Team Control Number

9564

Problem Chosen

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HiMCM

Summary Sheet

Over the past decade, electronic devices have rapidly permeated almost all aspects of our lives. More frequent usage has led to a higher demand in charging, both in private and public places. In this paper, we investigated how this demand in public places has increased and what the costs associated are. We focused on two types of electric appliances, namely mobile devices and electric vehicles.

The aim of public charging service is to help those who have pressing charging demands and allow them to charge as soon as possible. Thus, we developed a **dissatisfaction index**, which incorporates these two factors, to quantify how well the demands are met.

Our first model used simulation to investigate the effect of the increase in charging demand on the dissatisfaction index of electric vehicle (EV) owners. We used a **queuing model** and treated EV arrivals as Poisson events. In every simulation, we assigned to each EV a battery level, battery capacity, and service time. Based on that, we calculated the dissatisfaction index and electricity consumption for each EV, therefore deriving the general dissatisfaction index and associated cost.

In our second model, we investigated the charging demands for personal devices, mainly smart phones. Firstly, we approached the problem in a macroscopic manner, using the overall change in battery level of incoming and outgoing visitors to measure how well the demands are satisfied. We represented the battery level distribution as a matrix and modeled the process of electricity consumption and charging as **matrix transformations**. Secondly, based on the area and compactness of the public place, we investigated how the number of charging facilities affects the distance one needs to walk to get to the closest charging point, which is directly linked to their satisfaction level.

By varying the charging facility installation plan, we obtained the relationship between satisfaction level and associated cost, which we presented on graphs for the public place's reference. On top of that, by changing the time-relevant parameters, we calculated the amount of additional costs incurred if the public place is to maintain the same satisfaction level in two years' time. In order to achieve this, we found that the cost in providing charging for EVs will nearly double while that for mobile devices will increase by less than 10% (if the current demand is well satisfied).

Beyond these general models, we have provided a few **additional variations**, including EV fast charging, different types of phone charging facilities, laptop charging, etc. to make our model more comprehensive.

We tested our model in vastly different public places, from airports and nature parks to schools and cafés. As the results suggest, our model is able to provide suitable and realistic charging facility installation plan for them.

Finally, we then proposed numerous initiatives to bring down the cost from multiple dimensions by targeting at the technological, social and behavioural aspects of the issue, and hopefully provide insights to future development in this area.

Don't charge, walk slowly!

Team 9564 Nov 19th 2019

Quick question: how many of you do not own a mobile device? Probably not many. The undoubted increase in electronic device usage has resulted in a growing charging demand. We expect to find places to charge our devices even outside of our home, so that we can spare the potential disruptions caused by a dead battery.

Indeed, most public places nowadays provide free charging services, from phone chargers, sockets, even charging stations for electric vehicles. But catering to this increasing demand is not an easy job: public places need to pay extra dollars to install these stations, and bear a long term electricity expenditure.

Our team have investigated how much more does it cost for public places to cater to this increasing demand, and will here present you our findings. We focused on two main parts of this demand, which are mobile devices and electric vehicles.

Mobile Devices The number of smart phones in the US is still increasing. Smart phone ownership is expected to grow from 80.8% to 83.4%. The battery capacity of the smart phones is also constantly increasing to support better performances.

The two main charging facilities are open sockets and lockable charging kiosks. In order to derive the exact increase in the cost, we looked two components: number of visitors and area of the space. We looked at the change in overall battery level of the visitors in a certain space as well as the time required to walk to the closest charging point, and use these factors to measure the user's satisfaction.

We found that there will be an increased cost to provide for the charging facilities. The total cost is rather high, but if the charging facilities are sufficient in 2019, the increase in two years will not be very significant.

Electric Vehicles On the other hand, the infant industry of electric vehicles is flourishing. The number of electric vehicles on the roads is growing at an incredible speed: currently there are around 1.4 million on the road, and it's expected to double in 2 years and increase 10 fold by 2030. Therefore, the charging infrastructure needs to be improved as well.

Parking spots with Level 2 charging stations (slow charger) will become a necessity for almost all public places. We used a mathematical model to simulate the incoming of EV in one day, and derived the average satisfaction level based on whether they got a EV parking spot as well as their remaining battery level.

We found that the required cost almost doubled in order for the place to achieve the same satisfaction level. We have also looked at the case of level 3 charging stations (fast charger), whose results are similar.

Our suggestions In light of this increase in public charging demand, we have come up with several suggestions for government and companies to consider.

- Implement smart charging stations with dynamic power distribution capabilities;
- Increase funding in research in battery aiming to find more efficient ones;
- Integrate electricity generation facility into the charging stations.

Can you suggest some?

How is it relevant to us? We, as users of these services, may consider the costs as irrelevant, since we seem to be using them for free. However, while we enjoy the great convenience brought by the improving charging infrastructure, we need to avoid abusing them. So friendly reminder time:

- Remove the device from the charging station once it is fully charged;
- Use the charging station only when you need it and not occupy it when you have a decent amount of battery.

Don't charge, walk slowly!

Contents

1 Introduction

Over the past decade, electronic devices—from large ones such as electric vehicles to small ones such as smartphones—have rapidly permeated almost all aspects of our lives. Together with this increasing ownership of electronic devices is our growing demand for charging.

In light of this, many public places start to provide "free" charging services to satisfy this demand. Yet the cost for providing this service is clearly not negligible. This gives rise to a series of baffling questions: How much provision is enough? How much do they cost? Who are paying for them? And how can we reduce the cost?

Based on analysis of the question context and extensive research on past and future trend in electricity consumption, we have developed a mathematical model that aims to answer these questions. Our model analyzes the parameters of a public space (visitor flow rate, operating hours, etc.) and provides a series of charging provision plans (mainly in terms of number of charging facilities) with associated cost, each corresponding to a certain level of user satisfaction rate. We have also proposed special modifications to places with special features in order for our model to be more comprehensive. The trend is factored in our model in the manner of parameters. We have used two sets of data representing the year of 2019 and 2021 to see how our model respond to the demands of different times, and how the charging provision will change with the demands. Lastly, we have also proposed some initiatives to reduce the costs associated with free charging provision in public spaces.

2 A Qualitative Analysis of the Problem Context

2.1 Scope of analysis

We will be first setting our scope of analysis.

The pattern and trends of electricity consumption vary significantly across different countries. A generic analysis of global charging demand may result in a model that poorly fits public places in any particular country. Hence, we decided to base our analysis and model on only 1 country, which we decided to be the United States.

We only consider public places like airports, shopping malls and libraries where charging is provided as a free side service. This means that places like independent charging points and roadside charging stations are excluded since they have no additional functions other than providing charging services.

We found that most of charging services provided at public places fall into two categories:

1. Charging of battery electric vehicles (BEV, or EV for future reference in this paper);
   - We will not be considering plug-in hybrid electric vehicles, since firstly, they can switch to gasoline and charging is not a necessity for them; and secondly, battery EV is becoming the future trend and is more relevant to our paper.
2. Charging of personal devices (mainly mobile phones and laptops).
   - For mobile phones, we will only be considering smart phones. Other types of cell phones are not considered, since firstly, smart phones is the current trend and other types of cell phones are exiting the market; and secondly, they have drastically different charging patterns and requirements on facilities.

2.2 Trend in electricity consumption

The ownership of electric devices is increasing constantly. The booming development in electronic technology in the recent decade has brought smartphones to almost the entire population: 4 out of 5 Americans today, including elderly and children, own a smart phone, and this number is increasing. Electric vehicles, a more recent product, have also become a popular substitute for conventional vehicles due to its low fuel cost and environmental friendliness.

Ownership is not the only change. Our habits in devices usage is also evolving. The consistent upgrade of the smart phone function allows us to serve a larger range of purposes. This change has witnessed a significant increase in the average time spend on our devices. The average battery capacity of smart phones is also increasing gradually in order to keep up with the electricity consumption required for better performance.

In our model, will be using the statistics of the years of 2019 and 2021.

Factor	2019	2021	% increase
Total number of operating vehicles/ million	276.0	283.7	2.79%
Number of EVs on the road / million	1.4	2.6	85.7%
Percentage of EV on the road	0.507%	0.916%	80.7%
Population in US / million	329.0	333.0	1.22%
Number of smartphone users / million	265.9	277.8	4.48%
Percentage smartphone ownership	80.8%	83.4%	3.22%
Average time spent on mobile devices / min per day	223	234	4.93%
Average phone battery capacity / mAh	3500	3800	8.57%

2.3 Analysis of Demand, Impact and Requirements

Electric Vehicles

The demand for public charging of EV is pressing. Even though most EV owners may choose to charge their EVs at home, there are indeed frequent cases where they run out of battery on the go, which disrupts the normal functioning of the car and potentially cause inconvenience on the road.

That's why public EV charging stations are a necessary infrastructure for the blooming EV industry. All public parking lots should equip themselves with parking spots reserved for EV, where Level 2 charging stations (slow charging) are available. At places with large traffic volume, DC fast charging stations (fast charging) should also be available, be there EVs with urgent charging needs.

Usually, Level 2 charging stations do not charge an additional fee on top of the parking fee, and Level 3 charging stations are free for the first 30 minutes of charging.

Personal Devices

On the other hand, as people relying more on electronic devices in their daily life, it is also important to ensure that those who are running out of battery can restore electrical energy at nearby locations, so that they can avoid the inconvenience brought by a dead battery.

Currently there are two forms of charging points that can satisfy such demands: open sockets for people who stay around, and lockable charging stations where people can leave their devices, each catering to different type of public space. These charging points should be readily available within a short walking distance.

3 Assumptions and Definitions

3.1 General Assumptions

- The electric device ownership is uniform all across the US and uniform in all types of public places.
  - The variation, if any, would be rather small, and currently we do not have any more specific information for us to add in the detail.
- The increase in charging demand is within the maximum capacity of the public place's power grid.
  - There is usually spare power capacity due to expectations of potential future increase in energy consumption when constructing a building.
- Visitor flow rate of public places do not vary according to season.
  - Public places considered in our model generally do not have peak seasons and off-peak seasons (E.g. airports).
- All appliances considered in our model are not being used while getting charged.
  - We assume consumers will follow safety precaution guidelines by not using their personal devices while charging. Moreover, people who visit a public place usually have things to do (E.g. shopping) so they will leave their vehicles and appliances when getting charged.
- During idle time (when an appliance is already fully charged but still plugged in), there will be no electricity consumption.
  - In reality, there is still a small amount of power output from the source even when an appliance is fully charged. However, due to the aforementioned assumption that there is minimum usage when getting charged, the electricity wasted during idle time is negligible.

3.2 General Definitions

Dissatisfaction Index

In order to measure how well (or how badly) the demands are met, we have developed a general model to calculate a dissatisfaction index D, which has two components, need and impatience. The 3 indices varies from 0 to 1, with 0 indicating the most satisfied state.

The need index D_1 indicate how urgently the users need to charge, depending on the remaining battery level. This relationship may differ for different types of devices.

The impatience index D_2 indicate how long the user have to wait before accessing the charging facility. A reasonable maximum waiting time will be set. The index increases proportionately with waiting time and reaches 1 when the waiting time is maximum.

The dissatisfaction index will be calculated based on the need index and impatience index. The detailed method of calculation can be found in respective sections.

The dissatisfaction index of a place will be the average of all users. We will set a benchmark for dissatisfaction index that a public space need to have in order for it to meet the demand. For places that wish to have a higher or lower standard, we will provide the corresponding charging provision plan and associated cost for each level of satisfaction.

Costs

There are two types of cost that we are concerned with: the fixed costs C_f for installing the charging facilities, and the variable costs C_v, mainly to cover the electricity consumption, which is calculated on a yearly basis.

Since the cost for charging facilities vary significantly, we will be using an average value, based on our research. And since the changes in these costs (including electricity unit price), if any, are far more difficult to predict, we will be using the same set of data for both the year of 2019 and 2021.

The maintenance cost is not considered in the paper, since we are only concerned with the cost borne by the public space and the maintenance is usually covered by the provider of the charging facilities.

Parameters of a Public Space

The demand for public charging is contingent on the specifics of the public space. Below are some key features that are relevant to the charging demand that we modeled.

Parameter	Definition
N	The average number of visitors per day
r	The number of vehicles visiting the public space per day
T	The average length of stay of each visitor (in hours)
H	The operating time of the public space (in hours)
A	The floor area of the public space (in m^2)
$b\%$	The remaining battery level of a specific EV
q	The compactness index of the public space. This will be elaborated in Section 4.

These values can vary significantly from place to place, resulting in different requirements of charging services at each public place. Ideally, specific values of these variables should be given by each public place. To illustrate how our general cost model works (in Section 4), we will be using a mock set of statistics as shown below:

N	r	T / hours	H / hours	A / m^2	q
80,000	11,000	1.5	12	43,500	0.5

4 Cost Model for EV Charging

We first model the increase in demand for level 2 charging stations (slow charging), which should be available at all public parking lots.

Specific Assumptions

- All EVs will be parking at EV parking spots (if available) and other cars will not park at EV parking spots.
  - EV parking spots are only reserved for EVs.
- The frequency at which EVs enter a public place is constant.
  - Different public places have different peak hours, and thus different rates at which EVs enter the place throughout the day. In order to construct a generalized model for all public places in this section, we would assume that the number of EVs entering a public place is time-independent.
- Once parked, an EV will immediately start charging if its battery is not full.
  - Since the charging service is free, we assume that people will take advantage of it.

Specific Variables

Variable	Definition
m_e	The number of EV parking spots
r_e	The number of EVs entering the public place per day, which is the product of r and the percentage of EVs among all cars (0.507% in 2019 and 0.916% in 2021)
X	A random variable indicating the time (in hours) between the arrivals of two EVs
l	The actual length of stay of an EV
E	The amount of electricity consumed by an EV
$b\%$	The remaining battery level of a specific EV
B_{max}	The maximum battery capacity of a specific EV

4.1 Model Construction

We observed that the process of EV charging resembles a queuing process. Therefore, we constructed a queuing model to simulate the behaviour of EVs at a public place in a single day, where we varied the number of EV parking spots to investigate how the average dissatisfaction index of drivers and the cost incurred change accordingly.

Characteristics of the EV Queuing Model

EV Arrival Pattern By our Specific Assumption 2, The arrivals of EVs is a Poisson point process with the average frequency of r/H arrivals per hour. Thus, the time X between the arrivals of two EVs follows the exponential distribution

$$p(x) = \frac{r_e}{H} e^{-\frac{r_e}{H}x}.$$

Queuing Mechanism When each EV arrives, if there is still an available EV parking spot, it will immediately go to that spot, start charging and occupy the spot until it leaves; otherwise, it is considered that our system fails to serve it. In other words, in this version of queuing model, customers immediately leave the queue and become dropouts once the server is occupied.

Service Time Since charging is not the main purpose of the visitors, it is reasonable to assume that the EV will leave once the driver finishes his/her business at the place (e.g. shopping, exercising, etc.). If there is no existing distribution of length of stay provided, we will use the standard assumption in queuing theory that the lengths of stay of the drivers, l, follow an exponential distribution. Note that the mean of the exponential distribution $p(x) = \lambda e^{-\lambda x}$ is $1/\lambda$, so we can equate the average length of stay of visitors, T, to $1/\lambda$, obtaining $\lambda = 1/T$. Thus, the exponential distribution we use here is

$$p(x) = \frac{1}{T} e^{-\frac{1}{T}x}.$$

Electricity Consumption

An EV will stop consuming electricity either when it leaves or when the battery is fully charged.

In our queuing model, each arriving EV will be assigned a battery capacity since different models of EVs have different battery packs. We used the five EV models with the highest sales volumes to approximate the proportion of battery capacities of all EV models on the road:

Model	Battery Capacity	Sales Volume	Proportion in the Top 5
Tesla Model 3	75 kWh	163971	29.30%
Tesla Model S	100 kWh	147517	26.36%
Nissan LEAF	62 kWh	132227	23.63%
Tesla Model X	100 kWh	69702	12.46%
Chevrolet Bolt	60 kWh	46211	8.26%

Thus, we assume that about 29.3% of arriving EVs have a battery capacity of 75kWh, $26.26\% + 12.46\% = 38.72\%$ have a battery capacity of 100 kWh, etc.

We also assigned to each EV an initial battery percentage $b\%$ between 0% to 100% according to a uniform distribution. Thus, the amount of electricity required to fully charge an this EV is $B_{max}(1-b\%)$.

If this EV leaves before it's fully charged, the electricity consumed will simply be $6.6l$, where 6.6 (in kW) is the average power of a Level 2 charging station. Hence, the electricity consumed by an EV is

$$E = min(B_{max}(1 - b\%), 6.6l).$$

Costs

The installation cost, C_f, is the number of chargers multiplied by the cost to install a Level 2 charging station (including the charging station unit, labor and material), which is on average \$3000 [1]. Hence,

$$C_f = 3000m_e.$$

The annual electricity bill, C_v, is the sum of electricity consumed by each EV in a day multiplied by the electricity price (which is 0.11 \$/kWh in the EIA 2019 report[2]) and 365. Hence,

$$C_v = 365(0.11 \sum E) = 40.15 \sum E.$$

Dissatisfaction Index

For EVs, we calculate the dissatisfaction index, D, of each individual by multiplying the need index, D_1, and the impatience index, D_2.

The need index, D_1, is determined by the remaining battery level, which signifies the extent of the need to be charged. If the battery level is 0-9%, charging would be a must and the need index is 1 because most EV models will start warning drivers once the battery level drops to 9% [3]; from 9% to 40%, the need index decreases from 1 to 0; if the battery is above 40%, the need index is 0 (according to U.S. Department of Transportation[4], the average daily miles per driver is 37, while 40% battery can sustain an 80-mile drive which is more than sufficient for the driver to drive home and charge). Hence,

$$D_1 = \begin{cases} 1 & 0 \le b < 9 \\ -\frac{1}{31}b + \frac{40}{31} & 5 \le b < 40 \\ 0 & 40 \le b \le 100 \end{cases}$$

4.2 Results and Interpretation

Based on these rules, we simulated the queuing process (see Appendix for source code) to obtain the relationship among the number of EV parking spots, m_e, the dissatisfaction index, D, and the costs C_f and C_v. For each value of m_e from 1 to 15, we ran the simulation 500 times and recorded the average value of D, C_f, and C_v.

As mentioned in Section 2, the proportion of EVs among all cars will change from 0.507% in 2019 to 0.916% in 2021. Thus, by setting r_e as $0.916\% \cdot r$ in the above model, we also obtained the relationships among me, D, C_f, and C_v in 2021.

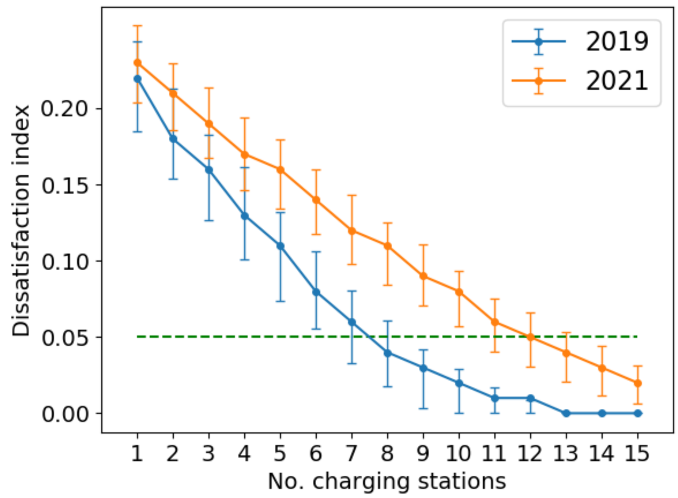


Figure 1: The Graph of D against m_e

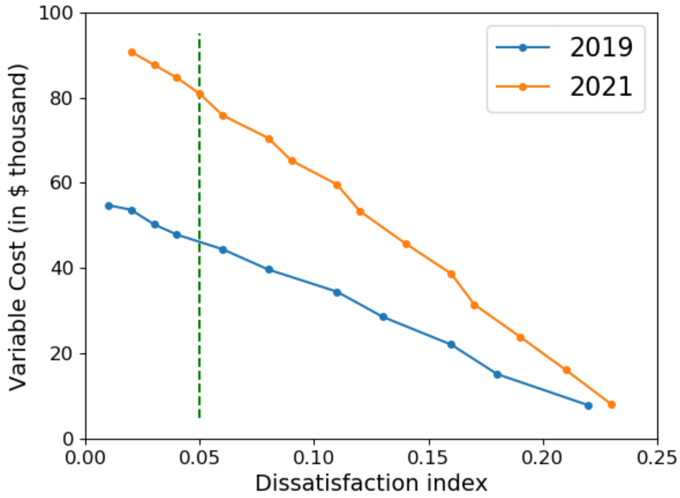


Figure 2: The Graph of C_v against D

Using the parameters for our hypothetical public place (see Section 3.2), the results are as follows:

Figure 1 shows that as the number of charging stations increases from 1 to 15, dissatisfaction level steadily decreases in both 2019 and 2021. Note that the initial dissatisfaction level are generally quite low, because most drivers do not have urgent charging demand, resulting in a low need index. Hence, even if no charging service is provided, a large number of drivers will still be satisfied. Figure 2 shows the amount of variable costs that will be incurred if a certain level of dissatisfaction is to be achieved.

The public place owner can make use of these graphs to estimate how many charging stations they need to install in order to bring down the dissatisfaction index to a certain level (our recommended value is 0.05). For example, if the public place currently has 6 charging stations, the current dissatisfaction index would be 0.14. If the owner wants to further bring the dissatisfaction level down to 0.05 in 2021, $11 - 5 = 6$ more charging stations need to be installed (from Figure 1), which means the amount of increased fixed cost, C_f, would be $6 \times 3000 = \$18000$; the annual electricity bill, C_v, will increase by about $80 - 30 = \$50$ (in thousands).

4.3 Adaptation to Different Places

Most public places with a parking lot (such as shopping centers, parks and hospitals) can directly apply this model by specifying the average number of vehicles per day and the average length of stay of visitors. Yet for the following two types of public places, our model can be modified to fit in the context.

Places with Large Car Traffic

At places with large traffic volume (such as airports and tourist attractions), there may be more EVs with extremely low battery (below 9%) that needs immediate and rapid recharge. At these places, DC fast charging stations also need to be provided to cater to their needs.

To model this demand for emergency charging, we modified the following parts of our queuing model:

- Instead of immediately leaving the queue when the server is occupied, EVs that really need emergency charging will queue up. Hence, the original model is changed to a single-queue-multi-server queuing model, similar to the queues in gas stations.
  - EVs with extremely low battery level may not be able to drive to the next charging station. Hence, we assume that drivers will not take this risk.
- EVs with more than 9% but less than 40% of battery will only charge here if the charger is unoccupied.
  - These are free-riders who take advantage of free fast charging. Since they are not in emergency, they will not wait if there is a queue.
- EVs with more than or equal to 40% of battery will not appear at the charging site.
  - They have sufficient battery to last for a week so will not take the trouble to visit a charging station.

- When calculating the dissatisfaction index, only EVs with battery level 9% or below are considered
  - We are modeling the demand for emergency charging here. Those with more than 9% of battery do not actually need this service.
- The impatience index, D_2, is now calculated based how long a car needs to wait before getting charged. We assume D_2 increases linearly from 0 to 1 when waiting time increases from 0 to 0.5 h; beyond that, the impatience index will remain at 1 as the driver is considered to have reached the maximum level of impatience.
- The charging speed is now 50kW and the installation cost is now $21,000.
  - These are the features of a DC fast charging station [1].

We will similarly calculate the dissatisfaction index and electricity consumption that correspond to number of fast charging stations, as well as the increase in cost in order to meet the future demand. Here are the results for our hypothetical data set:

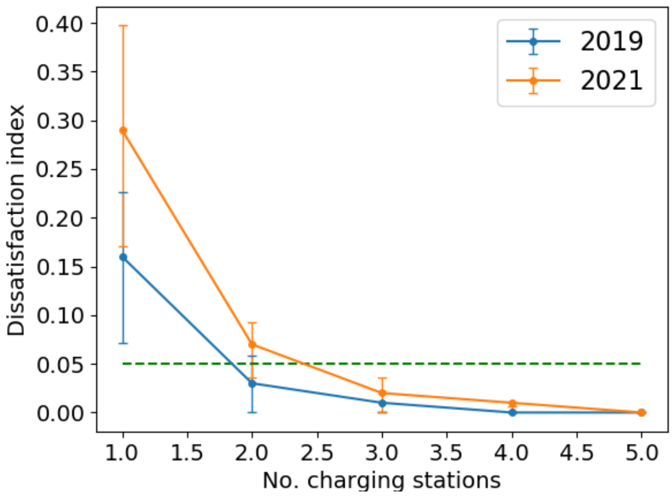


Figure 3: The Graph of D against m_e

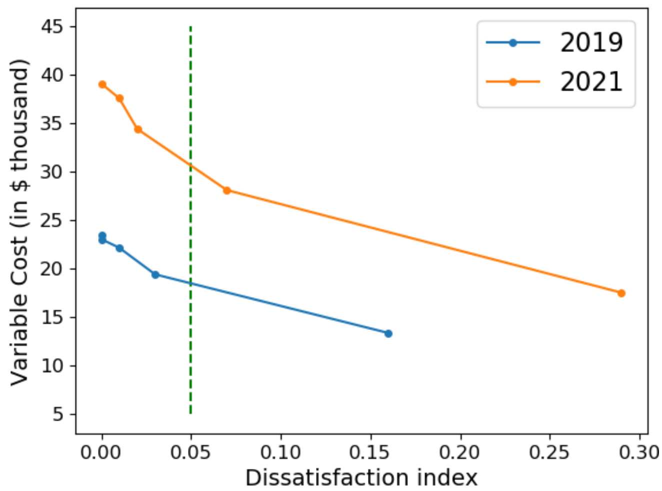


Figure 4: The Graph of C_v against D

Similar to slow charging, more charging stations give higher levels of satisfaction. We can also observe that in the hypothetical setting, to maintain the same level of satisfaction ($D = 0.05$), one more fast charging station will be installed, resulting in $21000 fixed cost and a $10000 increase in variable cost.

Workplaces

A special feature of workplaces is that there are regular visitors and visiting hours (such as offices and schools). At these places, the number of EV parking spots are usually calculated based on the number of workers who own an EV and drive it to work. In this context, a cost model can be more accurately constructed in this way:

A simple survey can be conducted among the regular visitors to get a rough estimate of EV ownership, and set up EV parking spots accordingly (for example, provide 2 spots for every 3 EVs). For the amount pf electricity consumed, we can reasonably assume that all EVs will be charged to its full capacity because of the long hours workers will stay at the workplace. The dissatisfaction rate will not be calculated in this case, as the best ratio between EV and parking spots can be surveyed. Thus, in this case,

C_f = number of EV $\times$ EV parking spot provision ratio $\times$ cost of level 2 charging station (which is $3000);

C_v = number of EV $\times$ EV parking spot provision ratio $\times$ average time to charge batteries to full capacity (taking into account the initial battery level) $\times$ power of level 2 charging station (6.6 kW) $\times$ electricity unit cost $\times$ 365.

5 Cost Model for Personal Devices Charging

The charging of mobile devices at public places works differently from that of EVs. Not only do we need to consider the total number of sockets to provide, we also need to consider where to put them so that it is available across the whole space. In this section, we will first investigate the relationship between maximum charging capacity of charging facilities and the need index of visitors. We will then investigate the relationship between the number of charging points (the number of locations where charging facilities are provided) and the impatience index.

Specific Assumptions

- The visitor flow is constant and there are no peak hours or off-peak hours.
  - The visitor flow pattern is very different for different types of public places. In order to construct a general model in this section, we assume a constant visitor flow.
- The battery level distribution of visitors arriving at the public place is relatively constant.
  - The battery level of arriving visitors is generally due to the functionalities and geographical features of a place (e.g. people arriving at a nature reserve may generally have low battery since it is far from their home), and these characteristics of a public place are unlikely to change.
- All smartphones have the same battery capacity, same rate of electricity consumption and same rate of charging at all times.
  - Different smartphone models can have very different battery consumption rate and charging rate. Nonetheless, when there are a large number of visitors, we can use the average battery consumption and charging rates to represent them as a whole.

Specific Definitions

Used in 5.1: Maximum Charging Capacity

Symbol/concept	Definition
A time unit	The time taken for the battery level of personal devices to decrease by 1%
m_p	Maximum charging capacity (the maximum number of devices that can be charged at this public place simultaneously)
p	The instantaneous number of visitors at this public space at any given moment
f	The number of people entering the public place in one time unit
L_E	A 100×1 column vector representing the proportion of visitors with each battery level at the public place
L_{change}	A 100×1 column vector representing the change in the proportion of visitors with each battery level when they enter and leave the public place
R	A 100×1 column vector representing the proportion of charging recipients with each battery level among all visitors
P	A 100×100 diagonal matrix representing the proportion of people who want to charge with respect to each a certain battery level
N	A 100×100 diagonal matrix representing the need index of each battery level
$M_{consume}$	A 100×100 matrix representing the battery consumption process
M_{charge}	A 100×100 matrix representing the charging operation
M_{adjust}	A 1×100 row vector of all '1's

Used in 5.2: Number of Charging Points

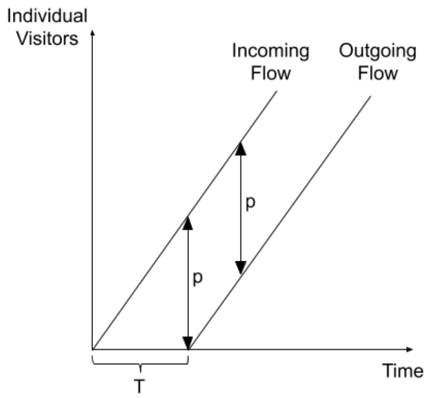
Variable	Definition
n	Number of PD charging points (locations where charging facilities are available)
d	The distance a visitor needs to walk to get to the closest charging point

5.1 Modelling the Need Index

At public places, people's phone battery levels are constantly dropping. If no charging service is provided, everyone will leave the public place with a lower battery level. Therefore, we see that the requirement of public places is to provide charging services to compensate for the loss of battery level while visitors stay at this place. In other words, if a visitor leaves this place with the same battery level as the time they entered, he/she will be considered satisfied and his/her need index will be 0. Thus, we will be calculating the need index by comparing the battery levels of visitors entering this place against those leaving the place. We started by abstracting public places.

Stage 1: Abstracting Public Places

In order to abstract public places, we disregarded the difference in peak hours and off-peak hours. This enabled us to approach the problem from a macroscopic point of view, perceiving public places as a container of people, where visitors flow in and out at a constant rate. The average length of stay of visitors, T, is also considered constant (in this section, T is time units as we earlier defined).



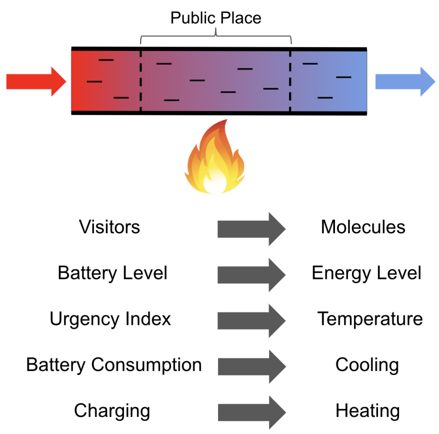
Due to these features, the rates at which visitors are entering and leaving the place must be the same (so that the public places retains a steady number of visitors over time). We defined this rate as f. Note that $f = N/H$, the daily number of visitors divided by daily operating hours. The relationships among f, T, and p are presented in the figure on the right: each visitor enters the place and stays for T time units; f, the rate of flow of visitors, is the gradient of both lines; p is the number of visitors at any given moment of time. Hence,

$$p = Tf = \frac{TN}{H} \tag{1}$$

According to Statista[5], the percentage of smartphone users among all people in the US is 80.8% in 2019. Hence, we estimate that the number of smartphone users at the public place is $0.808p$.

After constructing this crude model for a public place, we continued to add in relevant features to model the change in visitors' battery level.

Stage 2: Four Factors that Affect the Current Battery Level Distribution



Each visitor entering the place has an initial battery level and we assume that the battery level of arriving visitors has a fixed pattern (e.g. 1% of visitors has 1% battery, 3% of visitors has 2% battery, etc.). At public places, the battery level will be constantly dropping. Some visitors may charge their phone, thus having a higher battery level.

Thus, the entire process is analogous to the cooling of hot water in a water pipe in a cold environment, while a heater is placed to counter the overall cooling effect (as illustrated by figure on the right).

Imagine that the temperature of the water source and the power of the heather are kept constant. Then, we know that the distribution of energy level of molecules in a certain segment of the pipe will also be constant at a macroscopic level. Likewise, the distribution of battery levels of visitors will also be constant at any given moment of time. We denote this distribution by L_E, a 100×1 column vector representing the proportion of people with each battery level (ranging from 1% to 100% since most phones automatically switch off when the battery drops to 1%). As an illustration, $L_E = \begin{pmatrix} 0.02 \\ 0.03 \\ \vdots \end{pmatrix}$ means that 2% of the visitors have 1% of battery, 3% of the visitors have 2% of battery, etc. We drew the values of the entries of L_E from a normal distribution, since the battery levels of visitors in a public place are mutually independent and identically distributed randomly.

There are in total 4 factors that affects L_E at any given moment of time:

(a) Constant battery consumption;
(b) Charging service received by some visitors;
(c) The arrival of new visitors, whose battery levels are generally higher;
(d) The departure of visitors, whose battery levels are generally lower.

Note that L_E is the same at any given point of time (as we mentioned above). Hence, **in each time unit**, the net change in L_E brought by the 4 factors must be 0, which means that the net change brought by (a) and (b) is **equal** to that brought by (c) and (d). This means that we can measure the difference in the distribution of battery levels of arriving visitors (c) and departing visitors (d)—which is what we want to measure—based on the difference between the impacts of battery consumption (a) and charging (b)—which is what we can measure.

Stage 3: The Net Effect of Battery Consumption and Charging

We now present the exact effects of battery consumption and charging in a single time unit.

By its definition (see 'Specific Definitions' in this section), in a single time unit, everyone's battery level drops by 1%. We used a 100×100 matrix $M_{consume}$, as shown on the right, to represent this consumption process. When left multiplied by $M_{consume}$ (See Figure 5), each entry of L_E shifts 1 unit upwards, while the first entry of the new column matrix becomes the sum of the first two entries of L_E. This indicates the battery level distribution after a time unit. Thus, **the overall change in the proportion of visitors with each battery level** caused by **battery consumption** is

$$\begin{pmatrix} 1 & 1 & 0 & \dots & 0 \\ 0 & 0 & 1 & \dots & 0 \\ \vdots & \vdots & \ddots & \ddots & \vdots \\ \vdots & \vdots & \vdots & \ddots & 1 \\ 0 & 0 & 0 & \dots & 0 \end{pmatrix}$$

$$(M_{consume} - I)L_E,$$

where I is the identity matrix.

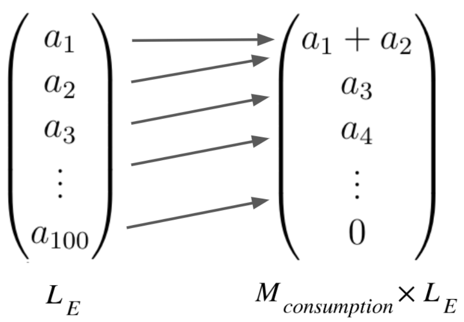


Figure 5: Battery Consumption

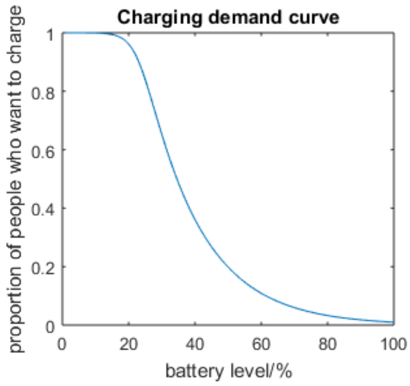


Figure 6: Proportion of Visitors with Charging Demand

On the other hand, charging is selective. It is only provided to visitors who want to charge, and the number of people that can receive the service depends on the maximum capacity of charging facilities.

We use a 100×100 diagonal matrix P to model the proportion of visitors with each battery level who want to charge. For example, $P = \begin{pmatrix} p_1\% & 0 & \dots \\ 0 & p_2\% & \dots \\ \vdots & \vdots & \ddots \end{pmatrix}$ means that p_1% of visitors with 1% battery want to charge, p_2% of visitors with 2% battery want to charge, etc. This proportion is drawn from the logistic distribution in figure 6. We determined the exact shape based on the following reasoning: when battery level is higher than 60%, people would have very low demand for charging; as battery level drops, the demand for charging rises; when it drops to 15%, the need for charging becomes very high. Thus, the total number of people who want to charge is $0.808pM_{adjust}PL_E$, where M_{adjust} is a 1×100 row vector whose entries are all '1's.

However, not all people with this charging demand can receive charging. We also need to consider the availability of charging facilities. Note that the maximum number of devices that can receive charging simultaneously is m and in reality, charging facilities are subject to inefficient use (there may be fully charged phone left by visitors who are not back yet). We consider the case where the facilities are only in efficient use in 80% of the time. Assuming all visitors who need charging have equal opportunity to charge, the proportion of visitors who actually received charging among those who need charging is $\frac{0.8m_p}{(0.808pM_{adjust}PL_E)}$, and thus the proportion of charging recipients with each battery level among all visitors is

$$R = \left(\frac{0.8m_p}{0.808pM_{adjust}PL_E}\right)PL_E.$$

For example, $R = \begin{pmatrix} 0.007 \\ 0.006 \\ \vdots \end{pmatrix}$ means that the number of charging recipients with 1% battery forms 0.7% of p, the number of charging recipients with 2% battery forms 0.6% of p, etc.

In cases where $\frac{0.8m_p}{(0.808pM_{adjust}PL_E)} > 1$, charging supply exceeds demand, and $R = PL_E$

Now we consider the charging speed. The most common phone charging outlets in public places have the rating of 5.0V and 2.0A, and the average battery capacity (in mAh) is approximately 3500 in 2019. The time taken to charge 1% of the battery will thus be $3500/(100 \times 2000) = 0.0175$ h. On the other hand, a full phone battery can generally last for 25 hours with normal usage[6]. Thus, the rate of charging is approximately $0.25/0.0175 \approx 14$ times of the rate of consumption. Swimilar to $M_{consume}$, we can define M_{charge} as a matrix whose entries 14 units above the diagonal and the last 14 entries of the last column are '1's and the all other entries are '0's. When left multiplied by it, the entries of a 100×1 column vector will shift 14 units downwards and the last entry will be come the some of the last 15 entries of the initial column vector. Thus, **the overall change in the proportion of visitors with each battery level** cause by **charging** can be represented by

$$(M_{charge} - I)R,$$

where I is the identity matrix.

Combining the effects of battery consumption and charging, we derive the change in the proportion of visitors with each battery level in a single time unit, which is

$$(M_{consume} - I)L_E + (M_{charge} - I)R.$$

Stage 4: Difference in Battery Levels between Arriving and Departing Visitors

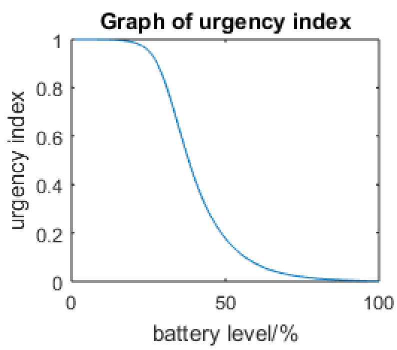
As derived in Stage 2, this change caused by consumption and charging must be compensated by the change caused by the incoming and outgoing visitor flow. However, in a single time unit, the resulting change caused by consumption and charging acts on p people, but the change caused by visitor flow is only brought by f people. Hence, in order to compare them, a scale factor p/f is needed. By formula 1 (in Stage 1), $p/f = T$. Hence, the total change in the proportion of people with each battery level in a time unit is

$$L_{change} = T \cdot ((M_{consume} - I)L_E + (M_{charge} - I)R).$$

For example, $L_{change} = \begin{pmatrix} 0.02 \\ \vdots \\ -0.05 \end{pmatrix}$ means when leaving, the number of visitors with 1% battery has increased by $0.02p$; the number of visitors with 100% battery level has decreased by $0.05p$, as compared to those entering the place. Note that D_1 can be negative when visitors generally leave the place with higher battery levels than they entered, meaning that the public place has provided more than necessary.

Stage 5: Calculating the need Index

Now, we calculate the difference in charging demands between arriving visitors and departing visitors. We defined a relationship between need index and the battery level of visitors. Here, the need index follows a logistic distribution with respect to battery level. The exact shape is determined by similar reasoning of that of charging demand (as mentioned in Stage 3). We used a 100×100 matrix N to record the need index corresponding to each battery level (the structure of N is similar to that of P in Stage 3). The average need index of all visitors in L_{change} is



$$D_1 = M_{adjust}NL_{change}.$$

We are thereby able to investigate how D_1 changes accordingly when the maximum charging capacity m_p varies.

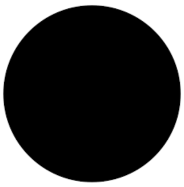
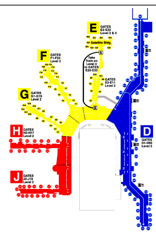
5.2 Modelling the Impatience Index

People with charging demand for personal devices can be dispersed across the whole public space, whereas charging facilities can only be found at charging points. Thus, it is important to ensure that visitors can always find a charging point within a reasonable distance. We noticed that the number of charging points, n, required for visitors to always find a charging point within d kilometers is determined by two geographic characteristics of the place—area A and compactness q. To derive the formula, we first investigated the relationships of the variables:

Relationship between n and A Set q and d as constants. The larger the area, the more charging stations we need. Therefore n is directly proportional to A.

Relationship between n and d Set A and q as constants. Note that a charging station can serve everyone in the circle with radius d whose center is the charging station. Hence, it covers an area of $d^2\pi$. In order to cover the public place, the smaller the value of $d^2\pi$, the more charging stations we need. Hence, $d^2\pi$ and n have an inverse relationship.

Relationship between n and q The compactness index, q, measures the compactness of 2D shape. There are many methods to estimate it, but the most accurate one is the measure of dispersion of elements of area, whose formula is $q = \dfrac{A}{2\pi(\sigma_x^2 + \sigma_y^2)}$ (MACEACHREN, 1985)[7]. It measures the extent of dispersion of each point on the shape from the centroid. In the formula, A is the area of the shape, σ_x^2 is the variance of the x-coordinates of all points from that of the centroid, and σ_y^2 is defined similarly. The index can take any value in the interval $(0, 1]$, where 1 means being the most compact. Here are the compactness of some shapes measured in this way:

			
1	0.9649	0.5383	0.1952

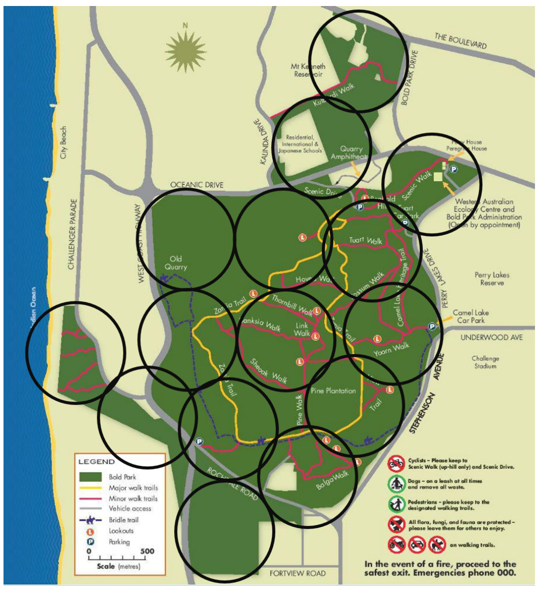
Hence, if A and d remain constant, the smaller the value of q, the more convoluted the area is, and therefore more charging stations need to be put to cover the entire public place. Hence, n is inversely related to q.

Combining the Relationships

Combining the relationships, we have

$$n = \frac{A}{qd^2\pi}.$$

To test the reliability and accuracy of this formula, we tested it on Bold Park in Australia (more testing cases can be found in appendix). Its area is 437 hectares $= 4.371\ \text{km}^2$ [8]; based on the map [9], we obtained $q = 0.5925$; we consider the case where visitors can find a charging point within 5-minute walking distance ($d = 5/12$ km). Our calculation revealed that $n = 14.90 \approx 15$, meaning that 15 charging stations are needed.



To test the accuracy of this result, we manually put charging points on the map to find out how many charging stations are needed. On the map below, each circle represents the coverage of a charging point. The radius of each circle (which is d) should be $5/12$ km, and we used the scale at the bottom left corner to obtain the size of the circle. As the map below shows, to cover the park, we need exactly 15 charging points, which shows that our formula is reasonably accurate.

Impatience Index

Making d the subject of the above formula, we obtained $d = \sqrt{\frac{A}{qn\pi}}$. The impatience index, D_2, increases when d increases. We assume that when the distance reaches 1.5 km, the impatience index would reach its upper bound at 1. Hence,

$$D_2 = \begin{cases} \frac{2}{3} & 0 \leq d \leq 1.5 \\ 1 & d > 1.5 \end{cases}$$

As mentioned earlier, for illustration purposes here, we set $A = 43500$ and $q = 0.5$. Then, we can investigate how the change in the number of charging points, n, affects the impatience index, D_2.

5.3 Results and Interpretation

Dissatisfaction Index

We can now combine the need index D_1 (which we obtained in Section 5.1), and the impatience index D_2 (in Section 5.2) to obtain the overall dissatisfaction index, D using a weighted average. We consider the need index to be slightly more important than the impatience index and assign to it a weight of 0.6, since it reflects one's extent of need instead of how quickly one's demand is met. Hence, the dissatisfaction index is

$$D = 0.6D_1 + 0.4D_2.$$

Cost

The number of working charging facility at a particular instant equals to $0.8m_p$. The average charging rate of mobile devices are 5V 1A, which is 5W. Therefore, the daily electricity consumption will be $0.004m_p \cdot H$ kWh. According to U.S. Energy Information Administration [2], the cost of electricity is 0.11$/kWh. Thus, the yearly variable cost will be

$$C_v = 365 \cdot 0.11 \cdot 0.004m_p \cdot H.$$

In cases where charging supply exceeds demands, $C_v = 365 \cdot 0.11 \cdot 0.00404p \cdot M_{adjust}PL_E \cdot H$

The fixed cost of installation is highly dependent on the electricity infrastructure as well as the charging provision plan (where to place the facility, which facility to choose). Thus the estimate we give here can only serve as a rough reference.

In our model, the number of charging points is more relevant to the installation cost as compared to the maximum charging capacity. The difference in the unit cost of sockets with different number of outlets is almost negligible compared to the cost to install one: A 2 receptacle 3 prong socket is usually below $5, that of a 6 receptacle below $15, whereas the average cost of installing a socket is around $200, including the cost of wiring, plastering and labor. The cost of installation of a charging kiosk is rather different and will be discussed in Section 5.6.

Here we will simply model the fixed cost of installation based on the number of charging points.

$$C_f = 200n.$$

Results

Using the parameters of our hypothetical public place (as specified in Section 3.2), we varied both the maximum charging capacity, m_p, and the number of charging points, n, to investigate how the dissatisfaction index, D, changes. Note that based on m_p and n, we can directly calculate C_v and C_f. The results for 2019 is presented in figure 7 below.

To model the case in 2021, we need to change the some parameters first. From the year of 2019 to 2021, the first main change is the proportion of smartphone owners, since smart phone ownership is expected to increase from 80.8% to 83.4%. Another change is charging rate. Since phone battery capacity will increase from 3500 to 3800 in 2021, the time taken to charge 1% battery will be comparative longer. Thus, the constant representing charging rate will decrease from 14 to 13. The results for 2021 is presented in figure 8.

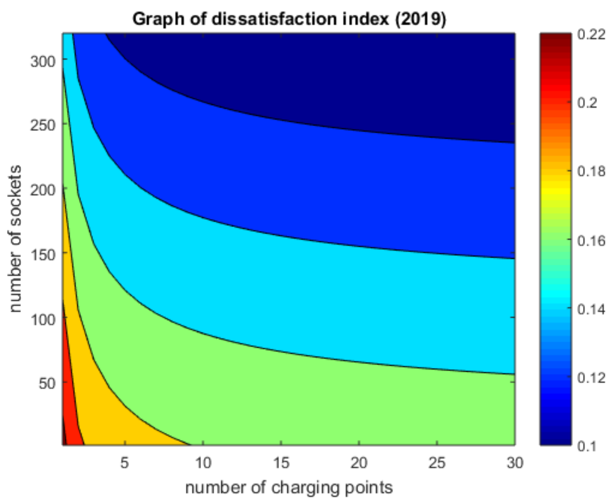


Figure 7: the Values of D for Each Combination of m and n in 2019

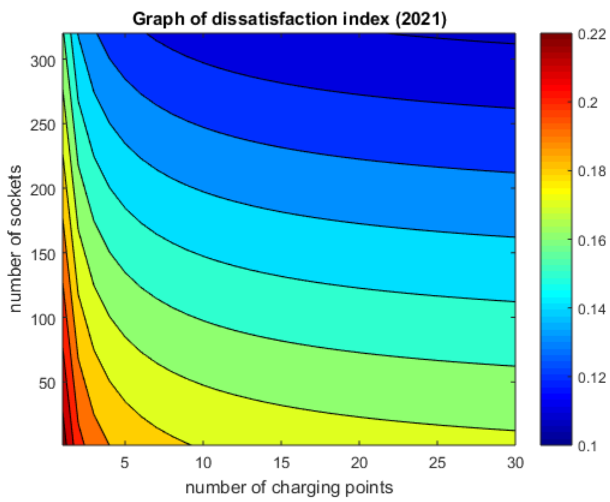


Figure 8: the Values of D for Each Combination of m and n in 2021

On both figures, the vertical axis represents m and the horizontal axis represents n. Each different combination of m and n will determine a dissatisfaction index, represented by a coloured point on the plane. As shown on the color map on the right, the redder the colour, the higher the dissatisfaction index; the bluer the colour, the lower. As we can see, as m and n increases, D gradually decreases from 0.22 to 0.1. The magnitude of D is not very large in this case since not much charging demand is generated in this public place. After all, visitors' length of stay is only 1.5 h.

The public place owner can make use of these graphs to estimate the maximum charging capacity and number of charging points they need in order to bring the dissatisfaction index down to a certain level. For example, if the public place currently has a maximum charging capacity of 100 and 10 charging points, the current dissatisfaction level would be 0.15. If the owner wants to double both the charging capacity and the number of charging points to further bring the dissatisfaction index down to 0.13 in 2021, the fixed cost C_f incurred will be 10×200 and the the annual electricity bill, C_v, will increase by about $365 \cdot 0.11 \cdot 0.004 \cdot 100 \cdot 12 = \$192.72$.

Although amount of charging services is freely determined by the owner of public places, based on the level of dissatisfaction level they aim to mitigate, we recommend that for the convenience of the public, it is best to keep the dissatisfaction level below 0.2.

5.4 Adaptation to Different Places

Sockets or Charging Kiosks?

There are two main types of charging facilities for mobile devices: open sockets and lockable charging kiosks.

Figure 9: Open sockets

Figure 10: Charging Kiosks

Which charging facility to install is mainly dependent on the mobility of the place. Mobility of a public space is defined as the tendency for its visitor to move around. We define the **mobility index** is the ratio between the amount of time when visitors walk around and the total length of stay.

Listed next page are the estimated mobility index for some typical public spaces.

Public space	Library	Cafe	Airport	Hospital	Park	Shopping Mall
Mobility Index	0	0	0.6	0.8	1	1

For places with high mobility such as shopping malls, people may not be willing to stay around an open socket and wait until their device is fully charged. A charging kiosk will therefore be more suitable. It allows users to lock their phones inside the charging station, go around to other places and retrieve it later. An 8-outlet charging kiosk typically costs $1200, and requires a 3 prong 120V socket.

For places with low mobility, sockets are usually provided instead of lockable charging stations. They are much cheaper (around $15 for 4 USB outlets) and less bulky compared to charging kiosks. There are usually seats are provided at these area, and sockets are attached to these seats – this may potentially result in a lower active index, since seats with sockets might be occupied by someone who is not charging, which may prevent others from accessing the facility. Walking time is less relevant for low mobility area, since people usually do not intentionally move to these area to charge.

There are exceptions as well. Parks, for example, is a large public space with high mobility. Yet installing charging kiosks may not be suitable since it would be overly costly, and it may also cause inconvenience for people to go all the way back to retrieve their phones. Therefore, sockets near benches might be a better option for people to juice up their devices while they sit and chill.

Places with a medium mobility such as airports usually incorporate features of both: there are area where people move around as well as area where people sit down and wait. Both types of charging facility can be installed in these places. The manager of the place may consider to set up more charging points in waiting area rather than mobile area so as to reduce cost by installing fewer charging kiosks.

Working index

Our general model mainly focuses on the charging demands incurred by smartphones. On top of that, another personal device that incur charging demand in public spaces is laptop. Unlike smart phones which which people brought with them all the time, laptops are only used in a limited number of spaces where people tend to do work. Therefore, we measure this tendency with a working index, which indicates the likeliness of a person who visit the place to do work on their laptop.

We assume that working area can only be area with low mobility: it would be ridiculous for a person to walk around with a laptop! And laptop can only charge at 3 prong sockets, which has a relatively low cost ($3 for two outlets).

Listed below are the estimated working index for some typical public spaces.

Public space	Office	School	Library	Cafe	Airport	Shopping Mall
Working Index	1.00	0.75	0.80	0.40	0.20	0

This index is used in the part where we consider the charging recipients. It will be multiplied with p to give the total number of laptop user in the space. For example, the expression for laptop charging recipients in cafe will be

$$R = \frac{0.8m_p}{0.4pPL} \cdot PL_E$$

Multi-storey buildings

Our current area model (Section 5.4) only considers places in 2D, disregarding the vertical dimension. For places with multiple storeys, we will be applying our area model multiple times to each storey and calculate the number of charging points required at each storey. The impatience index will be the average of each storey.

6 Model Testing

To test if our model generates useful and accurate results for different types of public places, we applied it to the following cases:

Airport Terminals Airport terminals are an ideal example of a extreme testing case due to their large numbers of daily visitors, long operating hours and long average length of stay. more importantly, airport terminals also have the lowest compactness index among almost all types of places due to their functionality (to connect to as many aircraft as possible). We estimated this set of parameters based on Singapore Changi Airport [10].

Nature Parks Nature parks are extreme cases with huge areas and relatively low number of visitors (as compared to its huge area). We estimated this set of parameters based on Bold Park in Australia.

Cafés Cafés are small and compact places with a small daily visitor flow. They also have low mobility index and medium working index.

Schools Schools have long operating hours, medium area and number of people. More importantly, they are typical places with high working index. We set the parameters based on our own school. (The results we obtained here is mentioned in our one-page newspaper article.)

For each place, we calculated the number of EV charging stations (m_e) needed in order to achieve our proposed threshold of dissatisfaction index for EVs, which is 0.05 as mentioned in Section 4.

For personal devices, we calculated the maximum charging capacity (m_p) and the number of charging points, n, needed to achieve our proposed threshold of 0.2. We noticed that this can be achieved by different combinations of m_p and n. We chose the combination that results in the lowest value of $C_f + 3C_v$, that is, the sum of fixed cost plus three years of variable costs. This is because the charging services provided may not be sufficient after three years and need to be updated again due to the rapid growth in charging demands.

The parameters and results are presented below:

Place	N	r_e	T/h	H/h	Working Index	A/m^2	q
Airport	96000	500	5 (visitors) 0.5 (drivers)	24	0.2	1.31×10^6	0.3
Park	3000	30	5	16	0	4.37×10^6	0.59
School	3000	NA	8	10	0.75	3.2×10^5	0.7
Cafe	240	NA	2	12	0.4	40	0.9

Table 1: Parameters

Place	m_e	C_f/\$	C_v/\$
Airport	11	33,000	270,000
	17	51,000	470,000
Park	9	27,000	26,000
	14	42,000	46,000

Table 2: Results for EVs

Place	m_p	n	C_f/\$	C_v/\$
Airport	1,449	197	394,000	394,550
	1,492	199	398,000	409,860
Park	81	20	36,000	4,300
	88	20	42,000	4,900
Café	6	1	2000	1100
	6	1	2000	1100
School	591	57	114,000	126,370
	616	57	114,000	130,650

Table 3: Results for Personal Devices

2019
2021

Analysis

Airport Terminal Based table 2, to meet the demand for EV charging, both fixed and variable cost would increase by more than 50%. This is a reasonable prediction, given the large daily visitorship and the rapid growth in the number of EVs on the road. To satisfy the demand for personal devices charging, 2 more charging points and 50 more sockets need to be provided, which is a steady growth. This growth rate may seem a bit small as compared to the rate of expansion of many airports. The main reason is that our generalized model does not consider the rapid growth in air travel, which greatly increases the airport passenger flow, as this growth is specific to airports.

Nature Parks For EV charging, nature parks has also seen a more than 50% increase in costs from 2019 to 2021 due to the rapid growth in the number EVs. However, as compared to airport, the extent of costs are considerably smaller due to the a smaller visitorship. To satisfy the increase in personal device charging, no more charging points need to be installed and the maximum charging capacity only needs to be slightly increased. Our model also suggests that the charging capacity of **each** charging point is about $81/20 \approx 4$, which is significantly lower than that of other places. Hence, we suggest that instead of having a centralized charging stations with large capacities, it is better for parks to have a large number of charging facilities with small capacities to cover a wider area, as this better improves the convenience of visitors and makes them more satisfied.

Café Based on table 3, our small café with a daily visitorship of 240 does not need to expand their charging provision plan. Indeed, many cafés already provides a socket per table, which is sufficient. Note that the number of charging stations is , but this does not mean that cafés need to install a charging kiosk with 6 sockets. Instead, the café itself can be viewed as a single charging point since the sockets are all in proximity to each other.

School As shown in table 3, For schools, not many additional facilities need to be provided. Indeed, most students and staff already own mobile phones and laptops. There is unlikely to be a large increase in demand in two years.

7 Costs relevant to the customer

Ostensibly, the public places are paying for these large amount of charging costs and we are enjoying this service for free. But is there such thing as a free lunch? According to the second law of demand, such an increase in cost will always be split between the producers and consumers.

Price Elasticity of Demand and supply In our first case, we assume that providing "free" charging service do not affect the demand for the goods this producer primarily produce (for example, restaurants primarily sell food). Hence, providing electricity and charging service leads to an increase in the cost of production and hence a decrease in supply because the producers will be less able to provide the goods. As shown in figure 8, the increased cost of production is represented by rectangle $ABCD$. The blue section is paid by the consumers whereas the green section is paid by the producers. The proportion of the two areas is determined by the gradients of the demand and supply curve. The gradients, also called price elasticity of demand and supply, measures the degree of responsiveness of quantity demanded and supplied of a good to a change in its own price. Hence, whoever is less responsive to changes in prices will bear more of the cost.

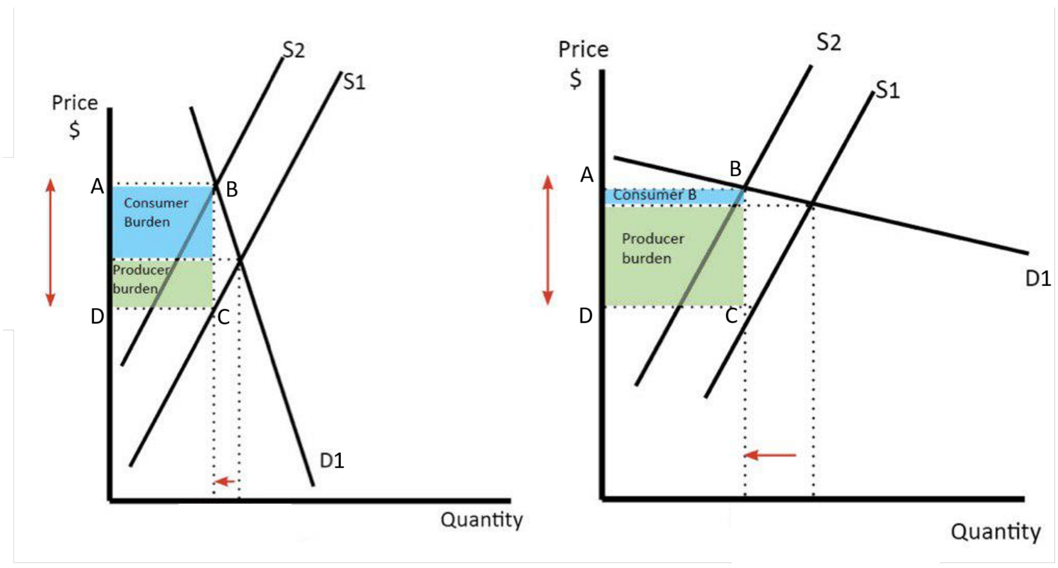


Figure 11: Market of goods with different PED and PES

The Principle of Reciprocity However, the assumption that providing free charging does not change the demand curve is not always true. According to the Principle of Reciprocity, human have the tendency to give something back when they receive something since we are compelled not to feel indebted to others. This tendency is the highest when the gift is given without any expectation of return. This effect makes a big difference in our second case—places like shopping malls where the provision of free charging is not a necessity and not expected to be part of their services. According to an experiment conducted by ChargeItSpot, one of the biggest charging station companies in the U.S., in places where free charging station is installed, customers stay 2.3 times longer and sales volume is boosted by 1.65 times. Similarly, EV drivers are more likely to purchase goods from shopping malls where EV charging is provided. Hence, the producers need to take into account of the customers‘ “gratitude” in order to optimize the cost and effect of their free charging service. Gratitude is dependent on the size of the “free gift” and the recipient’s income, and it indicates the tendency of recipients to return the favour. According to *The Economics of Reciprocity, Giving and Altruism* [11], the resultant effect of such an exchange-driven action is positively correlated with the income of the recipient. Hence, a higher cost in installing EV charging stations also brings higher resultant reward, because this free gift is larger, and EV drivers have a much higher average income than normal visitors.

8 Initiatives to reduce cost

In light of this increase in energy consumption in public places, we propose initiatives to make charging infrastructure smarter, more efficient and more sustainable.

8.1 Smarter

We suggest implementing smart EV charging stations with the capability of dynamic power distribution. This means automatic allocation of available power capacity of a public place to newly built charging stations, reducing the potential extra cost of overshooting and grid upgrades. Moreover, the power supplied to individual stations can be automatically adjusted to cater to the varying energy demand in peak or off-peak hours, thus have the electricity bill under control. This initiative is proven to be both effective and financially viable by similar enterprises such as EVBOX. These companies continue to improve their smart-charging technology so that a large-scale upgrade to the existing charging infrastructure can be made possible.

8.2 More efficient

On 9^{th} Oct, 2019, the Nobel Prize in Chemistry was awarded to three scientists “for the development of lithium-ion battery” because it “laid the foundation of a wireless, fossil fuel-free society”. Although this invention is not recent, its recognition signals a paradigm shift in our mindset and points the future direction of scientific research: the pursuit of more and more cost-efficient technology for energy generation, storage, transmission and consumption. Therefore, we propose the government to increase funding in research in relevant fields as well as to give subsidies for R&D of private firms so as to encourage reduction in energy usage and wastage in existing vehicles and gadgets. With these improvements, the annual electricity bill, C_v, is likely to decrease, reducing the variable cost of the increase in public charging demand.

8.3 More sustainable

According to our model, the large-scale installation of charging infrastructure is inevitable in order to cater to the increasing public charging demand. Consequently, these charging infrastructures take up a lot of space in this increasingly crowded world. Therefore, for maximum utilization of the public space, we propose integration of electricity generation into charging stations. Solar panels can be installed on charging stations to collect solar energy and convert it to electricity. As the industry leader of electric vehicles and charging infrastructure, Tesla introduced Supercharger V3 in July 2019 as an essential component of its worldwide Supercharger network. Although charging stations like Superchargers still purchase a large proportion of electricity from the grid, solar panels still bring down the cost by a considerable amount. With the future development of solar panel technology, we believe it is possible for charging stations to become completely self-sustained. This belief is attested to by Elon Musk, the CEO of Tesla, who suggested "the Tesla of the future could ditch grid power" and replace it with its own self- sustainable energy ecosystem. With this, the price for providing a unit of electricity will drop drastically, reducing the variable cost, C_v.

8.4 Policies and education

Apart from improvements to charging infrastructure, effective management of charging stations can play an important role, too. According to a JRC-led study of EV charging times in the Netherlands, 61.4% of the time that electric vehicles spend connected to public charging stations, they are idly occupying the charging spot. This results in inefficient use of public resources as well as a waste of electricity. To counter that, charging station operators can charge an extra fee for every minute after a vehicle is fully charged. This can be easily implemented for personal device charging as well. We foresee this to effectively change user behavior. Both the reduction in usage and extra fee collected can reduce the annual electricity bill, C_v.

We also propose moral suasion to transform the nature of public charging stations from first-come-first-serve to need-based. Public place operators can paste slogans to persuade users to allow people with very urgent charging needs to use the facilities first. This is meant to reduce user's inclination for abusing the free charging facilities as some may conveniently plug in their appliances even though they are almost fully charged.

This can lead to interesting changes to the cost model as now only devices with a certain level of battery(e.g. $0 \le b \le 40$) are charged. In the EV context, since cars with more than 40% battery do not contribute to dissatisfaction index($D_1 = 0$ for $100 \ge b \ge 40$), the facility operator can install less charging stations to meet the same level of satisfaction($D = 0.05$). This is seen in Fig 13 in which 3 less charging stations can be installed, reducing the fixed cost by \$9000. Moreover, total electricity consumption will also decrease as cars with high battery level will not use the facilities. This is seen in Fig in which when $d = 0.05$, \$11000 can be saved annually due to decrease in electricity consumption Both factors contribute to a decrease in C_f and C_v respectively, and hence reducing the overall cost C.

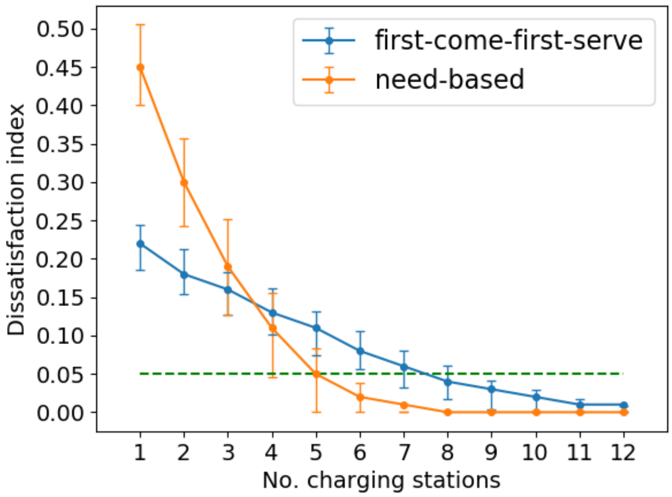


Figure 12: The Graph of D against m_e

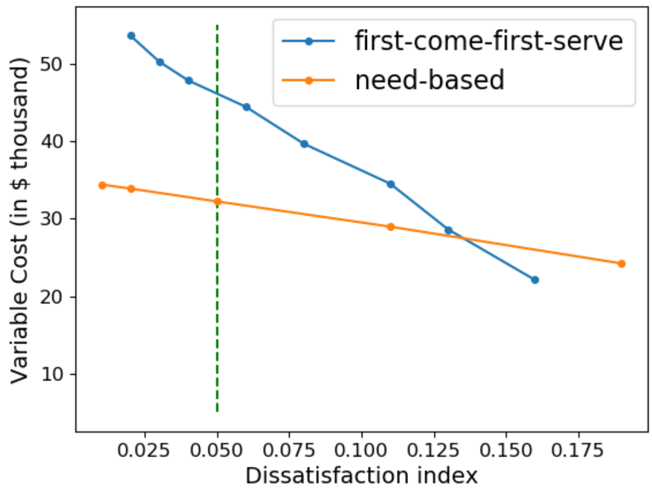


Figure 13: The Graph of C_v against D

9 Strengths & Weaknesses

9.1 Strengths

- Our model utilizes a comprehensive list of real-life data which ensures our simulation to be as realistic as possible
  - Using sales volumes of different EV models to represent their frequencies of appearing and their respective charging specifications to simulate real-life charging, our model makes the results of our simulation to be very convincing.

- Our model is flexible enough to adapt to different public places by capturing important features of public places as parameters, hence allowing simple adjustments to be made to differentiate places easily.
  - Users can customize features such as operating hours, average lengths of stay and area to suit their own situations.
- Instead of treating individuals as data points that display universal behaviour, our model takes into account of consumer psychology by incorporating behavioural concepts such as impatience, dissatisfaction and free-ridership.This can accurately capture real-life situations in our model which again ensures minimum simplification.

9.2 Weaknesses

- Our model does not take into account of the effect of peak hours.
  - It can possibly be improved by changing N, the variable representing daily visitor, into a function with respect to time. We leave this opportunity to the user of our algorithm to customize according to N of a specific place.
- Our model does not consider the battery wear level of individual devices, which can be a result of prolonged usage.
  - However, since electric vehicles have only become popular in these past 5 years, it is not unreasonable to assume that these batteries are all near full capacity.
- Our cost model does not consider electricity grid upgrade cost due to an increase in public charging demand.
  - However, since this demand only takes up a small portion of full grid capacity (the bulky ones being air-conditioning, lighting, etc.), and can also be addressed using smart charging stations introduced in the initiative section, it is reasonable to neglect this cost.

10 Conclusion and Future Work

In conclusion, we introduced a dissatisfaction index and calculated the costs of keeping the index at a reasonably low level. For EVs, we developed a queuing model in the SimPy library of python and ran over 75000 simulations for different public places and years. For personal devices, we modeled electricity consumption in a public place by using matrix transformation. Together with the area and compactness index, we can calculate the dissatisfaction index and its corresponding cost. Obtaining features of different public places and of different time, using them as inputs to our model, we were able to compare the difference in cost over time and space. We found that in order to maintain the same satisfaction level in 2021, the cost will stay relatively the same for mobile devices and will double for EVs. We then proposed numerous initiatives to reduce the cost from multiple angles by targeting at the technological, social and behavioral aspects of the issue.

In the future, we can seek to use a more data-analytical approach, as shown by recent astonishing developments in the field of machine learning. With the guiding principle that more data reveals a more accurate pattern and trend, the robustness of our model can be further improved. We can also expand our model to consider other countries, such as China, the largest electric vehicle market in the world with an exponentially increasing energy consumption.

The trend towards a fossil fuel-free society is almost irreversible, and there will certainly be rapid technological advancements coming along with it: better battery design, more powerful charging facilities, or even super-efficient solar panels. Therefore, our model will need to be constantly updated to catch up with the trend and hopefully, it will continue to provide relevant insights to future development in this area.

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Appendices

Queuing model for slow charging

```
from SimPy.Simulation import *
from random import expovariate,gauss,choices,seed,uniform
import os

def dissatisfaction_func(battery_percentage):
    '''
    calculate dissatisfaction based on battery percentage
    '''
    if battery_percentage <= 0.09:
        return 1
    elif 0.09<battery_percentage<=0.40:
        return battery_percentage*-1/0.31 + 0.4/0.31
    else:
        return 0

class Source(Process):
    def generate(self,number,meanTBA,resource,trial_num):
        for i in range(number):
            car = EV(name = '%d'%i)
            activate(
                car, car.visit(station = resource,trial_num = trial_num)
                )
            #arrival of cars is an exponential distribution
            t = expovariate(1/meanTBA)
            yield hold,self,t

class EV(Process):
    def visit(self,station,trial_num):
        battery_percentage = uniform(0,1)
        models = {
        'tesla_3':(75,50),'tesla_s':(100,50),'nissan_leaf':(62,50),
        'tesla_x':(100,50),'chevrolet_bolt':(60,50)
        }
        vehicle_type = choices(
            list(models.keys()), weights = [0.292,0.264,0.236,0.125,0.083]
            )
        battery_pack = models[vehicle_type[0]][0]
        battery_level = battery_pack*battery_percentage
        charging_speed = models[vehicle_type[0]][1]
        charge_to_full_time = (battery_pack-battery_level)/charging_speed

        arrive = now()
        print("%0.2f %s arriving"%(now(),self.name))
        #if free, start charging, if busy put in queue
        #set patience to be 0
        yield (request,self,station),(hold,self,0)

        if self.acquired(station):
            #how long a person stays is an exponential distribution
            staying_time = expovariate(1/1.5)
            yield hold,self,staying_time

            #done charging
            yield release,self,station
            leave = now()
            print("%0.2f %s finished"%(now(),self.name))
            dissatisfaction = 0
            actual_charging_time = min(staying_time,charge_to_full_time)
            consumption = actual_charging_time*charging_speed

        else:
```

```
            print('%s␣not␣waiting␣anymore'%self.name)
            leave = now()
            staying_time = 0
            dissatisfaction =  dissatisfaction_func(battery_percentage)
            actual_charging_time = 0
            consumption = 0

for station_number in range(1,10):
    for trial in range(500):
        #upper bound for vehicle arrival
        max_number = 99999
        #operating hours
        max_time = 16
        #parameter for exponential distribution
        TBA = 0.296
        num_stations = station_number
        k = Resource(capacity = num_stations,name = 'charging_station')
        initialize()
        source = Source(name = 'source')
        activate(source,source.generate(
            number = max_number,meanTBA = TBA,
            resource = k, trial_num = trial),at= 0.0)
        simulate(until = max_time)
```

Queuing model for fast charging

```
from SimPy.Simulation import *
from random import expovariate,uniform,choices,seed
import os
def dissatisfaction_func(wait):
    if wait >= 0.5:
        return 1
    else:
        return wait

class Source(Process):
    def generate(self,number,meanTBA,resource,trial_num):
        for i in range(number):
            car = EV(name = 'Car%d'%i)
            activate(
                car, car.visit(station = resource,trial_num = trial_num)
                )
            t = expovariate(1/meanTBA)
            yield hold,self,t

class EV(Process):
    def visit(self,station,trial_num):
        battery_percentage = uniform(0,0.4)
        models = {'tesla_3':(75,50),'tesla_s':(100,50),
        'nissan_leaf':(62,50),'tesla_x':(100,50),'chevrolet_bolt':(60,50)}
        vehicle_type = choices(list(models.keys()),
            weights = [0.292,0.264,0.236,0.125,0.083])
        battery_pack = models[vehicle_type[0]][0]
        battery_level = battery_pack*battery_percentage
        charging_speed = models[vehicle_type[0]][1]
        charging_time = (battery_pack-battery_level)/charging_speed

        arrive = now()
        print("%0.2f␣%s␣arriving"%(now(),self.name))

        if battery_percentage<=0.09:
            #<0.09 users will wait no matter what
            yield (request,self,station)
            wait = now() - arrive
            print ("%0.2f␣%s␣waited␣for␣%0.2f"%(now(),self.name,wait))
            staying_time = 0.5
            yield hold,self,staying_time #charging take place

            yield release,self,station #done charging
            leave = now()
            print("%0.2f␣%s␣finished"%(now(),self.name))
            dissatisfaction = dissatisfaction_func(wait)
            consumption = staying_time*charging_speed

        else:
            #free riders only charges when there are available spots
            yield (request,self,station),(hold,self,0)

            if self.acquired(station):
                staying_time = 0.5
                wait = 0
                yield hold,self,staying_time

                yield release,self,station #done charging
                leave = now()
                print("%0.2f␣%s␣finished"%(now(),self.name))
                dissatisfaction = 0
                consumption = staying_time*charging_speed

for station_number in range(1,16):
```

```
for trial in range(500):
    os.makedirs('%d/trial%d'%(station_number,trial))
    max_number = 9999
    max_time = 24
    TBA = 0.0667
    k = Resource(capacity = station_number,name = 'charging_station')
    initialize()
    source = Source(name = 'source')
    activate(source,source.generate(
        number = max_number,meanTBA = TBA,
        resource = k, trial_num = trial),at= 0.0)
    simulate(until = max_time)
```

Compactness of a public place

```
clear all; close all; clc;

P1 = imread('airport3.jpg');
x=findCompactness(P1)
Area=0.6968;
number=Area/(0.42^2*pi*x)

function compactness = findCompactness(map)
[BW,maskedRGBImage]=createMask7(map);
A = regionprops(BW,'Area');
Atotal=sum([A(:).Area]);
PixelL = regionprops(BW,'PixelList');
s=size(PixelL);
coordinate=[];
for i=1:s
    coordinate =[coordinate; PixelL(i).PixelList];
end

vX=var(coordinate(:,1));
vY=var(coordinate(:,2));

compactness=Atotal/(2*pi*(vX+vY));

function [BW,maskedRGBImage] = createMask7(RGB)
%  createMask  Threshold RGB image using auto-generated
%  code from colorThresholder app.
%  [BW,MASKEDRGBIMAGE] = createMask(RGB) thresholds image RGB
%  using auto-generated code from the colorThresholder App.
%  The colorspace and minimum/maximum values for each channel
%  of the colorspace were set in the App and result in
%  a binary mask BW and a composite image maskedRGBImage,
%  which shows the original RGB image values under the mask BW.

% Auto-generated by colorThresholder app on 12-Nov-2019
%------------------------------------------------------


% Convert RGB image to chosen color space
I = rgb2hsv(RGB);

% Define thresholds for channel 1 based on histogram settings
channel1Min = 0.000;
channel1Max = 0.000;

% Define thresholds for channel 2 based on histogram settings
channel2Min = 0.000;
channel2Max = 0.103;

% Define thresholds for channel 3 based on histogram settings
channel3Min = 0.788;
channel3Max = 1.000;

% Create mask based on chosen histogram thresholds
BW = ( (I(:,:,1) >= channel1Min) | (I(:,:,1) <= channel1Max) ) & ...
    (I(:,:,2) >= channel2Min ) & (I(:,:,2) <= channel2Max) & ...
    (I(:,:,3) >= channel3Min ) & (I(:,:,3) <= channel3Max);

% Initialize output masked image based on input image.
maskedRGBImage = RGB;

% Set background pixels where BW is false to zero.
maskedRGBImage(repmat(~BW,[1 1 3])) = 0;
```

Need index

```
function [dcap,dissatisfaction]=Dis(T,owningrate,type,p,m)
    p=p*owningrate; %number of devices
    chargingrate1=10; % charging rate:consumption rate for phones
    chargingrate2=2; % charging rate:consumption rate for laptops
    t=0.1; % time unit is 0.1 hour
    Battery=(1:100); % battery level
    I=diag(ones(1,100)); % Identity matrix
    sigma=40;
    mean=50;
    if type==1
        chargingrate=chargingrate1;
    else
        chargingrate=chargingrate2;
    end
    % distribution
    y = exp(-((Battery-mean).^2)/(2*sigma^2))/(sigma*(2*pi)^0.5);
    %normal distribution
    L=y'/sum(y); % distribution of people's battery level
    Dcharge=(1-1./(1+10000*exp(-0.4*Battery))).^0.15;
    % proportion of people who want to charge against battery level
    dis=(1-1./(1+10000*exp(-0.3*Battery))).^0.3;
    % dissatisfaction score against battery level
    ConsumeMat=circshift(I,[0,1]);
    ConsumeMat(1,1)=1; ConsumeMat(100,1)=0;
    ChargeMat=circshift(I,[0,-chargingrate]);
    ChargeMat(1:chargingrate,101-chargingrate:100)=0;
    ChargeMat(100,101-chargingrate:100)=1;

    A=diag(Dcharge);
    R=(ChargeMat-I)*A*L*m/sum(A*L*p);
    change=T/t*(ConsumeMat*L+R-L);
    changecap=T/t*(ConsumeMat*L-L);
    dcap=sum(diag(dis)*A*changecap);
    dObtained=sum(diag(dis)*A*change);
    % dnormalized=dObtained/dcap
    dissatisfaction=dObtained;
end
```

Installation plan for personal devices charger

```
function [result19,result21]=PDflow(tc)
tc.m1=ceil(max(tc.A/50000,tc.p*tc.T/100));
tc.m2=ceil(max(tc.A/50000,tc.p*tc.PCown));
tc.n=ceil(tc.A/tc.compactness/20000);
    function [userate,dObtained1]=Dis2(year,T,owningrate,type,p,mMax)
        m=(1:mMax);
        p=p*owningrate; %number of devices
        if year==2019
            chargingrate1=14; % charging rate:consumption rate for phones
        else
            chargingrate1=13;
            p=p*1.03;
        end
        chargingrate2=2; % charging rate:consumption rate for laptops
        t=0.1; % time unit is 0.1 hour
        Battery=(1:100); % battery level
        I=diag(ones(1,100)); % Identity matrix
        sigma=40;
        mean=50;
        if type==1
            chargingrate=chargingrate1;
        else
            chargingrate=chargingrate2;
        end
        % distribution
        y = exp(-((Battery-mean).^2)/(2*sigma^2))/(sigma*(2*pi)^0.5);
        %normal distribution
        L=y'/sum(y); % distribution of people's battery level
        Dcharge=(1-1./(1+10000*exp(-0.4*Battery))).^0.15;
        % proportion of people who want to charge against battery level
        dis=(1-1./(1+10000*exp(-0.3*Battery))).^0.3;
        % dissatisfaction score against battery level
        ConsumeMat=circshift(I,[0,1]);
        ConsumeMat(1,1)=1; ConsumeMat(100,1)=0;
        ChargeMat=circshift(I,[0,-chargingrate]);
        ChargeMat(1:chargingrate,101-chargingrate:100)=0;
        ChargeMat(100,101-chargingrate:100)=1;

        A=diag(Dcharge);
        R=A*L*m/sum(A*L*p);
        userate=m/sum(A*L*p);
        change=T/t*(repmat(ConsumeMat*L-L,1,mMax)+(ChargeMat-I)*R);
        %changecap=T/t*(ConsumeMat*L-L);
        %dcap=sum(diag(dis)*A*changecap);
        dObtained=diag(dis)*A*change;
        dObtained1=sum(dObtained,1);
        %     figure
        %     plot(dObtained1);

    end
%impatience idx
    function IDX=Impatience(Area,compactness,nMax)
        n=(1:nMax);
        d=(Area./(compactness*n*pi)).^0.5;
        IDX=(1./(1+10000*exp(-0.008*d))).^0.2;

    end


    function COST(userate,m,n)
        M=(1:2*m);
        Cv= 365*0.11*M*tc.H.*min(userate(M),1);
        N=(1:2*n);
        Cf=200*N;
```

```
        cost=3*repmat(Cv',1,tc.n*2)+repmat(Cf,m*2,1);
        figure
        contourf(N,M,cost)
        xlabel('Number␣of␣charging␣points')
        ylabel('Maximum␣Charging␣Capacity')
        title('Cost␣curve')
        colorbar;
    end

    function [a,b]=best(DD,cost)
        Ans=1000000000000000;
        [x,y]=size(DD);
        a=1;b=1;
        for i=1:x
            for j=1:y
                if DD(i,j)<=0.2
                    if cost(i,j)<Ans && i>=4*j
                        a=i;
                        b=j;
                        Ans=cost(i,j);
                    end
                end
            end
        end



    end

year=2019;
impatience=Impatience(tc.A,tc.compactness,tc.n*2);

%phone charging
[userate,p1]=Dis2(year,tc.T,tc.phoneOwn,1,tc.p,tc.m1*2);
COST(userate,tc.m1,tc.n);
DD1=0.6*repmat(p1',1,tc.n*2)+0.4*repmat(impatience,tc.m1*2,1);
figure
contourf(1:tc.n*2,1:tc.m1*2,DD1)
xlabel('number␣of␣charging␣points')
ylabel('Maximum␣Charging␣Capacity')
title('Graph␣of␣dissatisfaction␣index␣(2019)')
colorbar;
colormap(jet);

[a1,b1]=best(DD1,cost);
fix1=2000*b1;
variable1=365*0.11*a1*tc.H*min(userate(a1),1);

A1=0; B1=0;fix2=0;variable2=0;
if tc.PCown>0
    [userate,p2]=Dis2(year,tc.T,tc.PCown,2,tc.p,tc.m2*2);
    COST(userate,tc.m2,tc.n);
    DD2=0.6*repmat(p2',1,tc.n*2)+0.4*repmat(impatience,tc.m2*2,1);
    figure
    contourf(1:tc.n*2,1:tc.m2*2,DD2)
    xlabel('number␣of␣charging␣points')
    ylabel('Maximum␣Charging␣Capacity')
    title('PC␣dissatisfaction␣index␣(2019)')
    colorbar;
    colormap(jet);
    [A1,B1]=best(DD2,cost);
    fix2=2000*B1;
    variable2=365*0.11*A1*tc.H*min(userate(A1),1);
end

result19.capacity=a1+A1;
```

```
result19.cp=b1+B1;
result19.fix=fix1+fix2;
result19.variable=variable1+variable2;


year=2021;

%phone charging
[userate,p1]=Dis2(year,tc.T,tc.phoneOwn,1,tc.p,tc.m1*2);
COST(userate,tc.m1,tc.n);
DD3=0.6*repmat(p1',1,tc.n*2)+0.4*repmat(impatience,tc.m1*2,1);
figure
contourf(1:tc.n*2,1:tc.m1*2,DD3)
xlabel('number of charging points')
ylabel('Maximum Charging Capacity')
title('Graph of dissatisfaction index (2021)')
colorbar;
colormap(jet);

[a2,b2]=best(DD3,cost);
fix3=2000*b2;
variable3=365*0.11*a2*tc.H*min(userate(a2),1);

A2=0; B2=0;fix4=0;variable4=0;
if tc.PCown>0
    [userate,p2]=Dis2(year,tc.T,tc.PCown,2,tc.p,tc.m2*2);
    COST(userate,tc.m2,tc.n);
    DD4=0.6*repmat(p2',1,tc.n*2)+0.4*repmat(impatience,tc.m2*2,1);
    figure
    contourf(1:tc.n*2,1:tc.m2*2,DD4)
    xlabel('number of charging points')
    ylabel('Maximum Charging Capacity')
    title('PC dissatisfaction index (2019)')
    colorbar;
    colormap(jet);
    [A2,B2]=best(DD4,cost);
    fix4=2000*B2;
    variable4=365*0.11*A2*tc.H*min(userate(A2),1);

end
result21.capacity=a2+A2;
result21.cp=b2+B2;
result21.fix=fix3+fix4;
result21.variable=variable3+variable4;

end
```

EV slow charging at different public places

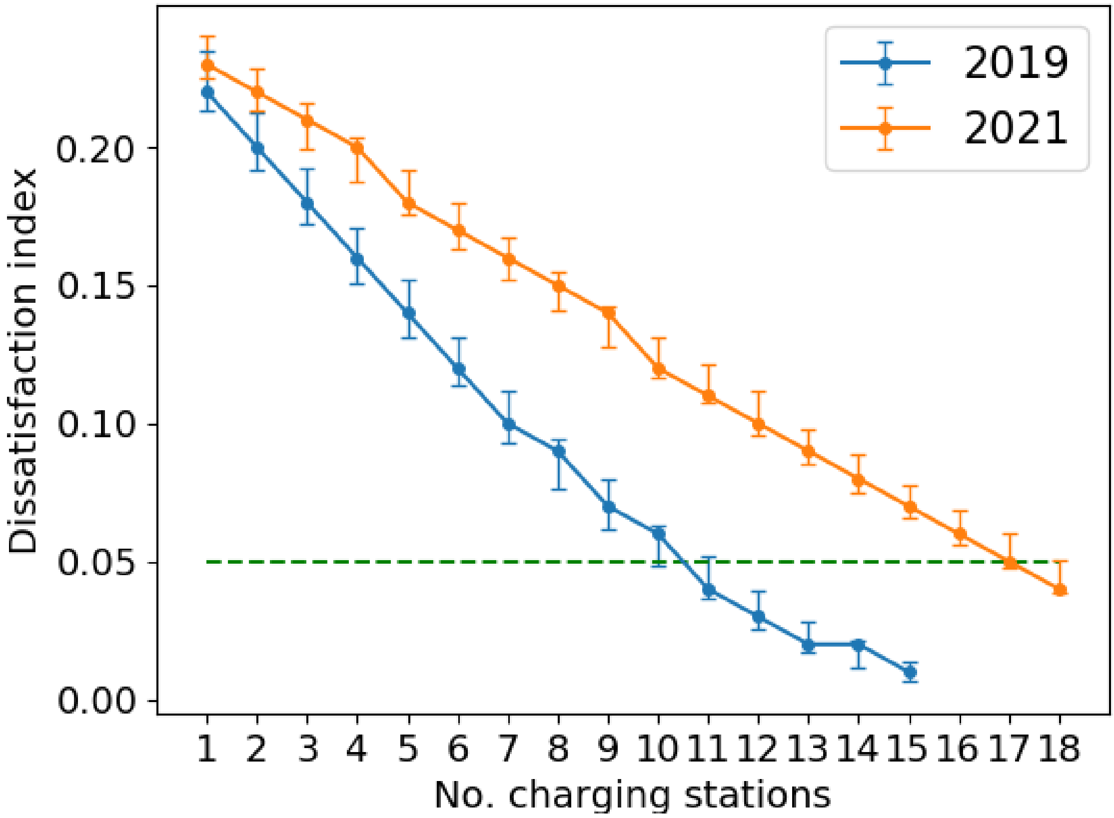

Figure 14: Airport EV charging station

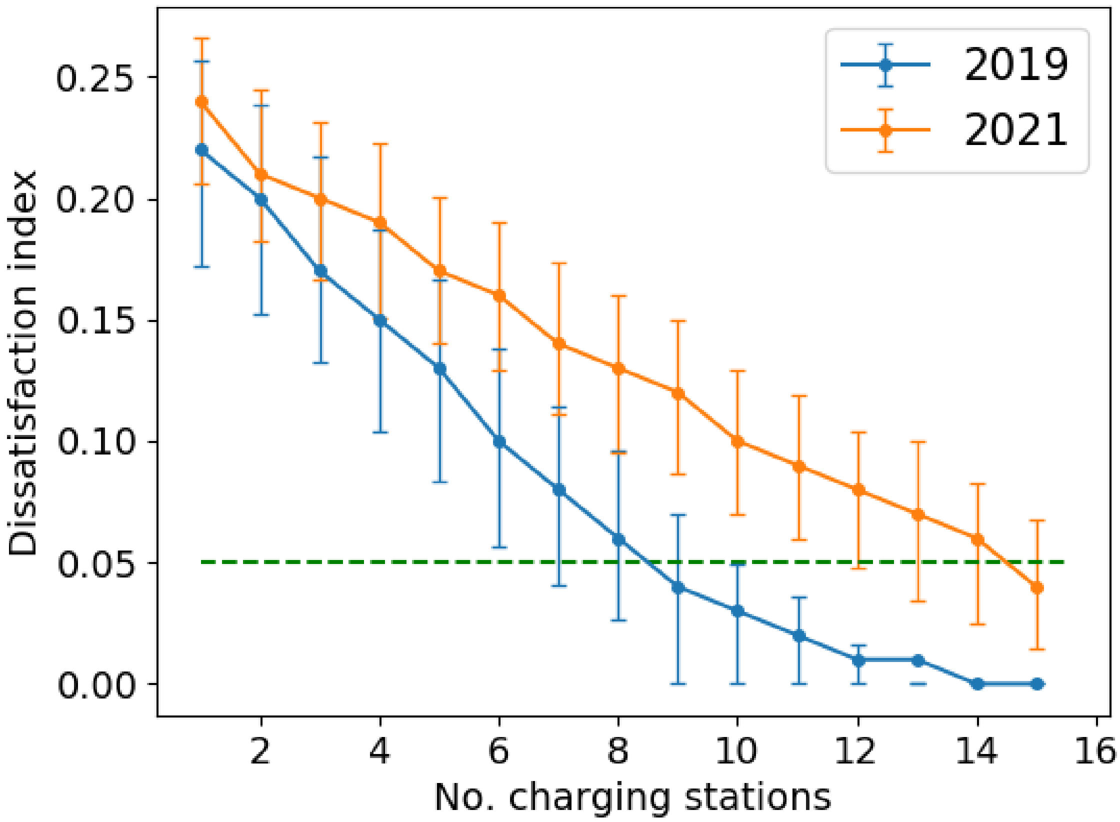

Figure 15: Park EV charging station

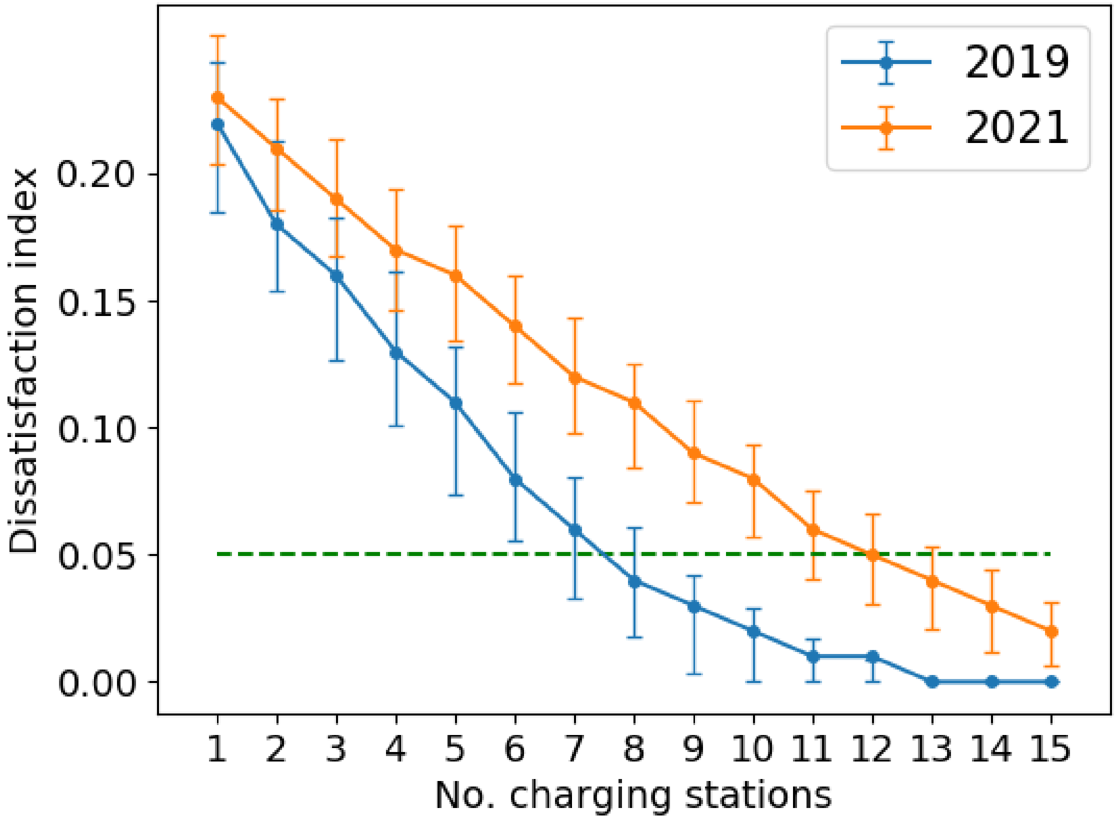

Figure 16: Shopping mall EV charging station

EV fast charging at different public places

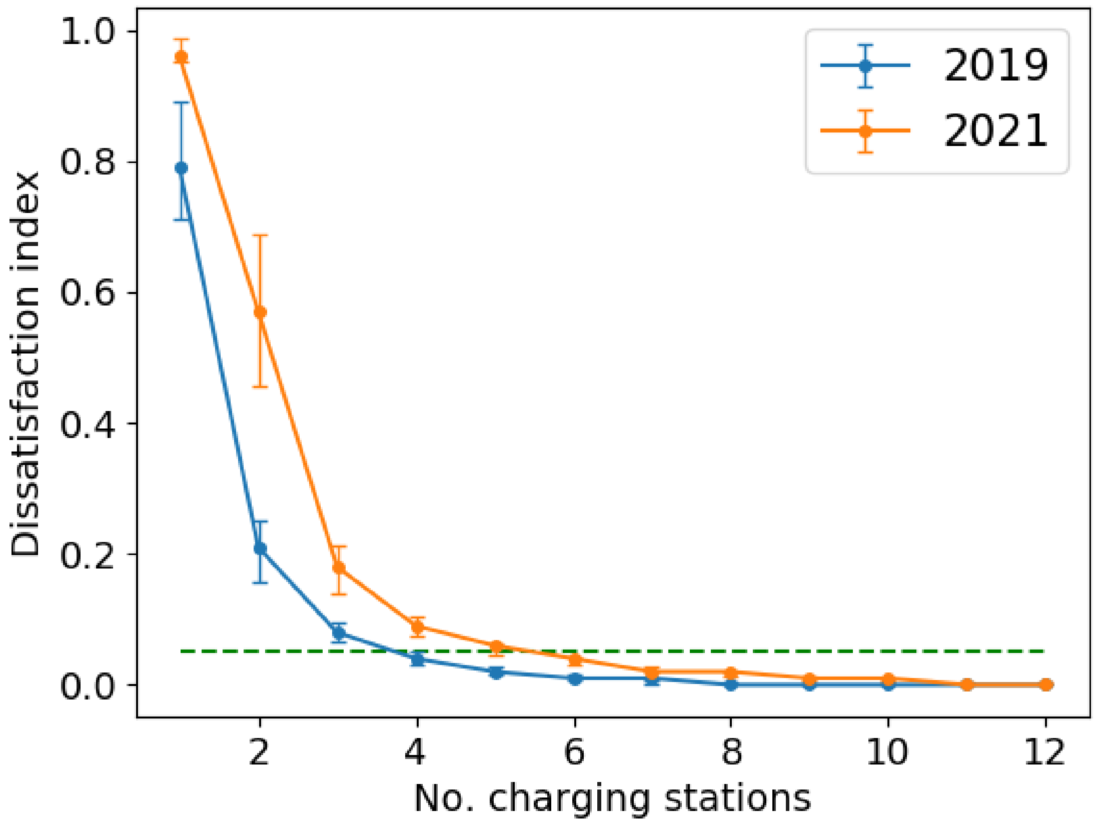

Figure 17: Airport EV fast charging station

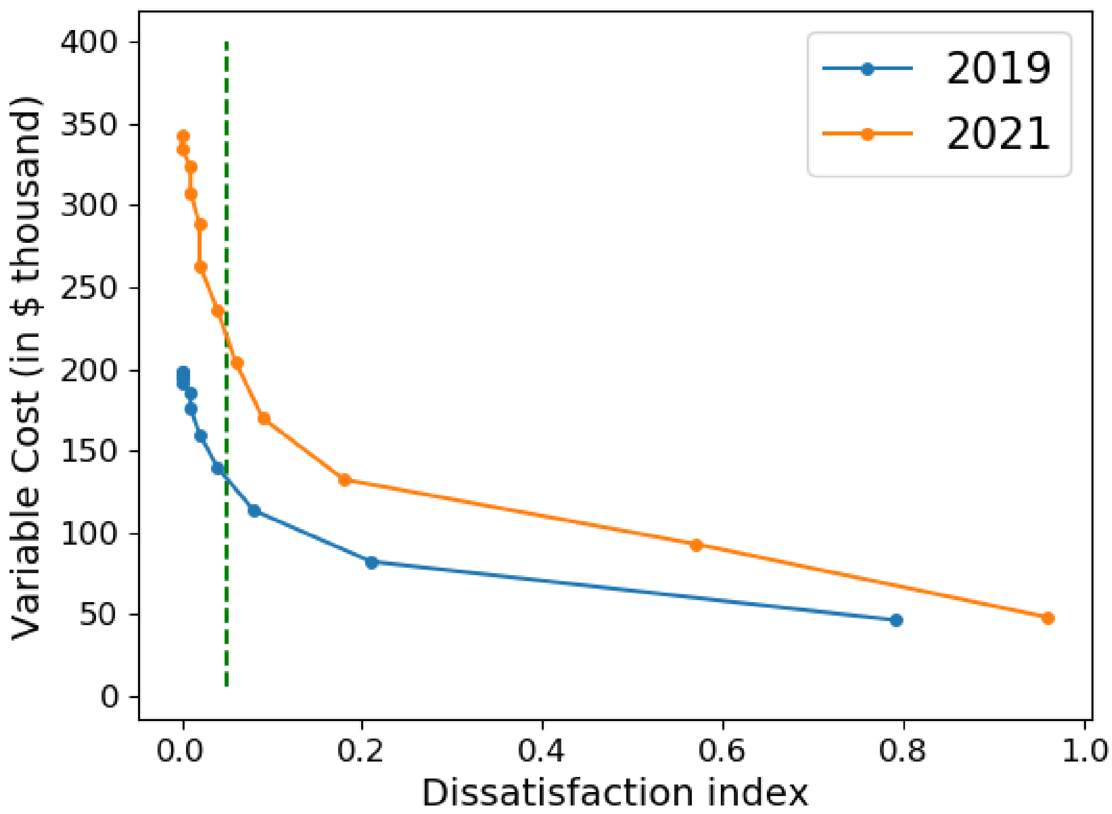

Figure 18: Cost of fast charging station in airport

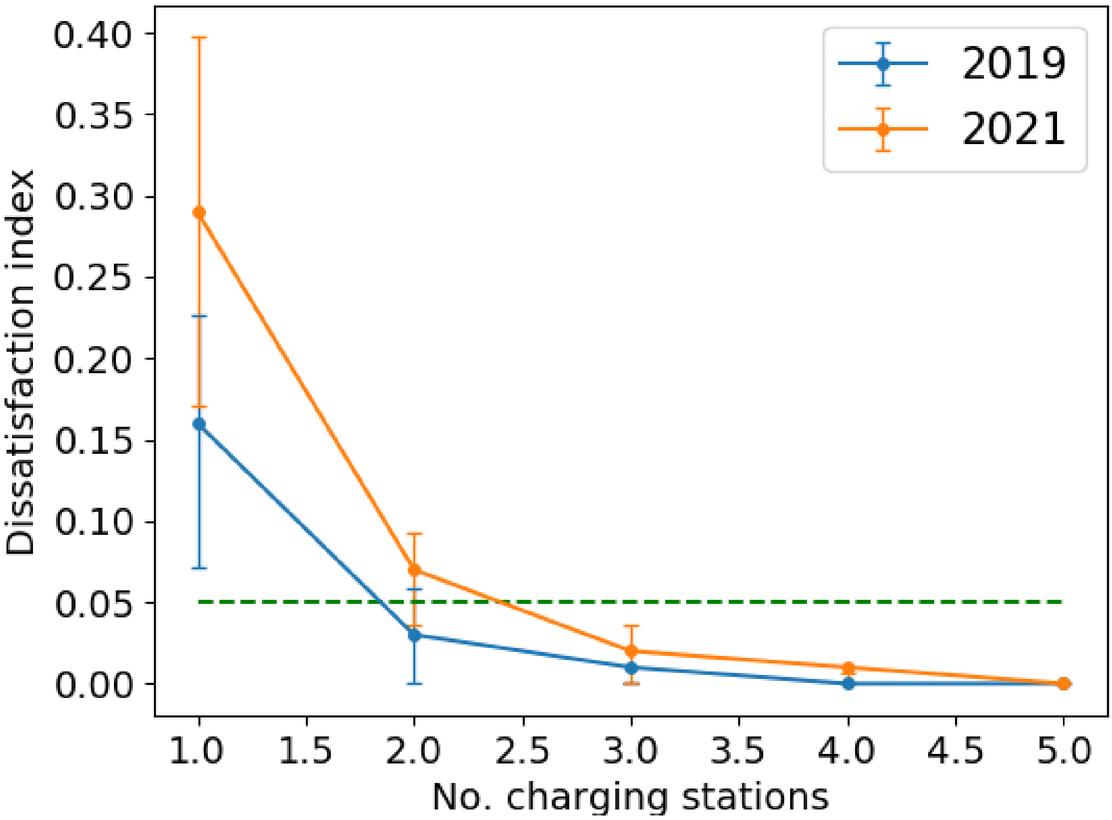

Figure 19: Shopping mall fast charging station

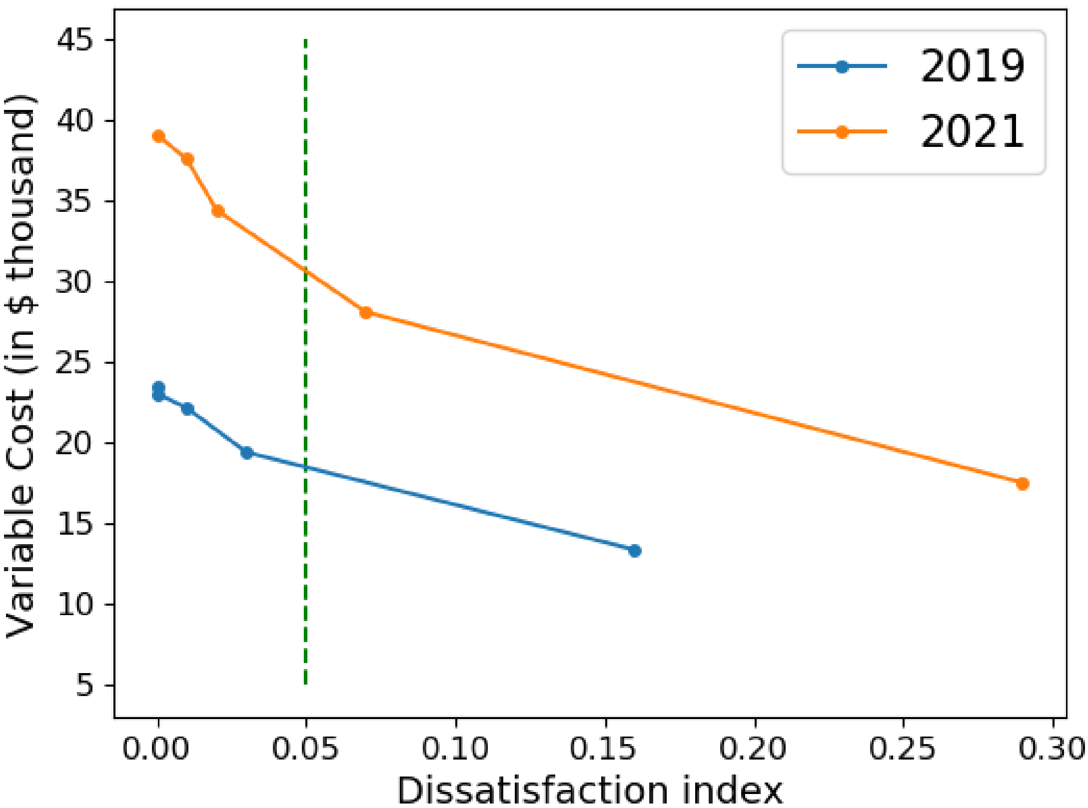

Figure 20: Cost of fast charging station in shopping mall