Assignment 1 - Home Energy Management

INF5870 - group 5

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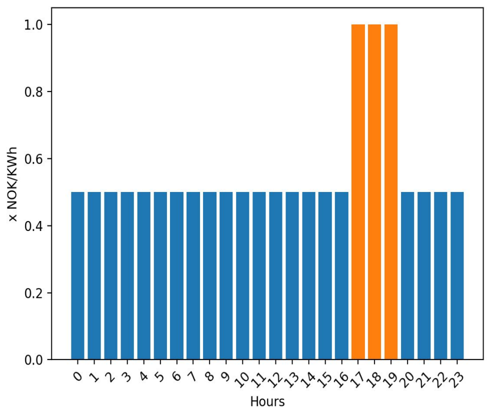
Contents

Question 1:

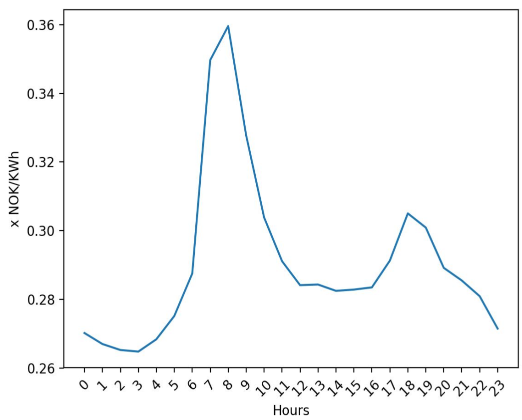
Background and assumptions

The general and most simplistic approach to solve this problem, is to avoid peak hours entirely, to minimize cost. Peak hours are in the range of 5pm to 8pm, hence giving 21 hours for off-peak hours, the total number of hours available for applications of each electrical appliance. Because pricing is cheapest during off-peak hours, the overall cost will thus be minimized. A visualisation of the peak hours can be seen in the following graph (left), with historical spot price data for the Oslo market (23.03.2017) from the Nordpool exchange, as a comparison measure:

Peak hours visualisation



Nordpool 23.03.2017



The price charts would abide to the ToU pricing, where the price would not change from time to time as the RTP pricing. The schedule can either be during the same time period for all appliances, or be distributed differently during off-peak hours. The operation time however, should be reasonable in relation to average usage of given appliances.

Total minimal energy cost

The total power consumption E_{total} would be the sum of the energy consumption E_{a_i} for each appliance $a_i \in A$, which is 13.28kWh. We can in this task assume with certainty, that the minimum price p_{min} always will be during the off-peak hours. With basis in this assumption, the minimum cost is thus the total power consumption for all appliances multiplied with 0.5 NOK, which formally can be expressed as the following, for this task:

Definitions:

$$A = \begin{bmatrix} 1.94 \\ 9.9 \\ 1.44 \end{bmatrix} = \begin{bmatrix} A_1 \\ A_2 \\ A_3 \end{bmatrix}$$

Formulation:

$$E_{total} = \sum_{i=1}^{n} E_{a_i}, \text{ where } \begin{cases} n = |A| \\ a_i \in A \end{cases}$$

$$p_{off} = 0.5 \text{ NOK}$$

where

$$p_{min} = p_{off} \times E_{total}$$

such that

$$p_{min} = 0.5 \text{ NOK} \times 13.28 \text{ kWh} = 6.64 \text{ NOK}$$

Strategy for appliance distribution during off-peak hours

The problem in question is how we distribute the application of each appliance during the off-peak hours. Intuitively, how do we design a strategy to avoid higher load during specific hours, potentially resulting in a new peak, so that the appliance usage is distributed over multiple hours, contributing to a reduced load?

This is important because we would like to avoid unnecessary load/congestion on the energy grid, in scaled solutions. As mentioned previously, high load (high demand) generates new peaks, and potentially generates new peak prices due to the increased demand in a given off-peak hour, or off-peak period. This is especially important for developing scalable solutions in terms of multiple appliances and households, and how this is possible to be programmed such that several houses can interact and optimize depending on each other and the grid load (essentially discussed in task 2 and 3).

Specifically, for all the appliances we are working with, the power load can reasonably be scheduled in the evening for EV (and night/morning) and washing machines, and on the day/morning for dishwashers (before work). This schedule would also be adaptive to some extent, in terms of a generic household. A specific example of a schedule could be the following:

$$EV = \begin{cases} \alpha = 22 \\ \beta = 6 \\ \text{usable hours } = 5 \end{cases} \quad WM = \begin{cases} \alpha = 21 \\ \beta = 24 \\ \text{usable hours } = 2 \end{cases} \quad DW = \begin{cases} \alpha = 6 \\ \beta = 9 \\ \text{usable hours } = 1 \end{cases}$$

Where the usable hour denotes how many hours each appliance actually has to be used in the range from α to β.

Question 2:

How the problem is solved

The general design approach is to find the cheapest alternative for each appliance and schedule it in a time slot that is suitable considering price. Each appliance is observed individually and does not take other appliances into consideration when it picks the optimal time slots.

We have dealt with the data in three types of sets. Firstly we have the non-shiftable, which can work in any of the 24 hours. These can understandably not avoid peak time and is reflected in the graph. The second set is the shiftable data, which has different time constraints that we've assumed is the reasonable time it takes to do the respective task, e.g charging EV takes 5 hours. Like this, we have made assumptions based on the multitude of appliances we have chosen. The last set is the random appliances; the number of appliances that can be chosen from this set can vary between 1-9, depending on what the random generator chooses for the house. The random appliances have a designated schedule when they can operate, which are within realistic usable hours, similar to the shiftable and non-shiftable appliances. All these operating schedules can be found in the appendix under “appliances.r”.

In relation to scalability, there is no difference in optimizing each appliance individually ,which essentially minimized the overall cost, versus handling all the data collectively in respect of cost minimization in our implementation, and for one household. The main consideration is defining reasonable time periods for when the appliances should operate, and optimize the schedules accordingly. A consequence of this, is potentially that new peaks might be generated. The following questions would therefore be how each appliances should be scheduled, if one includes the grid load as a factor in the optimization problem. The assignment however, does not state how each schedule should be relative to other appliances and that grid load should be included as a factor, but this is an important notice generally, and regarding our solution; how to avoid new peaks and distribute appliances accordingly, to reduce grid load.

Representing the equality constraints

The linear equations are parameterized by schedules for each appliance $a \in A$, where a schedule is defined as the operational time from start α to end β during a day, which essentially is our operational time constraints. The daily energy consumption x for a given appliance a, with some operational constraints in the range $[\alpha, \beta]$ can be represented as a boolean vector of size 24, indicating scheduled consumption:

$$x_a = [x^1, \ldots, x^h] \text{ where } 1 \leq h \leq 24 \text{ and } x_a^h = \begin{cases} 1 & \text{if } h \in [\alpha_a, \beta_a] \\ 0 & \text{if } h \notin [\alpha_a, \beta_a] \end{cases} \tag{2.1}$$

It is derived by the above mentioned definition, that reasonable allocation hours are provided, for instance with basis in an average household, e.g. that an EV is most probably charged between 10:00 pm to 06:00 am in a generic household, for a timespan of 6 hours.

The linear equalities for a given appliance a is given by the appliance daily usage. The total daily consumption (total energy constraint), with basis in our boolean vector for a given appliance, may mathematically be expressed as

$$E_a = \sum_{h=1}^{H} x_a^h, \text{ where } H = 24 \tag{2.2}$$

Representing the inequality constraints

The inequality constraints are defined as the maximum power level for a given appliance in 1 hour. With basis in the slides presented in the lecture about [demand response management](), we represent one hourly constraint as one boolean vector, indicating which hour the constraint applies for, and the inequality it relates to, which is the maximum hourly power level constraint for an appliance, γ_a^{max}. For H hours, there are H boolean vectors. The inequality constraints for a given appliance, at a given hour, can be expressed as:

$$x_a^h \leq \gamma_a^{max} \tag{2.3}$$

Representing the constraint vectors in a matrix for the solver

With our equality constraints and inequality constraints, our program can solve the problem when representing the constraints in a constraint matrix M, for a given appliance (which is optimized for all appliances $a \in A$). Let c_{nh} be the nth constraint, where h denotes the corresponding hour in one day:

$$M = \begin{bmatrix} c_{11} & x_{12} & \dots & x_{1h} \\ \vdots & \vdots & \ddots & \vdots \\ c_{n1} & c_{n2} & \dots & c_{nh} \end{bmatrix} \tag{2.4}$$

The first row in the matrix describes the daily energy consumption for one appliance, over 24 hours, represented as a boolean vector, as mentioned in (2.1). The subsequent rows denotes the power level constraints, represented as boolean vectors, for one appliance, at a given hour. This results in a matrix of dimensions 25×24 for each appliance.

The cost minimization problem as a mathematical formulation

More generally, and conclusively we can formally define our optimization problem the following way. We want to minimize the objective function, which is the sum of the hourly costs of price p^h multiplied by the total consumption used by all appliances at the given hour:

$$\min_x \sum_{h=1}^{H} p^h \times \left(\sum_{i=1}^{N} E_{a_i}^h \right), \text{ where } N = |A| \tag{2.6}$$

The objective function described above, is subject to the hourly power level constraint:

$$x_a^h \leq \gamma_a^{max} \tag{2.7}$$

and the total energy constraint E_a,

$$E_a = \sum_{h=1}^{H} x_a^h \tag{2.8}$$

with basis in our definitions:

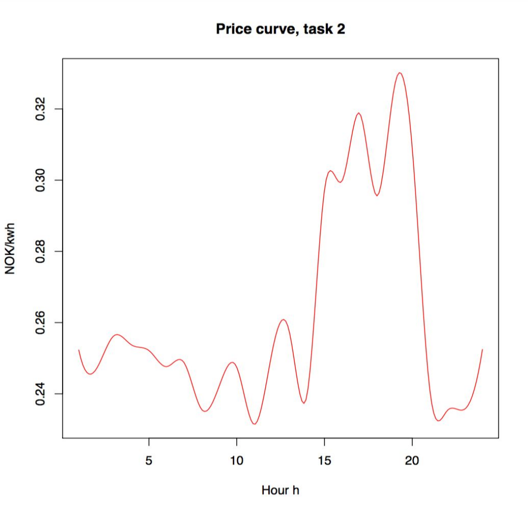
$$\text{H} = 24$$
$$1 \leq h \leq H$$
$$\text{a} \in A$$
$$\text{and} \tag{2.9}$$
$$x_a^h = \begin{cases} 1 & \text{if } h \in [\alpha_a, \beta_a] \\ 0 & \text{if } h \notin [\alpha_a, \beta_a] \end{cases}$$

for α and β being the operational time constraint.

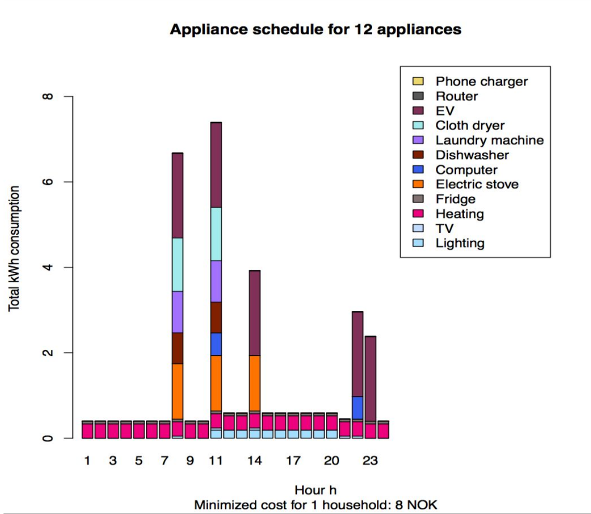
Figures and flowcharts

The pricing curve for task 2 is randomly generated from a Gaussian distribution, where the average and standard deviation is based on a randomly chosen sample from a set of 3 samples we have collected from Nordpool. These samples can be found in the file called "nordpool_samples.r"**.** The following figures are derived from one run of our algorithm.

Price curve



Corresponding appliance schedule



We can observe that it is generated a new peak from 8:00 am to 11:00 am, like we anticipated previously, as a consequence to avoiding the existing peak hours. Additionally, it is notable that by optimizing with respect to each appliance isolated, the appliances don't take into consideration of when other appliances are used, if in the same period of time. The peak prices is also in the range from 3:00 pm and 20:00 pm, and we can see that this time period is avoided in the appliance schedule. However, there is a tradeoff here and the question of how we approach the problem of reducing load/the new peak, which essentially is not part of the task, but something to take into consideration when solving scheduling problems similar to this.

The result for this household which inhibits the above appliances is 8 NOK. The result we have attained here shows that by optimizing in every aspect possible it is possible to minimize the energy cost by a lot. The flowchart is added in the appendix, for a more understanding of our code flow.

Question 3:

How the problem is solved

The design approach to 30 households is the same as appliances in question 2, but on a household level, rather than appliance level. The program is now scaled up to solve the optimization problem with 30 houses and corresponding appliances. The only variable appliance is the EV, and we have chosen to simulate a fraction of the households owning an EV as every fourth household.

One possible way to solve the problem of avoiding new peaks, is to mitigate the schedule for an appliance for a household (as referred in the DRM lecture). This makes it possible so that all the appliances would not have the same hours for when they can be charged/powered, and encourages intelligent load control. For instance if an EV has 5 hours of charging time, we could mitigate time slots it can be charged so that all EVs have somewhat different charging schedules during the high load times which again improves grid reliability. This ensures us that the resulting schedules would not result in congestion and increased grid load, but also gives flexibility for optimization of the chosen hours to get the cheapest solution possible.

The cost minimization problem as a mathematical formulation

The cost minimization problem and the representation of our linear system is essentially the same as defined in $(2.6) - (2.9)$, but the formulation has to be tweaked a bit in terms of 30, more generally M households. We essentially want to minimize the cost for the whole neighbourhood, and can rephrase our problem to the following; let the energy consumption for one household C, be defined as:

$$C = \sum_{i=1}^{K} E_{a_i}, \text{ where } \begin{cases} A = \begin{bmatrix} A_1 \\ A_2 \\ \vdots \\ A_n \end{bmatrix} \\ K = |A| \end{cases} \tag{3.1}$$

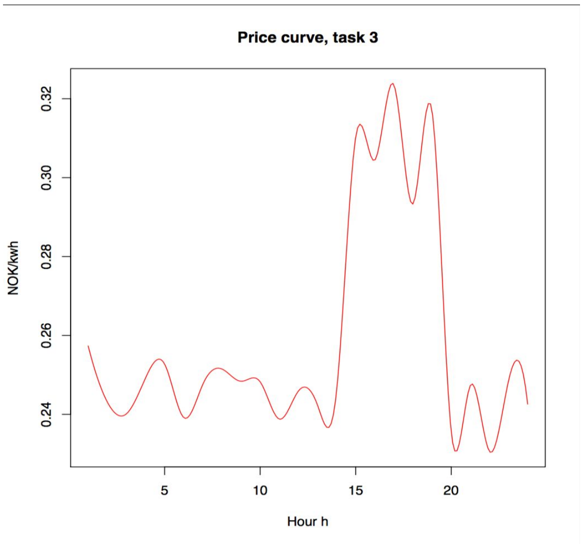
and A is the appliances used in a given household. The objective function is expressed as the following:

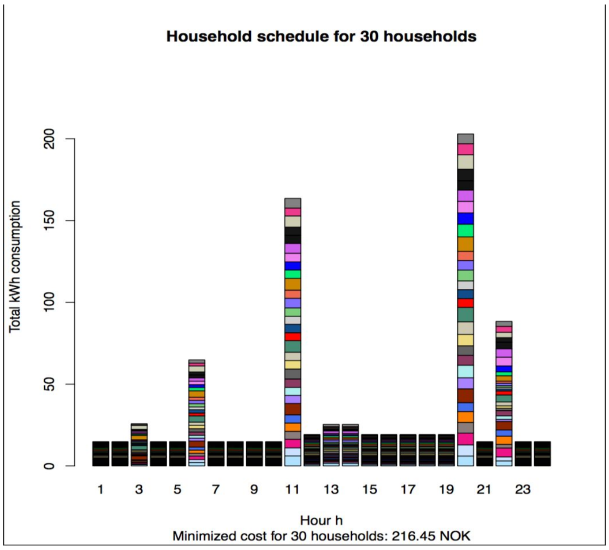
$$\min_{x} \sum_{h=1}^{H} p^h \times \sum_{n=1}^{N} C_n^h, \text{ where } N = |M| \tag{3.2}$$

and M is the set of all households.

Figures and flowcharts

The pricing curve for task 3 is generated similar to task 2. The following figures are derived from one run of our algorithm, for 30 households.





Running our program for 30 households, we can see that there are some peaks occasional times during the day. As anticipated and discussed above, a more beneficial solution in terms of balancing between grid load and minimum energy cost could be mitigation of the power load.

From the figures above, we can see that each household would only use most of the appliances during specific hours, outside the existing peaks, without taking grid load into consideration. If new peak hours were taken into consideration, there would be a tradeoff between the cost and grid load. The flowchart is added in the appendix, for a more understanding of our code flow.

Question 4:

Time-of-Use (ToU):

Traditional utility prices involves a set rate per kwh, which can fluctuate during season change. A sliding rate scale, which is structured according to peak and off-peak times of day is called a “time-of-use” rate plan. Under such a plan, your bill will be determined by how much energy you use and when you use it. ToU pricing is usually released in advance, and wouldn’t be changed afterwards in the set time period it is placed for.

Real-time pricing (RTP):

Real-time pricing means tariffed retail charges for delivered electric power and energy. RTP is usually released on an hour-ahead pricing or day-ahead pricing basis. The price may therefore vary at different time intervals of a day. The result of this is that each hour is priced on the go, this makes it possible to be more in sync with the actual marked. Implied that you could “experience” that your provider gets better or worse deals in real time.

Real-time pricing vs Time Of Use

Both of the pricing schemas have their own way of impacting the energy cost. RTP will make it a bit harder to schedule appliances because the rate can vary more often than the ToU. ToU has a pricing scheme advanced ahead of time which can be both positive and negative for the users. The schemes gives a price for the current energy consumption, and ToU might give a decent outcome for the user since the price is defined for a longer period. But it can also affect the price where it might be higher compared to the overall market. For example in task 1) you can see how the ToU impacts the energy consumption. Since there is a designated area for peak hours we chose to avoid this area when scheduling the appliances. In this approach the ToU impacts the energy cost because we chose to use the appliances at low peak. In the two last tasks (2 & 3) we use RTP which might not make as big impact on the energy cost as ToU does. Because the RTP prices varies more, and we might not know exactly when to schedule the appliances to get the lowest price since the prices are different from hour to hour. The impact RTP might make is that it can create new peaks if the scheduling algorithm or if the users change the charging time to another time than the originals peaks. But the impact itself is not as big as in ToU where we can avoid the peaks, since the peaks are defined earlier than the RTP. In our example there are 24 prices for each hour which are collected from Nordpool, the prices are random from 3 random days from 2017. Since the prices vary from hour to hour it makes our program try to chose the lowest possible cost. But this does not happen all the time, some of the appliances have some constraints which makes the time non-shiftable e.g lighting. The appliances will therefore run when they can, but the system will try to push them in the lowest cost area as long as it is possible and cost beneficial. These arguments are based on RTP and ToU usage in Norway, since the schemes might have other outcomes and impacts in different geographical regions.

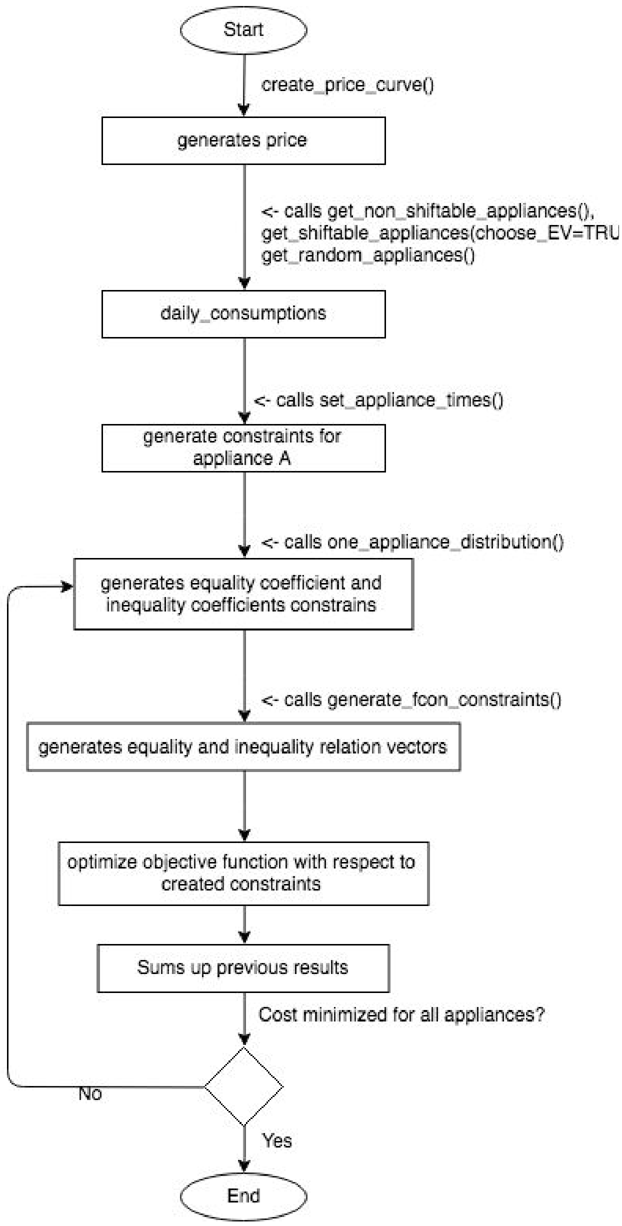
References and links:

Nordpool spot prices, 2017
https://www.nordpoolgroup.com/globalassets/marketdata-excel-files/elspot-prices_2017_hourly_nok.xls

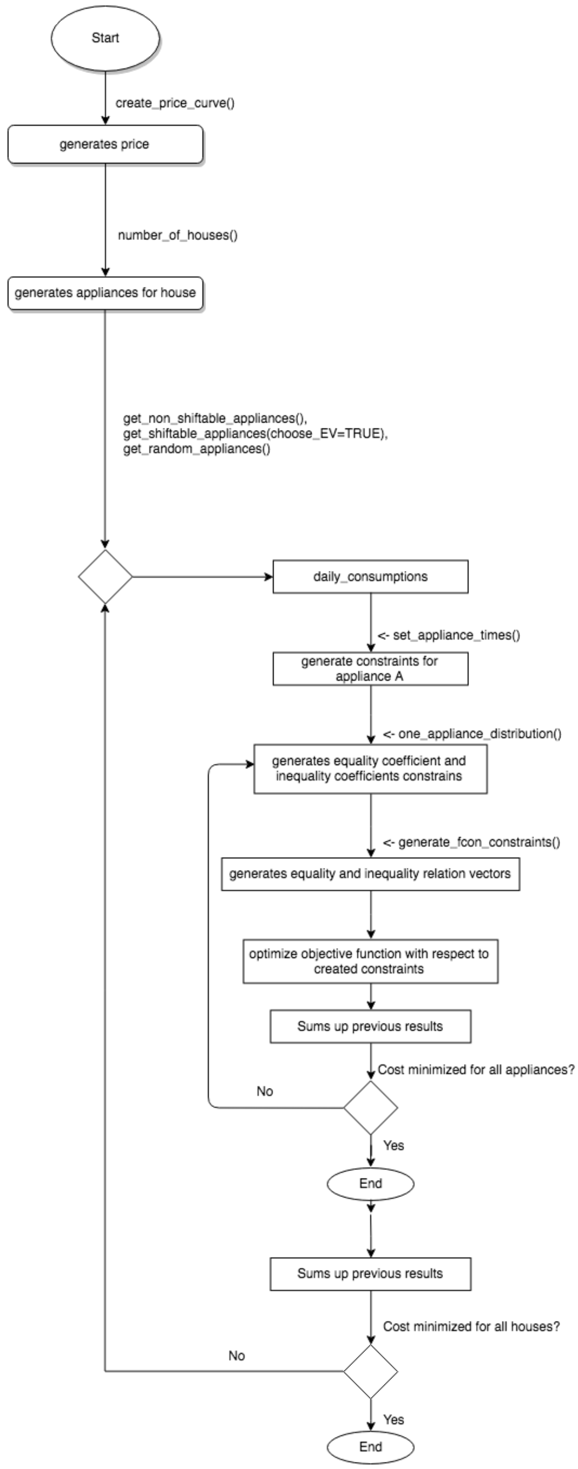
Demand Response Management
http://folk.uio.no/yanzhang/INF5870-2018/DemandResponse-Lecture3.pdf

Appendix:

Task 2 Flowchart



Task 3 Flowchart



Additional files may be found in the *appendix* folder