Electric Vehicle Charging Station Network Optimization

Course Project

ME308 : Industrial Engineering and Operations Research (Spring 2021-22)

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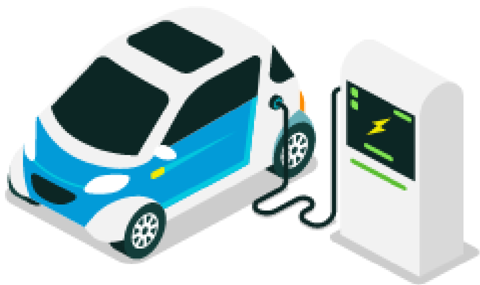

Work Report

Group 23

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Code available at the GitHub repository

Abstract

There has been a clear rise in demand for electric vehicles in the past few years. This has led to an increased impetus on setting up infrastructure (which includes charging stations, production and maintenance units) that can cater to this increased demand of EVs.

The goal of this project is to explore the various ways in which charging stations can be placed and operated in a given region so as to reduce the number of stations and the total costs involved in constructing and/or operating them. An optimal charging station network will minimize capital cost and improve driver experience.

Introuduction

The Electric Vehicle (EV) industry has seen tremendous growth in recent times due to favourable government regulations and/or incentives and growth in demand among middle-aged urban consumers. Across the globe, there has been an increased focus on shifting to electric mobility. The US and some Nordic countries (Norway, Sweden and Finland) have seen an exponential increase in the number of EVs owned per unit population. In recent years, EVs have become a hot topic for discussion in India as well - for politicians, businessmen and tech giants alike. Several points have been made in favour of EVs, the most common one being that they are environment-friendly (which in hindsight may not be very accurate).

Advantages of electric vehicles

- Economical in the long run (low Total Cost of Ownership)
- Much fewer emissions than IC engine based vahicles
- Quiet operation (no sound pollution)
- Smooth running and good pickup
- Good resale value

However, the limiting factors to the growth of the industry today are

- Lack of infrastructure available for charging
- High purchase costs, and maintainance costs (mainly in the form of battery replacements)

Problem Statement

We assume the role of a **policy consultant**, working with the government, which has decided to build a charging network in a city like Mumbai, to decide where to place the charging stations. The main reason for governments to do this is to increase EV adoptation by people in the city, and encourage car-buyers (many of whom still think that EVs are impractical because of charging availability issues) to buy EVs. While it is true that many car manufacturers do provide at-home charging setup installations, having a network in place would make it possible to buy an EV without such a setup, thus reducing costs, and increasing EV adoption rates. Thus, the project aims to optimize a charging station network in a city assuming no existing charging infrastructure.

The city is divided into several **demand hotspots**, where the demand of a particular locality is assumed to be concentrated. Given a set of possible locations for constructing charging stations, we need to choose a subset which will lead to minimum total customer travel from demand hotspots to charging stations.

The problem is tackled by a mathemtaical **formulation** that has evolved over the course of of the project. Two major versions of the formulations will be discussed in the subsequent sections along with the accompanying results, which aim to give a detailed insight into our project.

Formulation 1.0

Assumptions

This version of the formulation makes the following assumptions:

1. All vehicles from a particular demand hotspot travel to a single charging station. There is no splitting of vehicles into multiple charging stations.

2. All vehicles at any demand hotspot always go to the nearest charging station available.

3. All the charging stations which can be built are assumed to be identical in costs and size.

4. Each charging station that we build has a very high capacity, and can handle as many demands as arrive at it.

Parameters

As dicussed in the Problem Statement, two sets of locations are important for the mathetical formulaion:

$$\begin{aligned} i \in [1, N] &\ : \text{ Charging station locations} \\ j \in [1, M] &\ : \text{ Demand hotspots} \end{aligned}$$

The formulation will depend on a few input parameterss that are described below:

$$\begin{aligned} D_j &\ : \text{ Demand (value) at demand hotspot } j \\ S_{i,j} &\ : \text{ Distance (by road) between station location } i \text{ and demand hotspot } j \\ G &\ : \text{ Number of stations required to be built in the network } (\leqslant N) \end{aligned}$$

Apart from the parameters mentioned above, another variable important which we define for the formulation is the **Distance Penalty**, or the **Loss**, $\boldsymbol{L_j}$. It is defined as the distance between demand location j when it and its **assigned** charging station. The "assigned" charging station is in fact the closest charging station in our case.

Decision Variables

Two decision variables are used to finalize the charging station location and the corresponding assingment of demand hotspots to charging stations. These are:

- **Assginment variable, $\boldsymbol{\alpha_{i,j}}$** - Binary

$$\alpha_{i,j} = \begin{cases} 1, & \text{if demand hotspot } j \text{ is assigned to station } i \\ 0, & \text{otherwise} \end{cases}$$

- **Should-build decision variable, $\boldsymbol{x_i}$** - Binary

$$x_i = \begin{cases} 0, & \text{if station should be built at location } i \\ 1 & \text{otherwise} \end{cases}$$

Objective Function

The objective function should minimize the combined ditance travelled by all the vehicles as they travel to their assigned charging stations. This is represented mathematically as:

$$\text{minimize } \sum_j D_j \times L_j$$

The nomenclature *distance penalty* now makes sense - greater the value of L_j, greater is the distance travelled by the vehicles at demand hotspot j. This goes against our objective of minimizing the distance, hence a penalty has to be imposed which will be be proportional to the value of L_j

Constraints

Assignment variable bounds

If a station is not built at a certain location ($x_i = 0$), then we cannot assign this location to any demand ($\alpha_{i,j} = 0$ must hold for all j's). However if the station is built at location i, then $\alpha_{i,j}$ can be 0 or 1 depending on whether demand hotspot j is assigned to i or not. Hence,

$$0 \leqslant \alpha_{i,j} \leqslant x_i \quad \forall i \in 1, 2, \ldots, N, j \in 1, 2, \ldots, M$$

Exactly one assignment

This constraint ensures that only one $\alpha_{i,j}$ is 1 and the rest are zero, that is, each demand is assigned one and only one charging station. This puts in place the one-to-one map discussed earlier.

$$\sum_{i=1}^{N} \alpha_{i,j} = 1 \quad \forall j \in 1, 2, \ldots, M$$

Distance penalty definition

The distance penalty is defined mathematically as follows:

$$L_j = \sum_{i=1}^{N} S_{i,j} \times \alpha_{i,j} \quad \forall j \in 1, 2, \ldots, M$$

Since only one assignment variable takes a non zero value for a particular i, the value of L_j is the distance bewteen hotspot i and one of the charging station locations among the N. The rationale behind this definition is that when this is passed to the objective function, only station which minimizes L_j is chosen and the assignment is made to the **closest available charging station** location.

Number of stations

The number of stations which our model suggests building should be equal to the number required to be built (which is, G). Thus:

$$\sum_{i=1}^{N} x_i = G$$

Case Study : Mumbai

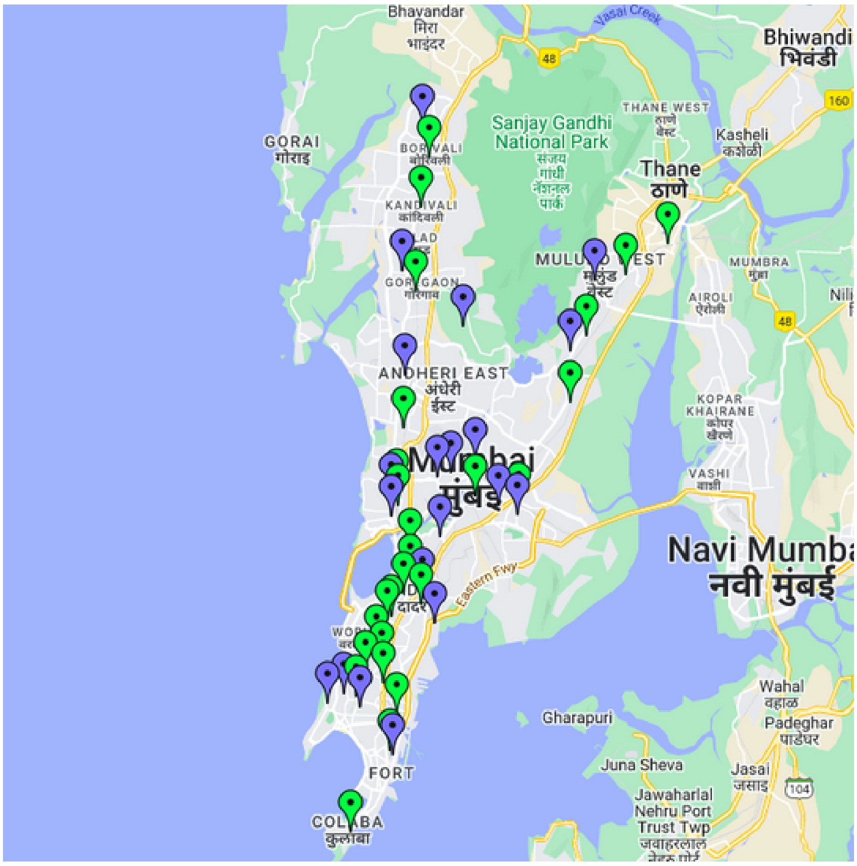
Once the formualtion has been made, it is important to verify wheteher it actually works, i.e. whether it gives any logical results or not. For this purpose, we decided to focus on implementing our formulation for the city of **Mumbai**.

As mentioned previously, two sets of locations are critical for the formulation - (i) charging station locations, and (ii) demand hotspots.

- To create a working baseline model, the possible charging staion locations were chosen as the existing gas stations of **Bharat Petroleum** in Mumbai. A set of **20** such stations, spread over the city, were chosen and their coordinates (latitude, longitude) were recorded

- The boundaries of the demand hotspots were chosen as the boundaries of established localities in Mumbai e.g. Kandivali, Bandra, Thane, etc. The *centres* of these demand hotspots were assumed to be coincident with the **railway stations** in those respective localities. This assumption was done primarily because pinpointing the centre of population in an area is an extremely involved task. **29** such localities (railway stations) were chosen.

The selected locations can be seen in the figure below. The blue markers indicate the demand hotspots and the green markers indicate the charging station locations



Data Collection Methodolgy

After fixing the locations, the next major task was to calculate:

i. The distance between the charging station locations and the demand hotspots

ii. The demand (number of EVs) at an particular hotspot

Disance matrix

While the coordinates of all the locations between which distances were to be measured were readily available, calculating the distances between any two locations was not straightforward. Although it was quite easy to calculate the cartesian distance btween any two points, that would have been of no use to us. What we needed was the ***on-road*** distance between points.

A possible solution was to use the **Distance Matrix API** offered by Google Cloud, which would have immediately given us the required distances, however it required a paid subscription, which we could not avail. Hence we decided make use of Google Maps for finding the distances.

It should be noted that for our case we would have had to calculate $29 \times 20 = 580$ distances manually using Google Maps, which was clearly not feasible. hence we decided to automate the process.

Automating the process : Selenium

Selenium is a Python package that offers the functionality of browser automation. It can essentially go to any webpage, and simulate actions like typing text, clicking buttons, among other things. It can also view the page source and extract any information from it. All this can be done by running a Python code by utilizing Selenium's API. This is what we did. Using the coordinates of all the locations as inputs in the Selenium code, we were able to extract all the required distances from the Google Maps API.

Once the distances were available, a **distance matrix** was generated, indicating the distance between any charging station and demand hotspot. The distance matrix is a 29×20 matrix, part of which is shown in the figure below (distances are in kilometers).

	BYCULLA	MUMBAI CST	ANDHERI	GOREGAON	BANDRA
Station locations \ Demand hotspots	18.97695,72.833211	18.944481,72.836903	19.1174289,72.846853000 00001	19.164447,72.849389	19.05445443,72.84045439
19.243954296872108,72.8529434603869	36.2	44.8	18.7	12.7	27
19.17003394335311,72.94014743738498	28.3	33.2	19.4	19.7	28.6
19.17457386937238,72.8426437780643	26.9	35	9.9	1.8	16.8
19.147981095613833,72.87354282503213	25.8	31.7	7.9	7.7	18
19.136304865074102,72.92778781859785	22.1	28.9	2.6	16.2	24.6
19.124627808817085,72.84401706904065	18.3	20.2	7.2	5.5	8.3
19.08407606953931,72.88006595716978	18	21.3	8	13.5	9.9
19.077911335151516,72.86770633838265	17.7	21.7	7.5	14.8	8.2
19.075964529259785,72.86083988350092	12.1	19.1	7.9	17.4	7.2
19.067203619693668,72.837493936903	12.2	19.1	11	14.6	1.6
19.056819719873673,72.83715061415892	11	18.8	9.8	16.6	0.7
19.06233624668009,72.89139560768537	12.2	16	14.7	21.5	9.6
19.057468731722224,72.9010086445198	13.1	17.1	15.5	22.6	10.4
19.047408748158396,72.8618698516939	9.4	18.1	11.6	18.3	6.5
19.022093834296356,72.85328678309173	6	12.5	15.7	20.1	6.6
19.005864295435078,72.85912326975102	5.7	8.1	18.5	26.3	14.4
18.96755630994767,72.80487827618529	5.4	7.6	22.2	27.7	13.1

Demands

Calculating the demands at the hotspots was another challenging part of the data collection process. Since the data regarding number of EVs in a location was not readily available, we adopted a slightly different approach. Our stategy was looking at the **economic** scene of the hotspots. Since the purchase cost of an EV in India is a little on the higher side, it is logical to say that people belonging to the upper middle class and upper class families were the primary buyers of EVs. Thus family income had to be considered.

The issue with family income was the same as that with number of EVs - unavailability of data. Hence a simplifying assumption was made - family income is directly related to the property rates in a particular locality. If the housing prices are high, more number of affluent peoples are bound to buy homes in that area, and these people will be the primary purchasers of EVs.

Suppose `prop_rate` is the average value of property rate in a particular location. The family income in that area is directly proprtional to `prop_rate` and is given by

$$\text{Income} = K_1 \times \text{prop\_rate}$$

where K_1 is some constant.

Also, the number of families that can afford EVs in an area can be given as

$$\text{Num\_fam} = K_2 \times \text{population}$$

where K_2 is another constant.

The demand (number of EVs) in a particular locality can thus be given as

$$\text{Demand} = K_1 \times \text{prop\_rate} \times K_2 \times \text{population} \times K_3$$

where K_3 is a scaling constant.

By assuming the constants to be same for all localities, we can see that these constants will eventually get eliminated when the objective function is minimized. Hence the values of these constants are irreleveant.

The product of `prop_rate x population` yielded a fairly large value. Hence the demands were scaled down with respect to the average demand. It is possible to do so, since our objective function being a simple summation, does not get affected by any constant multipliers added or removed. These scaled demands were used in the objective function. A snippet of what these demands look like is shown in the figure below.

[Lat,Long]	Station Name	Property rates (Rs /sq ft)	Population	Demand	Scaled Demand
[72.833211, 18.97695]	BYCULLA	32669	132,376	4324591544	1.41890
[72.836903, 18.944481]	MUMBAI CST	29844	117744	3513951936	1.15293
[72.84685300000001, 19.1174289]	ANDHERI	16800	395292	6640905600	2.17889
[72.849389, 19.164447]	GOREGAON	16900	211,489	3574164100	1.17269
[72.84045439, 19.05445443]	BANDRA	28000	165630	4637640000	1.52162
[73.087316, 19.078901]	TALOJA PANCHAND	6000	9640	57840000	0.01898
[72.839733, 18.962311]	MUMBAI SANDHURST ROAD	16155	98364	1589070420	0.52138
[72.859587, 19.250166]	DAHISAR	11500	181063	2082224500	0.68318
[72.835426, 19.00694]	MUMBAI ELPHINSTONE ROAD	36310	61518	2233718580	0.73289
[72.832659, 18.986789]	MUMBAI CHINCHPOKLI	20930	10741	224809130	0.07376
[73.11494900000001, 19.035116]	KALAMBOLI GOODS	6900	88,577	611181300	0.20053
[72.84906600000001, 19.136550999999997]	JOGESHWARI	20000	127806	2556120000	0.83867
[72.840078, 19.069166]	KHAR	33800	93907	3174056600	1.04141
[72.852098, 19.204551]	KANDIVLI	15200	360944	5486348800	1.80008
[73.11480900000001, 19.035625]	KALAMBOLI	6700	88577	593465900	0.19472
[72.84917, 19.187089]	MALAD	15500	384,137	5954123500	1.95356
[72.84687600000001, 19.040547]	MUMBAI MAHIM JN	33500	83662	2802677000	0.91956
[72.847143, 19.028606]	MUMBAI MATUNGA ROAD	30400	88668	2695507200	0.88440
[72.838561, 18.952385]	BOMBAY MASJID	19434	19609	381081306	0.12503

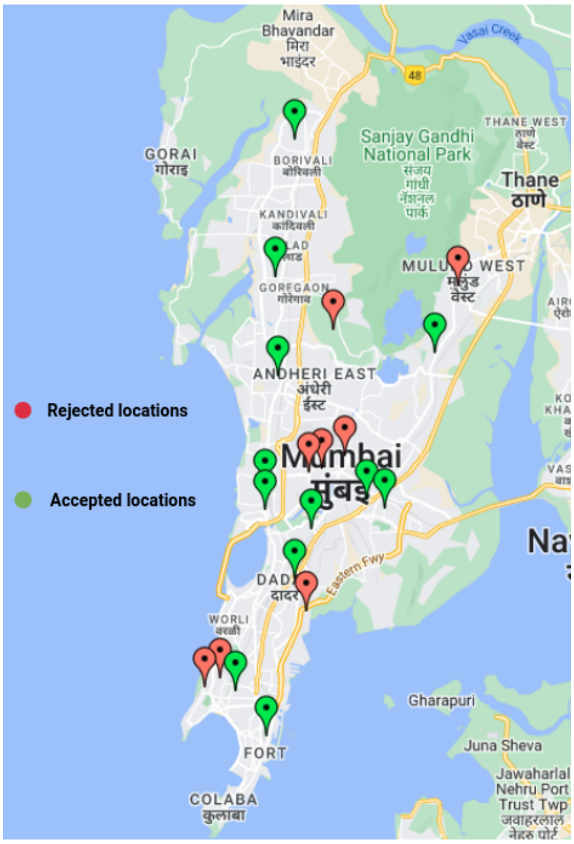
By scaling, we can easily observe the relative demands between two hotspots. For instance, the demand in Kandivali is almost twice that in Mahim.

Results (1)

After acquiring the data regarding demands and the distance matrix, the formulation was implemented in **AMPL**, and results were generated which depicted the choices of charging station locations that minimized the objective function, and also the corresponding value of the objective function. The figure below shows the selected charging station locations and the value of `objective` when the value of G is kept as 12.

```
objective 92.958562
should_build [*] :=
 1  1
 2  0
 3  1
 4  0
 5  1
 6  1
 7  0
 8  0
 9  0
10  1
11  1
12  1
13  1
14  1
15  1
16  0
17  0
18  0
19  1
20  1
;
```

Thus, for example, a charging station should be built at location 1 but not at 2 if the objective function is to be minimized. Also, the minimum value of the objective function is 92.958562. The chosen charging station locations can also be seen on a map as shown below, where green means selected, red means not selected.



Note that these results correspond to a set of 12 charging stations that cater to the demand of Mumbai city, hence these results are representative in nature. The actual number of charging stations required for this purpose would probably be much larger.

Formulation 2.0

1. Over and above telling **where** the charging stations should be built, the model now also tells us what **capacity** charging stations should be built at each location.

   Assuming that, there is a fixed of charging station designs, having capacities $c_1, c_2, \ldots,$ we create a set T (**assumed to be the same on all station locations**), of all $k's$, where $k_r = c_r / d_{\text{avg}}$. Here, d_{avg} is the **average expected demand**, over all demand hotspots. In our case, since we have already scaled down all the demands with respect to the mean, $\boldsymbol{d_{\text{avg}} = 1}$.

   This construction of the set essentially gives us a non-dimentional form of station capacities. The decision variable x is then changed as follows:

$$x_i = \begin{cases} 0, & \text{if no station should be built at } i \\ k \in T, & \text{if a station at } i \text{ should have capacity equal to } k \times d_{\text{avg}} \end{cases}$$

Thus, if the model settles on having some $x_i = k$, then that means we should build a charging station having capacity $k \times d_{\text{avg}}$ on the location i. Note that, given how we have defined the k's, this capacity is not a random value, but corresponds to one of the available station desings.

We also now need to add a new **capacity constraint**:

$$\sum_{j=1}^{M} \left(\frac{D_j}{d_{\text{avg}}}\right) \times \alpha_{i,j} \leqslant x_i \quad \forall i \in 1, 2, \ldots, N$$

2. Since the charging stations which we built now may be different from one location to another, it is required to define a **budget** available to build the network, instead of just taking the total number of stations to build as input. Let us introduce a new budget parameter as follows:

   B : The maximum budget available for building the charging network

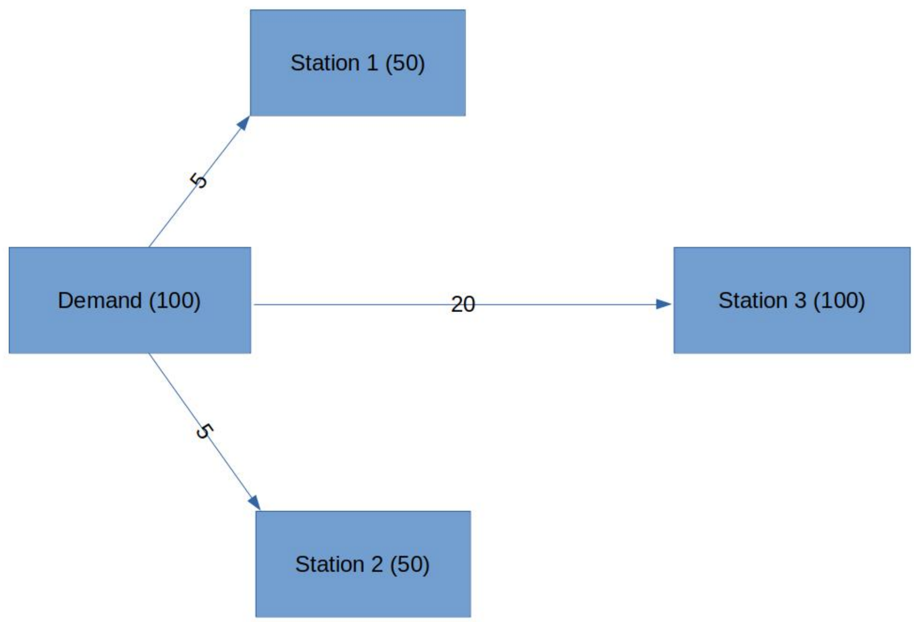
   Assuming that the cost of building a station is C times it's capacity, we add a budget constraint:

$$\sum_{i=1}^{N} x_i \leqslant \frac{B}{C}$$

   Here, B/C is the non-dimentional form of the total available budget.

3. Because of the added capacity constrint, it is now necessary to allow for **demand splitting**, meaning, the assumption used in formulation 1.0 that all vahicles on a demand hotspot would only go to a single charging station, may not work well here.

   We have assumed, for ease of formulating that, in (1) that the set T is the same for all station locations, but in real world situations, this probably won't be the case. One station location may be much smaller than another, meaning that the maximum capacity on such a station would be smaller than the other station. In such cases, the following (undesired) scenario may occur:



There is a demand (of 100 units), and the two charging station locations closest to this demand have maximum possible-capacities of 50 units each. A third station having maximum capacity of 100 units is much far of.

If we defined α as before, the model would now, considering capacity constraints, assign this demand to station 3, leading to a much higher objective function. This is undesired, and it would be much better if the demand of 100 **split** and utilized the two smaller (but closer) charging stations. To make choosing the two closer charging stations possible, and thus to make the demand→station assignment more efficient, we re-define α as follows:

$$\alpha_{i,j} \ : \ \text{Fraction of demand at } j \text{ assigned to station } i$$

Results

The output of the model is different, as described in the changes in the formulation. For example, in the image below, $1 \to 3, 2 \to 0,$ and $5 \to 2$ mean that stations of capacities $3\,d_{\text{avg}}, 2\,d_{\text{avg}}$ should be built at locations 1 and 5 respectively, while no station should be built at location 2.

```
objective 102.323716
should_build [*] :=
 1  3
 2  0
 3  3
 4  1
 5  2
 6  3
 7  0
 8  0
 9  0
10  3
11  3
12  2
13  0
14  1
15  3
16  0
17  0
18  1
19  3
20  2
;
```

```
fraction_assigned [*,*] (tr)
:      1      2   3        4        5         6          7   8   9   ...
1      0      0   0        0        0         0          0   0   0   ...
2      0      0   0        0        0         0          0   0   0   ...
3      0      0   0        0        0.917899  0.0821014  0   0   0   ...
4      0      0   0.417689 0        0         0.582311   0   0   0   ...
5      0      0   0        0        0         0          0   0   0   ...
6      0      0   0        0        0         0          0   0   0   ...
7      0      0   0        0        0         0          0   0   0   ...
8      1      0   0        0        0         0          0   0   0   ...
       .      .   .        .        .         .          .   .   .
       .      .   .        .        .         .          .   .   .
       .      .   .        .        .         .          .   .   .
```

The fractional demand values can be seen in the above image. For example, the entry of 0.917899 in row 3, column 5 means that, 91.7899% of the demand hotspot 3 is assigned to the charging station built at location 5.

Model response

To get a better feel of how the model works, we now study how the model responds to changes in the paramters.

Variation of fractional margin with budget

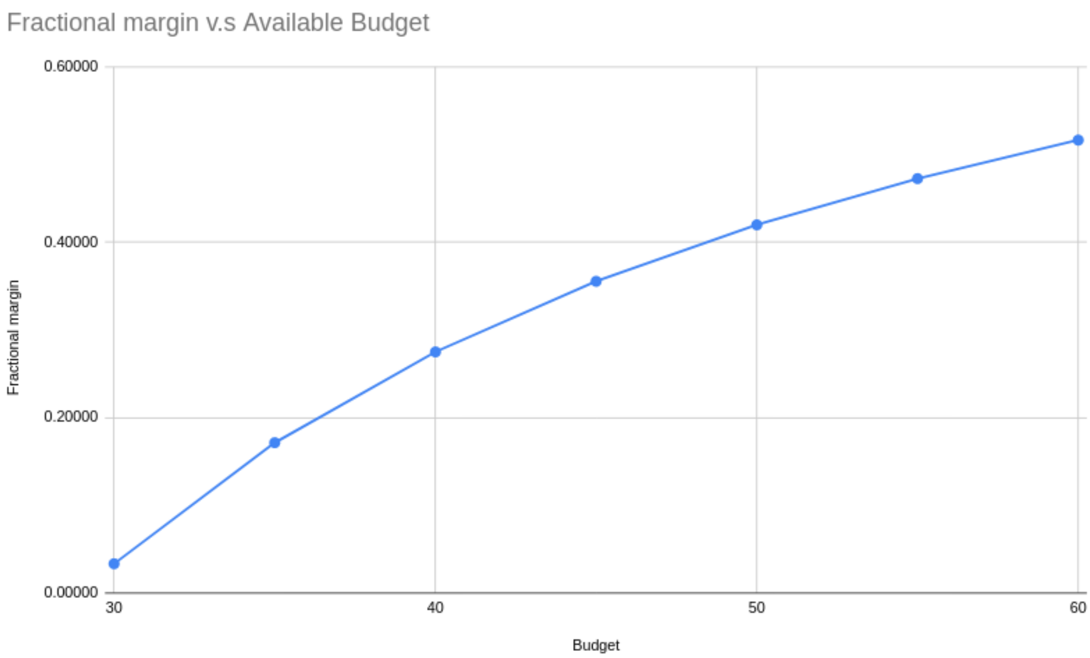
Our model tells us the where (and how big) to build the charging stations. However, all this has been calculated while keeping in mind a certain d_{avg} : the average expected demand over all the demand hotspots. It is very much possible that the d_{avg} that we have taken is off from the actual value, or the actual value changes with time, after we have built the network.

To handle such cases, it is important that the charging network is built keeping some marging available. Define the fractional margin as follows:

$$\text{Fractional margin} := \frac{\text{Total capacity} - \text{utilized capacity}}{\text{Total capacity}} = \frac{\sum_i x_i - \sum_j (D_j / d_{\text{avg}})}{\sum_i x_i}$$

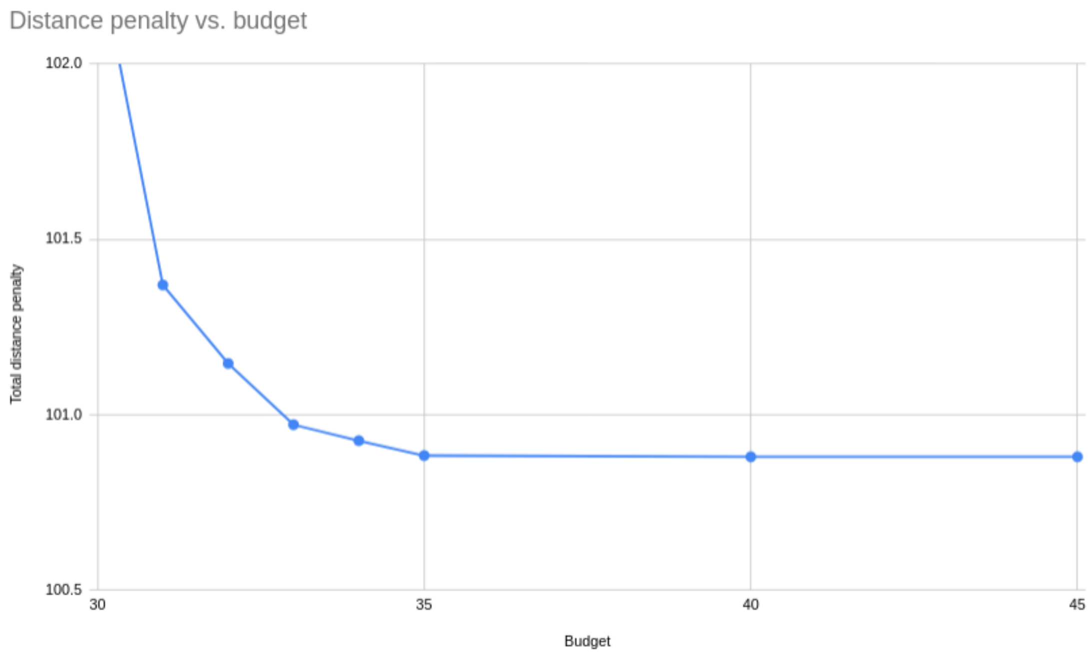
This is a measure of how much the network (once built) can handle fluctuations in the demand. A more robust network would have a higher fractiona margin. However, from a utilization perspective, having the fractional margin too high is a bad idea.

The following plot shows the variation of the fractional margin with the budget. Clearly, if the budget is high, we can build more stations, and the fractional margin is also higher.



Variation of distance penalty with budget

If the available budget is higher, we can build more stations so as to reduce the total distance penalty (which is the objective function). This is shown in the plot below. After a certain point, the curve flattens out, which corresponds to the case where all vehicles go to the closest charging station (which is in turn built at the highest possible capacity). After this point, it is no longer possible to reduce the distance penalty any further.



Conclusions

Given a budget, demands and distances between demands and station locations, our model can tell us if it is possible to satisfy all demands within the budget.

If it is possible to do so, it will choose that optimal subset of charging station locations, and the capacity of the charging stations to be built at these locations, which will lead to minimum customer travel time.

Further work

- The total time spent by a vehicle for getting it's batteries charged is actually made up of two factors:

    1. The time spent travelling to a charging station, which depends on the distance to the station

    2. Waiting at the charging station in a queue, and while the batteries are actually getting charged (which is also a significant amount of time)

    In our project, we have touched only the first component, i.e the travelling time. Further work in this project should be on expanding the formulation to include the second component, which would involve working on a **job-scheduling** problem having very different parameters and semantics.

- The data which we have used is the one which was easily available and reasonable to work with. However, in actuality, there are various government norms in place which put restrictions on where charging stations can be built. For example, the minimum distance between two charging stations must be ∼3km. Further work on this project may take into account such government norms and regulations, and will need to collect on-ground data as appropriate.

- There exists different type of chargers like AC/DC, which we haven't considered in this project. Updating the formulation for such types could be a good follow-up task.
- We have taken a simplistic formula for the charging station cost, considering it to be proportional to the capacity. In reality, the cost would depend on not just the capacity, but also the rate at which the land is leased from the government, the **operational costs** of the charging station (which in turn would depend on how much demand is assigned to that station, making this a recursive problem!) and many other factors. We can improve the project by accounting for some or all of these factors.

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