UiO : Department of Informatics
University of Oslo

Authors: David Fordham, Oskar Våle, Hui Zhang

Assignment 1: Use appliances intelligently at your home

IN5410/IN9410 — Energy Informatics: Group 3

Spring 2024

This report outlines our solutions for Assignment 1 on Demand Response as part of the Energy Informatics course.

Demand response refers to the adjustment of electricity usage patterns by end-users in response to variations in electricity prices over time. It can also encompass incentive programs aimed at reducing electricity consumption during periods of high wholesale market prices or when system reliability is at risk. There are generally two types of demand response programs: Incentive Based Programs and Price Based Programs.

In this assignment, we would focus on Price Based Programs which include Time of Use (ToU) Pricing scheme and Real Time Pricing (RTP) scheme, and we would explore the differences between ToU and RTP schemes and their applications in residential areas with households equipped with various appliances.

1 Question 1

We have a simple household that only has three appliances: a washing machine, an EV and a dishwasher. We assume the time-of-Use (ToU) pricing scheme: 1 NOK/kWh for peak hour and 0.5 NOK/kWh for off-peak hours. Peak hours are in the range of 5:00pm - 8:00pm while all other timeslots are off-peak hours. We assume the peak hours start at 17:00, and finish at 19:59, which means starting from 20:00 the peak hours finish.

1.1 Assumptions

Below are some assumptions we made related to the consumers' preferences for using their appliances:

Washing machine and dishwasher

We assume that there is no specific time these have to be used or cannot be used. We do not know enough about the people living in the households to determine when exactly they would use these machines.

EV

We set the consumption of power of the EV to be outside of possible working and commuting hours, as we feel it is fair to assume the car will typically be gone in these hours.

1.2 Optimization Problem

The pricing scheme used for this problem is the Time-of-Use (ToU) pricing scheme:

- For the cost of electricity during peak hours (from 5:00pm to 8:00pm):
  price = 1 NOK/kWh
- For the cost of electricity during off-peak hours:
  price = 0.5 NOK/kWh

Consumption of the three shiftable appliances:

- Dish Washer: (daily usage: 1.44 kWh)
- Washing machine: (daily usage: 1.94 kWh)
- Electric Vehicle (EV): (daily usage: 9.9 kWh)

Since the curve is this predictable and flat, our strategy is clear to see. We should only use our shiftable appliances in the off-peak hours. Other than that, we should spread out the usage across the off-peak hours since the shiftable appliances can only use a limited amount of power at a time.

To solve the optimization problem and find the minimum cost, we used the Python library PuLP. We defined the decision variables for whether each appliance runs during peak hours as binary values 0 or 1.

- x_1 as binary variable of Washing Machine if it works during peak;
- x_2 as binary variable of EV if it works during peak;
- x_3 as binary variable of Dish Washer if it works during peak.

We defined the objective function (total cost) as:

$$\min(1.94(x_1+0.5(1-x_1))+9.9(x_2+0.5(1-x_2))+1.44(x_3+0.5(1-x_3)*0.5)). \quad (1)$$

The summary of the algorithm can be checked in figure 12.

1.3 Results and Strategy

The total optimized energy cost is 6.64 NOK.

A visualization of the ToU pricing curve used in this problem can be found in figure 1, and an example of how one might design the consumption profile of shiftable appliances around the ToU pricing curve can be seen in figure 2. The key is to not use power in the peak hours.

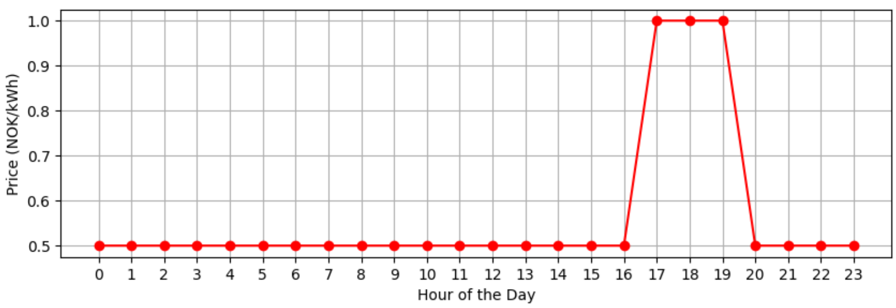

Figure 1: ToU pricing curve considered in question 1.

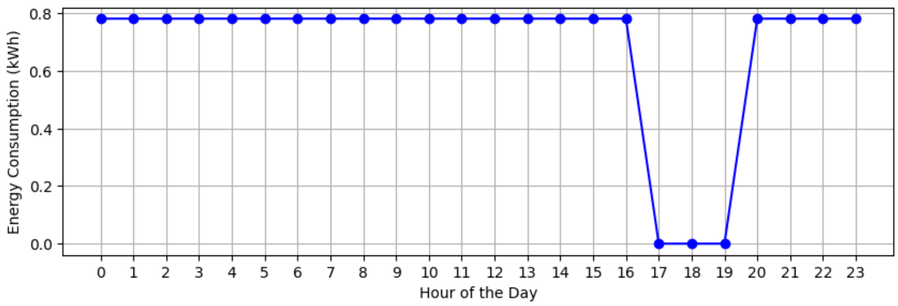

Figure 2: Example of consumption profile of shiftable appliances under ToU pricing scheme.

2 Question 2

We have a household with shiftable and non-shiftable appliances, as listed in the assignment. In addition to these, a random combination of extra appliances is to be selected for the household. Real-Time Pricing (RTP) scheme is to be used. The RTP model uses a random function to generate the pricing curve in a day, which consider higher price in the peak-hours and lower price in the off-peak hours. The goal is to minimise energy cost.

2.1 Optimization Problem

We first select the additional appliances, in our case a router, a coffee maker, and a toaster. They are all non-shiftable, as the router must be on the whole day, and the two latter for an hour during breakfast. The detailed array of appliances considered can be seen in table 1, and typical consumption and power rating values, when not available in the assignment description, were obtained using the calculator [3].

Appliance	Shiftable?	Daily use (kWh)	Power rating (kW)	Start hour	End hour
Lighting	N	1	0.1	10	20
Heating	N	9.6	0.4	0	24
Refrigerator	N	3.96	0.165	0	24
Stove	N	3.9	1.3	13,19	14,21
TV	N	0.6	0.12	17	22
PC	N	0.6	0.15	17	21
Router	N	0.144	0.006	0	24
Coffee Maker	N	0.3	0.3	7	8
Toaster	N	0.6	0.6	7	8
Dish Washer	Y	1.44	1.8	?	?
Washing Machine	Y	1.94	1	?	?
Tumble Dryer	Y	2.5	3	?	?
EV	Y	9.9	3.6	$\notin [8, 18)$	$\notin [8, 18)$

Table 1: List of appliances considered and assumptions taken. Data was either taken from assignment description or from the energy calculator [3].

Regarding the price curve, we define morning hours, 6h-11h, peak hours, 17h-20h, and off-peak hours, and attribute a price range typical for each period, resorting to past data from Tibber. These ranges are 0.9-1.3 NOK/kWh for peak hours, 0.8-1.1 NOK/kWh for morning hours, and 0.5-0.8 NOK/kWh for off-peak. We then generate the curve by applying the random method from python to each of these ranges, obtaining a semi-random profile, and seed it to guarantee reproducibility.

Regarding the mathematical formulation of the problem, we can define it as in equation (2):

$$\begin{aligned} \min \quad & \sum_{i,t} P(t)(x_s(i,t) + x_{ns}(i,t)) \\ \text{s.t.} \quad & \sum_t x_s(i,t) = E(i), \\ & x_s(i,t) \leq \gamma(i), \\ & x_s(\text{EV},t) = 0 \quad \forall \quad t \in [8, 18), \\ & x_s(i,t) \in \mathbb{R}_0^+, \end{aligned} \tag{2}$$

for each and every appliance i and time slot t, where P is the price curve, x_s is the energy usage of device i at time t for shiftable appliances, x_{ns} is the analog for non-shiftable appliances, E is the daily consumption of the appliances, and γ is their maximum power rating. The first constraint guarantees that the daily energy usage is achieved, the second that the power rating is not exceeded, the third that the EV is only scheduled for charging outside of working hours, when the user is home, and the last one that we don't have negative consumptions. This is therefore a linear optimization problem, that will ultimately find the ideal shiftable power consumption profile $\boldsymbol{x_s}$.

We implement this optimization problem in Python's Pyomo framework, and solve it using the COIN Branch and Cut solver (CBC), which uses a primal or dual simplex algorithm for LP optimizations. Please refer to figure 12 for the process flow.

2.2 Results and Strategy

The RTP price curve method results in figure 3. As expected, it results in a price point for each hour of the day, and has clearly defined morning, peak, and off-peak periods, despite the apparent randomness of the individual data points themselves.

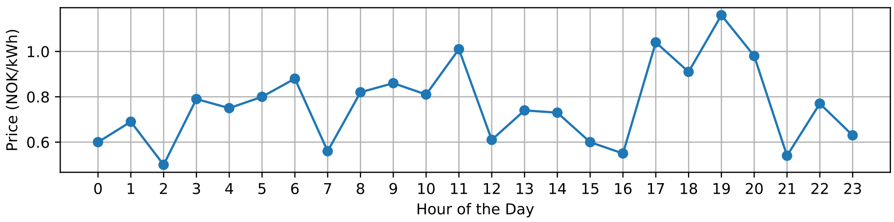

Figure 3: Semi-random pricing curve taking in account morning, peak, and off-peak hours, according to RTP pricing scheme.

The resulting shiftable and non-shiftable appliance consumption profiles can be checked respectively in figure 4 and 5. Additionally, a direct comparison of shiftable, non-shiftable, and total consumption can be found in figure 6. As expected, this algorithm will attempt to max out the power rating of shiftable appliances at time slots with lower energy prices. These consumption spikes make up the largest chunk of the total energy consumption when they occur, and are largely out of proportion with the non-shiftable consumption, though they are mostly scheduled for off-peak hours, as opposed to a big part of the non-shiftable appliances.

The optimized total daily energy cost is 25.6 NOK.

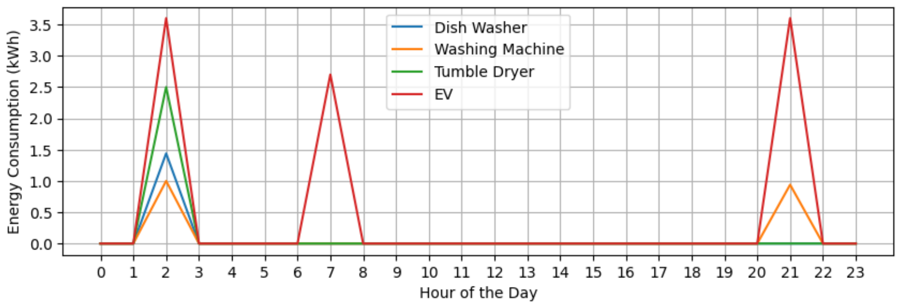

Figure 4: Energy consumption profile of shiftable appliances.

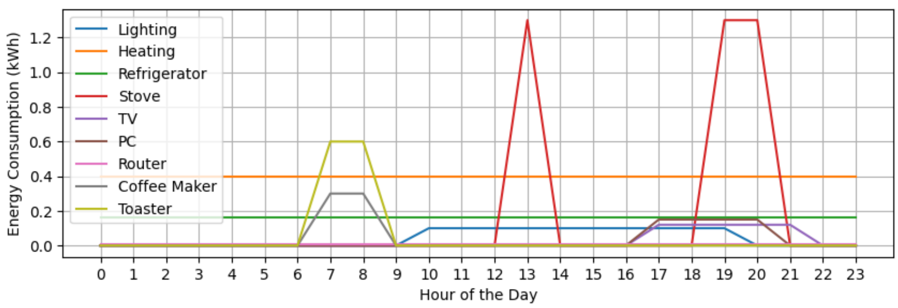

Figure 5: Energy consumption profile of non-shiftable appliances.

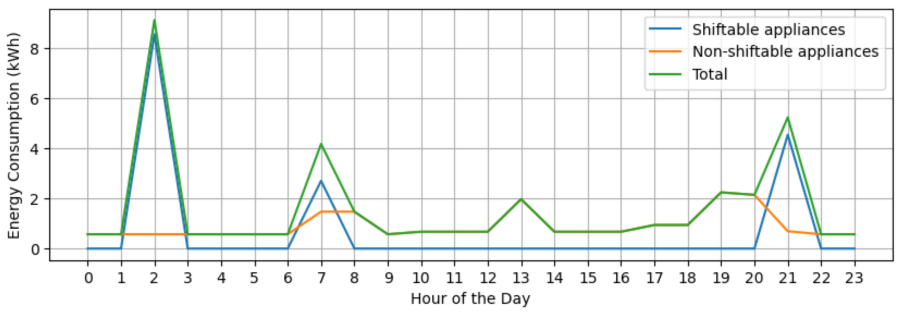

Figure 6: Total household energy consumption profile.

3 Question 3

We consider a small neighborhood that has 30 households. Each household has the same setting as that in question 2, but only a fraction of the households owns an EV. We use the Real-Time Pricing (RTP) scheme, and use a random function to generate the pricing curve in a day, which has higher prices in the peak-hours and lower prices in the off-peak hours. We compute the best strategy for scheduling the appliances and write a program in order to minimize energy cost in the neighborhood.

3.1 Optimization Problem

For finding our best strategy for scheduling the appliances in this case, we used the exact same settings for the non-shiftable appliances as in task 2 for each household. Furthermore, we let 10 of the households have an EV ("EV-households"). The mathematical definition of this optimization problem is as follows:

$$
\begin{aligned}
\min \quad & \left(\sum_{t \in T} \sum_{j \in J} \sum_{i \in I_s} \left(P(t) \cdot x_s(i,j,t) \right) + \sum_{t \in T} \sum_{i \in I_{ns}} \left(P(t) \cdot x_{ns}(i,t) \right) \right) \\
\text{s.t.} \quad & \sum_{t \in T} x_s(i,j,t) = E(i), \quad \forall i \in I_s, \forall j \in J, \\
& x_s(i,j,t) \leq \gamma(i), \quad \forall i \in I_s, \forall j \in J, \forall t \in T, \\
& x_s(\text{EV},j,t) = 0, \quad \forall j \in J_{\text{noEV}}, \forall t \in [8,18), \\
& x_s(i,j,t) \in \mathbb{R}_0^+, \quad \forall i \in I_s, \forall j \in J, \forall t \in T,
\end{aligned}
\tag{3}
$$

where:
- J is the set of households, with $J = \{0, \ldots, \text{NUM\_HOUSEHOLDS} - 1\}$
- I_s is the set of shiftable appliances, $I_s = \{0, \ldots, \text{NUM\_APPLIANCES} - 1\}$
- I_{ns} is the set of non-shiftable appliances
- J_{noEV} is the set of households without an EV
- T is the set of time slots in the day
- $P(t)$ is the price of electricity at time t
- $x_s(i,j,t)$ is the energy consumption of shiftable appliance i in household j at time t
- $x_{ns}(i,t)$ is the energy consumption of non-shiftable appliance i at time t
- $E(i)$ is the daily energy requirement for shiftable appliance i
- $\gamma(i)$ is the power limit for shiftable appliance i

Based on the results of solving the optimization problem, we will be able to form a strategy. Once again, the algorithm used can be checked in figure 12.

3.2 Results and Strategy

Solving the problem with pyomo, given the RTP curve from problem 2, gives us an optimized schedule for using our power. As one might expect, the suggested consumption schedule for the shiftable appliances was the same for all non-EV households. It was also the same for all EV households. The solution ended up suggesting restricting our use of the shiftable appliances to only three hours of the day. Since the solution is no different from one household to another, we can show the results in only two plots; one for EV households, and one for non-EV households, as can be found in figure 7.

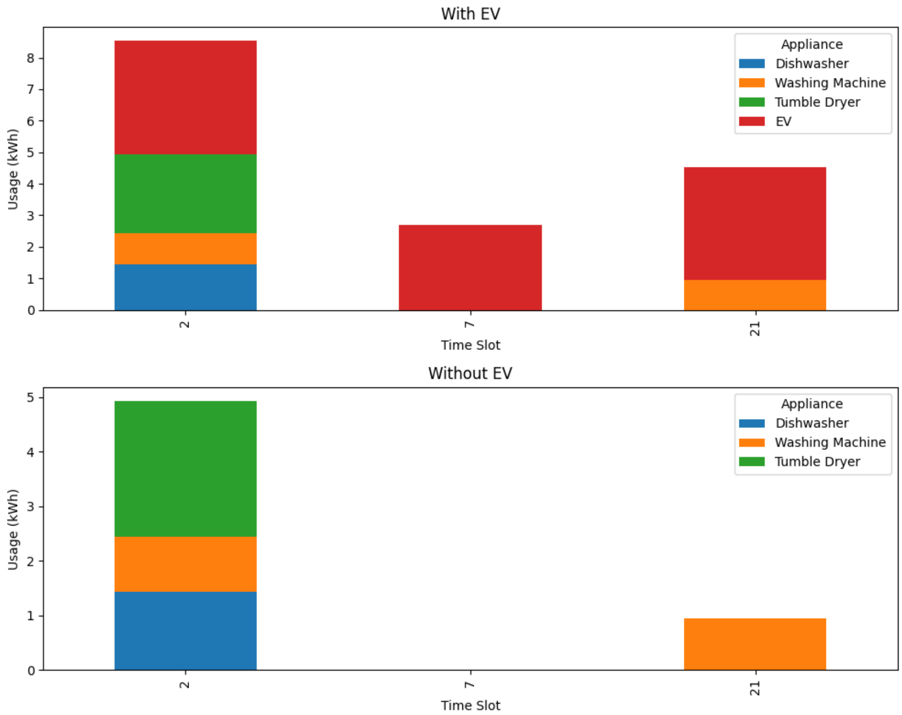

Figure 7: Consumption of shiftable appliances in non-EV and EV households.

Figure 7 shows the optimal usage of the shiftable appliances for two example households (one with and one without an EV), given our RTP curve. As one can see, the household without an EV actually only uses shiftable appliances in two timeslots. Furthermore, the consumption timings of all appliances (other than the EV) are equal between the EV households and the non-EV households. Due to the EV using so much power though, we have to spread the consumption across more than two timeslots. Looking at figure 3, we can tell that the timeslots chosen by our optimization algorithm were simply the cheapest possible (given the constraints).

As we can tell from the results in figure 7, the optimal strategy here is to find out how many timeslots we need to spread our shiftable appliances' consumption across (based on their power draw and limits), and then choose the timeslots with the lowest prices.

4 Question 4

In question 2 we may observe that, in some timeslots, energy consumption is very high. Such peak load phenomena may damage the smart grid stability.

In this task, we address this issue. One possible approach is to introduce a new variable L representing the peak load. Then, the objective function should consider both energy cost and the peak load.

4.1 Optimization Problem

There are several methods for dealing with this issue, such as multi-objective optimization and weighted optimization. Here, we attempt to bring the issue closer to reality using real data, while keeping to the simplicity of linear programming.

Our strategy is therefore to include the new peak load variable L in the original objective function, by transforming it into a price. In Norway, there already is a system that charges users based on the peak daily consumption, called *fastledd*. It is charged monthly, and has discrete price levels depending of L, which can be checked in Elvia's website [2]. To apply it to our function, we attempt to approximate it to a polynomial function, resorting to applying a linear regression using the bin midpoints, and divide it by 30 to give return an equivalent daily *fastledd* cost, i.e. what it would cost if it were to be charged daily instead of monthly. We then include this cost in the objective function and add a peak load constraint, while still using the price curve shown in figure 3, and the appliance assumptions in table 1. The mathematical formulation of the problem will now look as such:

$$
\begin{aligned}
\min \quad & \sum_{i,t} P(t)(x_s(i,t) + x_{ns}(i,t)) + P_f(L) \\
\text{s.t.} \quad & \sum_{t} x_s(i,t) = E(i), \\
& x_s(i,t) \leq \gamma(i), \\
& x_s(\mathrm{EV},t) = 0 \quad \forall t \in [8,18), \\
& x_s(i,t) \in \mathbb{R}_0^+, \\
& \sum_{i} (x_s(i,t) + x_{ns}(i,t)) \leq L,
\end{aligned} \tag{4}
$$

for each and every appliance i and time slot t, where $P_f(L)$ is the linear regression of the *fastledd* price levels as a function of the peak load L. Notice also the new and last constraints, which guarantee that the total consumption at each timeslot does not surpass the peak load. This way, both $\boldsymbol{x_s}$ and L will be optimized through an LP problem. We will once again use Pyomo to formulate the problem, and the open-source CBC solver to solve it. Please refer to figure 12 for the process flow.

4.2 Results and Strategy

The resulting linear regression of the *fastledd* price levels can be seen in figure 8. We obtain an R-value = 0.999, indicating a very good adjustment to our approximation of linearity.

The non-shiftable consumption profile is evidently the same as in question 2, and the shiftable one can be found in figure 9.

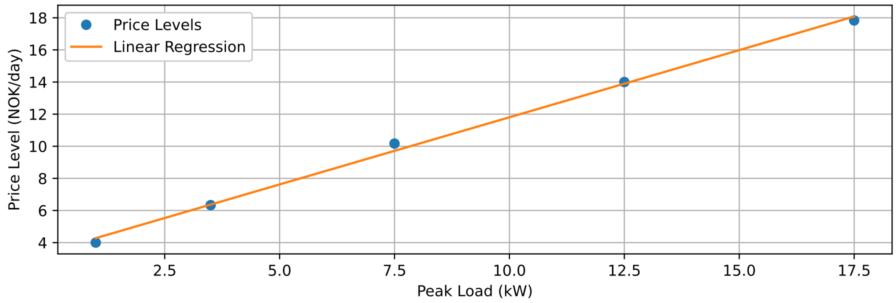

Figure 8: Linear regression of *fastledd* price level [2].

A comparison between the total shiftable consumption profiles in question 2 and 4 has also been plotted in figure 10. Here we can observe a clear difference between the scheduling results of these two questions. While the same peaks are present in both schedules, question 4 has them considerably shaved, and redistributed to other time slots that were previously not in use.

The total energy cost of this schedule is 26.58 NOK, and the peak load is $L = 2.63$ kW. Comparatively, question 2's peak load came out to 9.11 kW, meaning that we achieved a 71% reduction of peak load, but only incurring a daily price increase of approximately 4%. This translates into greater grid stability and health, thus demonstrating the power of smart scheduling.

Additionally, we can see the total energy consumption profile for this schedule in figure 11. In this exercise, the scale of shiftable to non-shiftable consumption is drastically more comparable, indicating a closer resemblance to a real-world scenario.

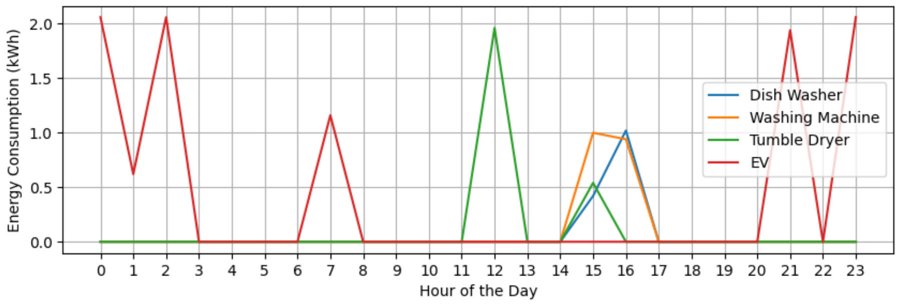

Figure 9: Energy consumption of shiftable appliances considering peak load.

Comparison of ToU and RTP Pricing Schemes

While no direct comparison has been made between these pricing schemes under this assignment, both due to the question requirements and to the difficulty of assigning comparable price signal, a broad appreciation of the two can still be made. ToU is defined by reliability and predictability, while RTP introduces an element of semi-randomness, in order to better reflect the real cost of energy production.

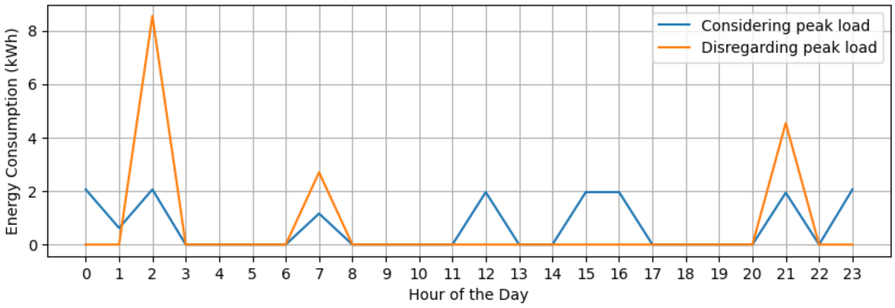

Figure 10: Comparison of total shiftable consumption when considering and disregarding peak load.

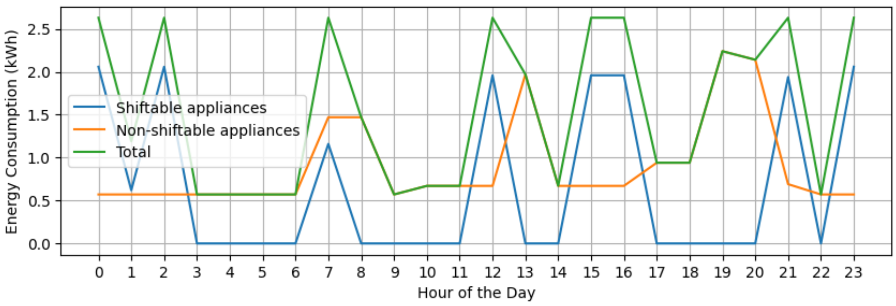

Figure 11: Total household energy consumption profile considering peak load optimization.

Assuming in a real case scenario that consumers mostly have semi-shiftable appliances, i.e. devices that must be utilised within a certain time range but whose use is flexible within said range, this scheme allows in theory for a lower energy cost, as users can beat the average by scheduling power consumption to the lower values of the price fluctuations, regardless of time of day, as found for example in [4]. In contrast, under the ToU scheme, if a user must use a device during peak-hours, they must incur the high price with no possibility of optimization. Additionally, the natural distribution of loads throughout the day also allows for peak load reduction, inducing improved grid health and stability, while under ToU consumers might be tempted to schedule all shiftable appliances to similar off-peak time slots, increasing peak load and grid stress.

However, reports such as [1] have shown that consumer habits are deeply rooted, and that user are generally not able or willing to adapt their demand to hourly price signals that change on a daily basis. This means that, unless automatic smart scheduling and metering are widely implemented, ToU will in general result in lower energy costs than RTP.

Flowchart

For the flowchart diagram, please see figure 12 for the illustration of our main algorithms from Q1 to Q4.

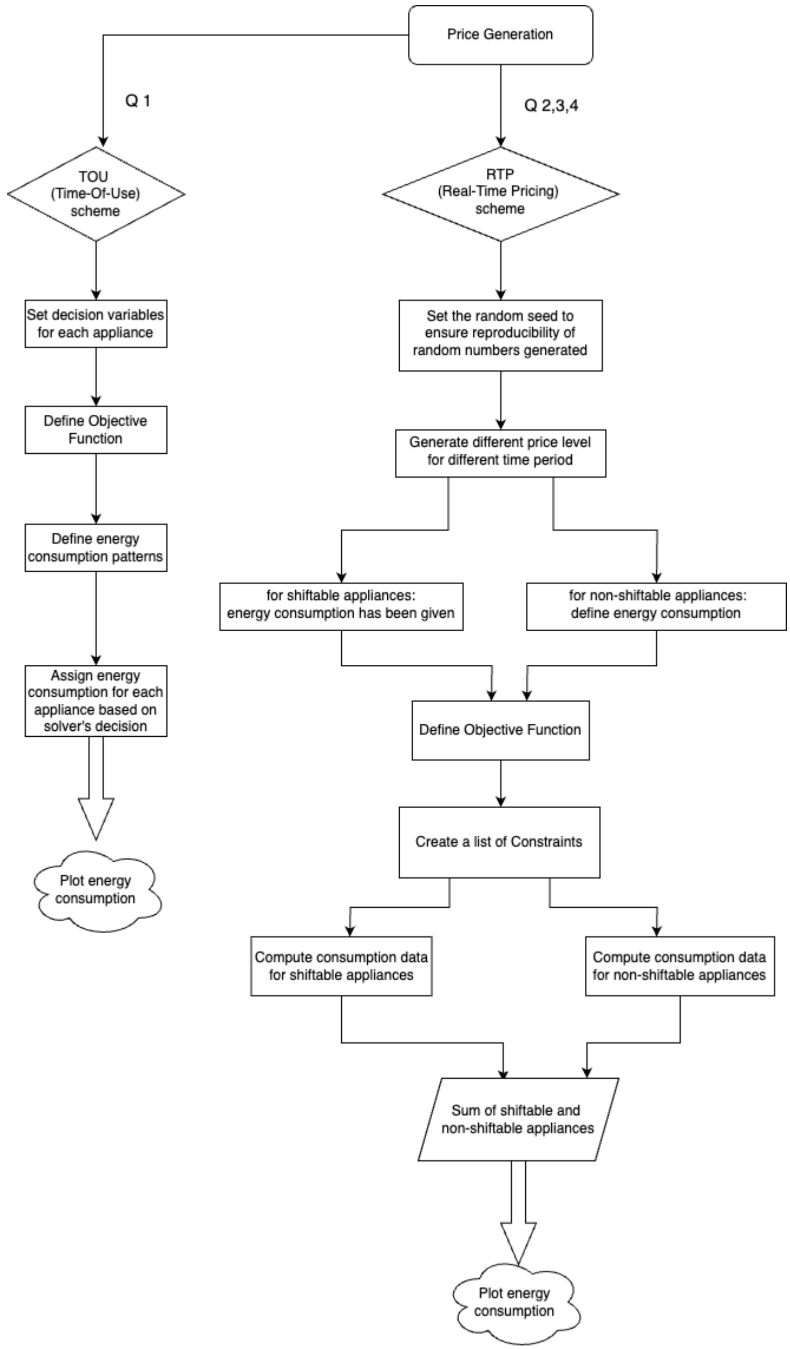

Figure 12: Flowchart diagram with main algorithms used throughout the report.

References

[1] Ioana Bejan et al. *The hidden cost of real time electricity pricing*. eng. IFRO Working Paper 2019/03. Copenhagen, 2019. URL: http://hdl.handle.net/10419/204432.

[2] Elvia AS. *Slik fungerer fastleddet*. https://www.elvia.no/nettleie/alt-om-nettleiepriser/slik-fungerer-fastleddet/. Accessed: March, 2024.

[3] *Energy Use Calculator*. https://energyusecalculator.com. Accessed: March, 2024.

[4] Xueyuan Zhao et al. "Electricity cost comparison of dynamic pricing model based on load forecasting in home energy management system". In: *Energy* 229 (2021), p. 120538. ISSN: 0360-5442. DOI: https://doi.org/10.1016/j.energy.2021.120538. URL: https://www.sciencedirect.com/science/article/pii/S0360544221007878.