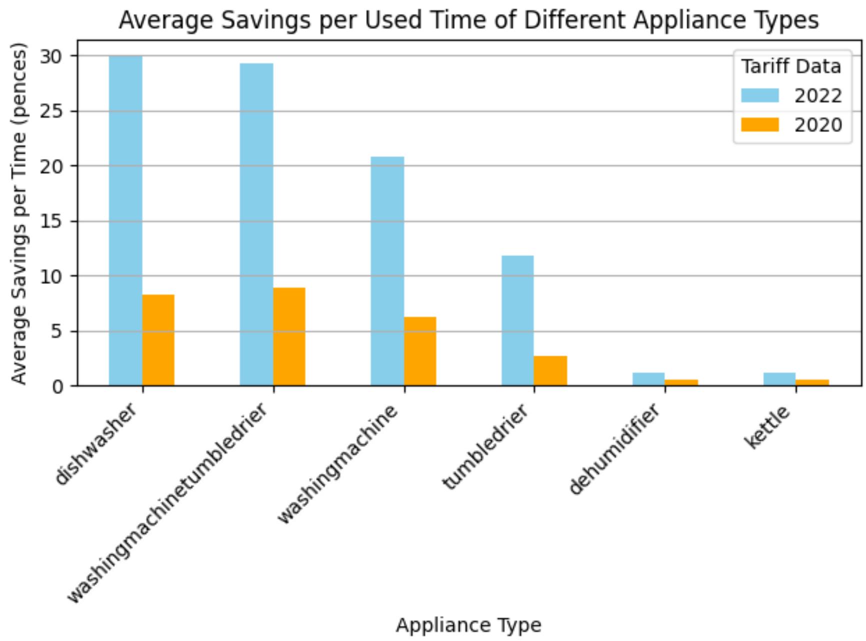

Figure 4.4: Comparison of average savings per used time between 2020 and 2022

From table 4.1, we can see that if households choose to move their large appliances (washing machine tumble drier, washing machine and dish washer) to cheapest time, they could save nearly 160 pounds a year. I think this number of money is meaningful for the family who are in straitened circumstances, especially the poverty.

4.2 Comparison between 2020 and 2022

We have also implemented the cost saving calculation based on the tariff in 2020. The purpose of this step is to make a comparison between the cost savings of these 2 years, and it could tell us how fast the electricity price has increased. It could mean more savings if we choose to do the home appliance scheduling as stated in this paper.

The figure 4.4 visualizes the average saving per used time between these 2 years. From this graph we can easily find that the average saving per time in 2022 is nearly 3 times of that in 2020 although the time difference is only 2 years between them. The most possible explanation is that the tariff has risen more than 3 times in these 2 years, and that means customers can save more cost in this circumstance.

The figure 4.5 which records the average saving per year of these two years has reflected a similar feature. Obviously, people could really save much more in 2022 than in 2020 if they shift the appliances to off-peak times. With the year of 2024 coming

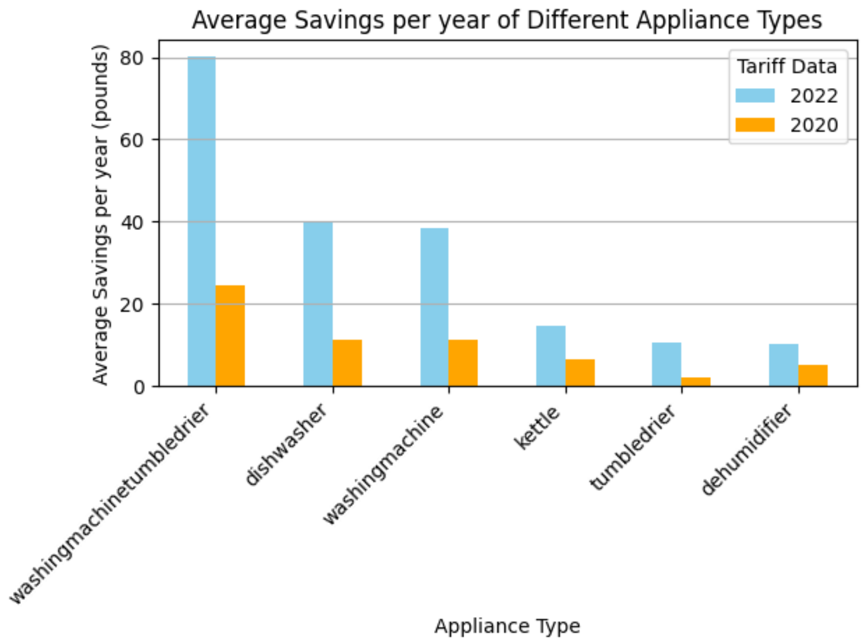

Figure 4.5: Comparison of average savings per year between 2020 and 2022

soon, we could assume that there will be a rise in tariff with such a wide range as well. Although the cost saving calculated by us is based on the tariff data in 2022, the possible cost savings in the next years can only be larger than the data presented in this paper.

We have visualized the distribution of cost savings in 2020 as well, just as shown in figure 4.6. The purpose of presenting these figures is to verify that the distribution of cost savings for one appliance would not differ too much when the year changes.

From the comparison between figure 4.6 and figure 4.3 we can conclude that the distribution of one appliance is similar no matter which year of tariff data is used. The graphs for washing machines and washing machine tumble driers still have two peaks when those of dish washers and kettles still have one. This result matches the result in figure 4.3 well.

4.3 Savings for households

In this part we have counted the savings according to individual households. For each individual household, we added up the saving per year of all their appliances which were collected in data.

The disparity in the number of appliances counted in different households has led to an limitation of this analysis. The majority of households in the dataset have data

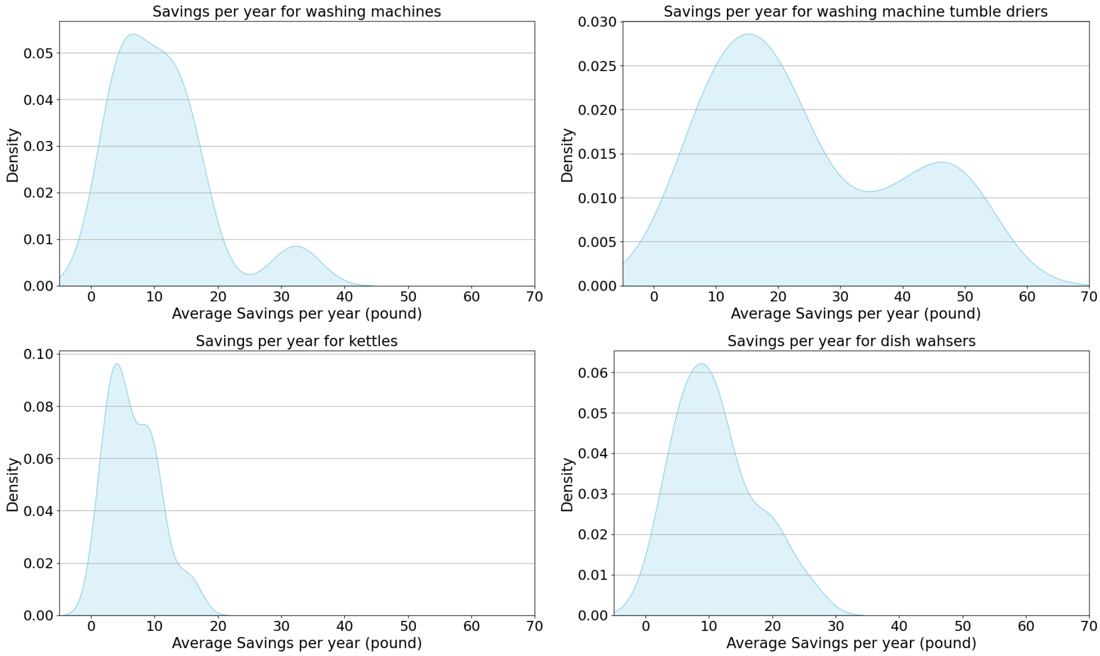

Figure 4.6: Distribution of savings per year for appliances in 2020

recorded for two or three appliances, indicating that these households likely have a moderate number of devices being monitored or studied. However, there are also cases where only one appliance has been recorded, suggesting a simpler setup, while others have data for five appliances, hinting at a more comprehensive monitoring approach.

Therefore, we can make some simple assumptions to analyze the distribution of households' total savings per year as shown in figure 4.7. There are a total of 3 local minimums in this graph. The first local minimum, which means about 25 pounds of savings per year, can be collected from households which had only 1 appliance been recorded. The second peak is about £80 per year, and those households might have 2 or 3 appliances collected in the data. For the last peak with a saving which is more than 150 pounds per year, the reason could be that those houses had more than 3 appliances been recorded.

Although the graph could not be referential for any customer, we can conclude from it that a household could save about 80 pounds a year in average when applying our scheduling method. In fact, It's normal for different households to have different numbers of appliances to be shifted. Most family could not shift using time of all their large appliances. As a result, the data shown in figure 4.7 can still be meaningful.

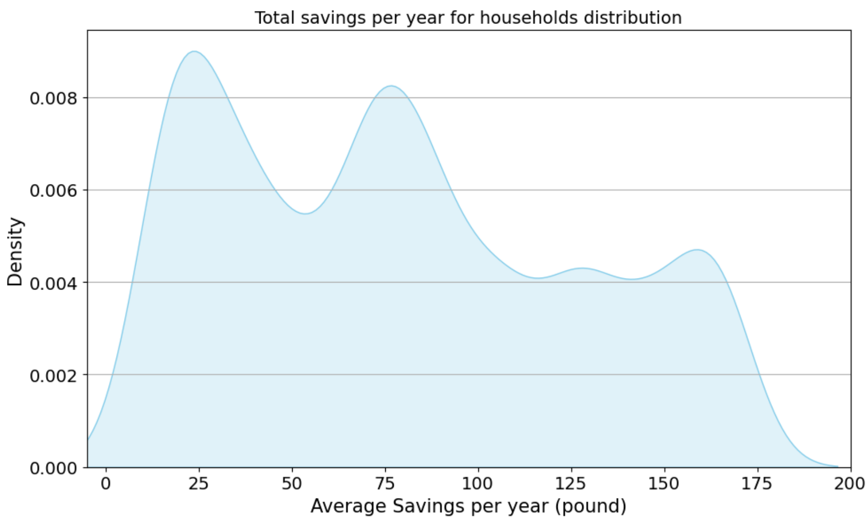

Figure 4.7: Distribution of households' total savings per year

Chapter 5

Conclusions

In this paper, we have calculated the estimated cost savings of electric appliances when shifting them to the cheapest periods, and analyzed why that data could be so meaningful.

According to the tariff data in 2022, if households could move their large appliances to cheapest time, they would save nearly £40 for each of these appliances every year. This can be helpful for households who are now struggling with energy poverty [3]. We have also visualized the comparison of cost savings among different types of appliances. The result shows that the potential saving from large appliances are more than twice times that from small ones. This data is referential for people to decide which appliances to schedule in priority and how many appliances they should schedule.

From the comparison between the result of year 2022 and 2020, we could conclude that the estimated cost savings had a good chance to be higher in the future years. That conclusion might give people more motivations to schedule their appliances smartly.

There are some other things which can be done to improve the work in the future. To begin with, It's possible for some appliances to be run for more than one time a day, and the cheapest period should not be overlay within the same range. In this research, we have assumed that each activation could be moved to the cheapest period and we avoided the situation that the same appliance might have already been scheduled to that period. if we could optimize this problem, the calculation result would be more accurate.

Collecting more data can be another possible method to improve our work. Murray et al. created the REFIT Electrical Load Measurements dataset which includes cleaned electrical consumption data in Watts for 20 households at aggregate and appliance level, timestamped and sampled at 8 second intervals [13]. The structure of that dataset closely resembles the ideal dataset that this research study has utilized. This means that we could utilize the Refit dataset in the future to extend our work.

Last but not least, we could use NILM technique as a way to make the estimated cost savings more accurate. NILM provides online feedback on the energy consumption of households to let users be well aware of the situations and help them to change use patterns when needed [14]. If households could use NILM to measure their use of the most cost-saving appliances, then we could have more reliable data to make a more accurate result possible.

Overall, there is significant potential for UK households to reduce their energy expenses through strategic scheduling of appliance usage. We are optimistic that the findings of this study will prove beneficial to individuals facing energy affordability challenges, providing them with valuable insights on optimizing their appliance usage timings.

Bibliography

[1] Martin Pullinger, Jonathan Kilgour, Nigel Goddard, Niklas Berliner, Lynda Webb, Myroslava Dzikovska, Heather Lovell, Janek Mann, Charles Sutton, Janette Webb, and Mingjun Zhong. The ideal household energy dataset, electricity, gas, contextual sensor data and survey data for 255 uk homes. *Scientific Data*, 8, 05 2021.

[2] Stein W. Wallace Zhan Pang Pedro Crespo Del Granado. The value of electricity storage in domestic homes: a smart grid perspective. 03 2014.

[3] Janice A Foster. Domestic energy consumption: temporal unregulated electrical energy consumption in kitchens in scottish affordable and social housing. *Energy Efficiency*, 2023.

[4] Yingkui Yang, Mingyue Wang, Yu Liu, and Li Zhang. Peak-off-peak load shifting: Are public willing to accept the peak and off-peak time of use electricity price? *Journal of Cleaner Production*, 199:1066–1071, 2018.

[5] Jonathan; Pullinger Martin; Arvind D.K; Lovell Heather; Moore Johanna; Shipworth David; Sutton Charles; Webb Jan; Berliner Niklas; Brewitt Cillian; Dzikovska Myroslava; Farrow Edmund; Farrow Elaine; Mann Janek; Morgan Evan; Webb Lynda; Zhong Mingjun Goddard, Nigel; Kilgour. Ideal household energy dataset. Technical report, University of Edinburgh. School of Informatics, 2021. url https://datashare.ed.ac.uk/handle/10283/3647 .

[6] Ahmad Faruqui, Dan Harris, and Ryan Hledik. Unlocking the €53 billion savings from smart meters in the eu: How increasing the adoption of dynamic tariffs could make or break the eu's smart grid investment. *Energy Policy*, 38(10):6222–6231, 2010. The socio-economic transition towards a hydrogen economy - findings from European research, with regular papers.

[7] Peter Bradley, Matthew Leach, and Jacopo Torriti. A review of the costs and benefits of demand response for electricity in the uk. *Energy Policy*, 52:312–327, 2013. Special Section: Transition Pathways to a Low Carbon Economy.

[8] Frontier Economics and Sustainability First. Demand side response in the domestic sector-a literature review of major trials. *Final Report, London*, 2012.

[9] Xiaodao Chen, Tongquan Wei, and Shiyan Hu. Uncertainty-aware household appliance scheduling considering dynamic electricity pricing in smart home. *IEEE Transactions on Smart Grid*, 4(2):932–941, 2013.

[10] Sai Mounika Errapotu, Jingyi Wang, Yanmin Gong, Jin-Hee Cho, Miao Pan, and Zhu Han. Safe: Secure appliance scheduling for flexible and efficient energy consumption for smart home iot. *IEEE Internet of Things Journal*, 5(6):4380–4391, 2018.

[11] O. A. Alimi and K. Ouahada. Smart home appliances scheduling to manage energy usage. In *2018 IEEE 7th International Conference on Adaptive Science Technology (ICAST)*, pages 1–5, 2018.

[12] Ping Zhang. Home automation and housing for the future. *Diss. Faculty of Graduate Studies and Research in partial fulfilment of the requirements for the degree of Master of Architecture School of Architecture, Carleton University Ottawa*, 2003.

[13] David Murray, Jing Liao, Lina Stankovic, Vladimir Stankovic, Richard Hauxwell-Baldwin, Charlie Wilson, Michael Coleman, Tom Kane, and Steven Firth. *A data management platform for personalised real-time energy feedback*. 2015.

[14] Antonio Ruano, Alvaro Hernandez, Jesus Ureña, Maria Ruano, and Juan Garcia. Nilm techniques for intelligent home energy management and ambient assisted living: A review. *Energies*, 12(11), 2019.