Optimization of waste collection routing by a new bi-criteria decision-making method: A case study

1. Project Summary

To minimize the fuel consumption and CO_2 emission by solid waste pickup trucks and prevent air and soil pollution caused by overflowing waste from wastebins, this study proposed a technological process involving collecting real-time data of wastebin holding amount by infrared sensors, selecting an optimum pickup route by a new bi-criteria decision-making method, and generating display of optimum route for end-users through internet.

This study provides a decision-making method for optimizing solid waste pickup routing in both urban and suburban areas.

Yet, due to lack of residence committee's consent, I was not able to actually install sensors in the trashcans. Instead, I ran the simulation trials at my home, using self-made bins and varying their distance between each other in each trial to increase variability and approach real life. After examining results of trails, I found out that compared to average route, the optimal route calculated using the program significantly reduced CO2 emission in a year, and residents had less likelihood of encountering funny smell issued from kitchen waste disposed outside of the garbage tank. I believe, in the future, if enough investment and time is allowed, this project can be applied in large scale, solving the inefficiency of waste collection in all the districts across the country with the only cost being purchase of detection sensors.

2. Introduction

Global warming is caused by emission of greenhouse gases, including CO_2 and CH_4. CO_2 emission from transportation sector was accounted for 28% of the total CO_2 emission in cities (*Gately, Hutyra, and Wing, 2015*). Approaches to reduce CO2 emission from transportation sector include studies on electrocatalysts to produce low-carbon fuels, promotion and improvements of electric vehicles, optimizing traffic routing, etc.

On average, New York city generates 12,000 tons of solid waste per day (NYC data, accessed Feb 2, 2022). When solid waste generation exceeds the holding capacity of wastebins, overflowing waste falls on the ground as shown in Figure 1 and 2, which may lead to degradation of soil environmental quality over time. Accumulation of municipal waste, especially kitchen waste, often causes unpleasant order and impacts the air quality in residential areas.

Therefore, optimizing waste collection routing can reduce energy consumption and CO_2 emission, as well as ensure the air quality and soil environmental quality in residential areas. One report (*Kinobe, Bosona, Gebresenbet, Niwagaba, Vinneras,* 2015) has shown that optimizing waste collection routing can reduce commuting time by 39%. This study used GID model application, but there was limitations such as it failed to take status of trashcans into account, instead only focusing on travelling distance. To reduce CO_2 emission and prevent air and soil pollution from overflowing solid waste from wastebins in cities, this study collects real-time data by installing infrared sensors on wastebins, develops a bi-criteria decision-making method to select the optimal route for waste pickup which can be displayed on mobile devices of the drivers. Subsequently, a case study in Chongqing City, China was performed and CO_2 emission reduction was quantified.

Figure 1 A small-sized, overflowing wastebin with scattered solid waste on the ground

Source: https://www.sierrasun.com/news/environment/trash-problem-piling-up-around-lake-tahoe/

Figure 2 A large-sized, overflowing wastebin with scattered solid waste on the ground

Source:https://www.nytimes.com/2020/08/28/nyregion/nyc-parks-trash.html

Figure 3 Manual pickup of solid waste in a wastebin

source: https://safestart.com/news/4-unspoken-hazards-of-waste-collection/

3. Objective

The project seeks to achieve the following goals:

1. reduce fuel consumption and therefore CO_2 emission of garbage pickup trucks
2. reduce the probabilities of odor from overflowing bins

4. Glossary

Bin: a Python class to store each trash site's information (Height and Time)

comparison matrix: a matrix in which each element is a value either 1, 2, 3, ... to 9 or 1, 1/2, 1/3, ... to 1/9 representing the importance of the corresponding row compared to that of the corresponding column

Deviation: how different a certain route is than the Standard Model

Graph: a Python class to store the map's information (paths between two sites and sites themselves)

Height: the height of kitchen waste inside a bin

path: the alternatives paths between two trash sites

Permutation: a function in which a set of elements can be sorted and arranged to produce all combinations of arrangements of this set

Prototype: routes generated from Permutation, which will be used later to produce another permutation because the round 1st Permutation only produces combinations of order of sites being visited while neglecting multiple paths between each two sites. So, for 2nd round of permutation, take a certain route 1 -> 3 -> 5 -> 2 -> 4 for example. 1 -> 3 has 3 paths, 3 - >5 has 2 paths, 5 -> 2 has 5 paths, 2 -> 4 has 1 paths, so the permutation gives variants of this route with a number $3 \times 2 \times 5 \times 1 = 30$. This process will be done on every route.

route: the order of sites to be visited, stored in a list.

Satisfaction: how Ill a route performs in matching Standard Model

Standard Model: a list that stores order of sites to be visited, sorted by site's Urgency Degree from greatest to shortest

Time: time trash remains in a bin

Total Distance: the total distance of a route

Urgency Degree: a characteristic of Bin that tells how pressing one trash site is to be picked up.

5. Method

Generally, the whole method can be divided up to 5 steps as the figure 5 below: 1) collecting data; 2) selecting trashcan; 3) selecting the optimal route; 4) displaying result to driver; 5) analyzing results, where step 3 and 5 can be further divided up to sub-steps.

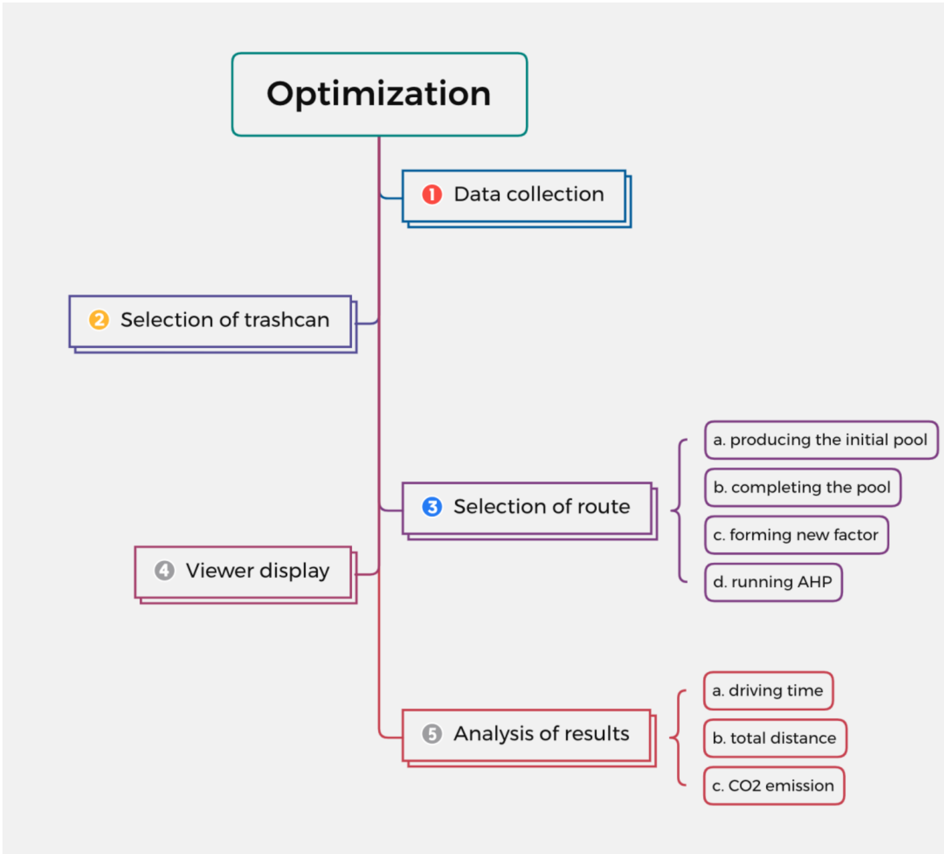

Figure 4 Flowchart of overall process

In the following descriptions, I will discuss the implementation of each step in details.

5.1 Data collection

In collecting data, I first applied detection sensors under self-made bins to simulate the filling process. The sensors started measuring each bin's status and decided if this bin was worth being picked up today. If yes, then sensor stored the data and sent it to my computer where a map object would be created that stored paths between valid bins. If no, then this bin had no need to be picked up and therefore skipped today's following procedures. Figure 5 illustrates the process described above.

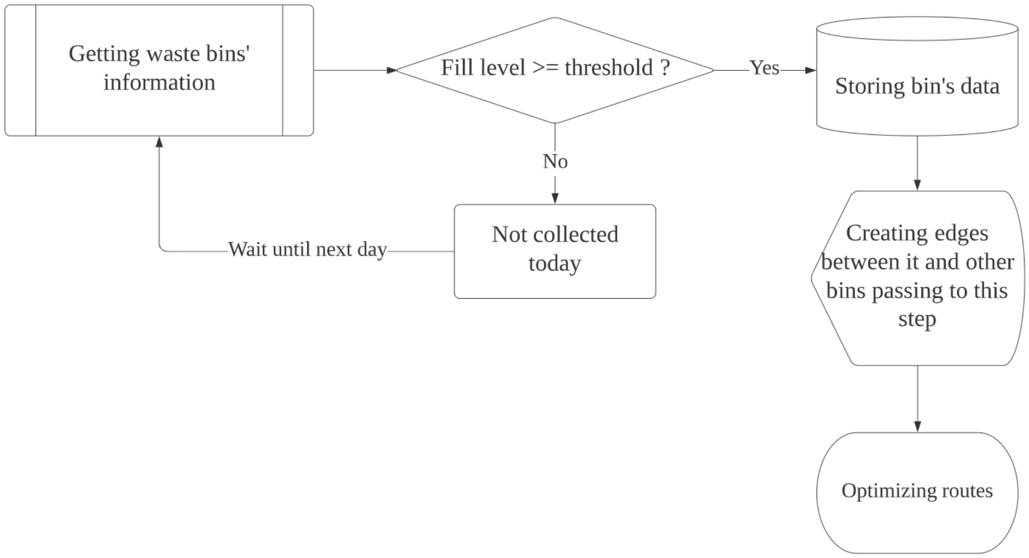

Figure 5 Flowchart of determining a bin to be picked or not

Realizing that choosing a fixed route daily lies in the fact that drivers lack information about each trashcan's status, I proposed to use detection sensors installed on each trashcan and record the time and height of trash inside the bin in real time, such that I can get the most immediate feedbacks about bin's information. To do this, I bought Arduino Infra-red detection sensors which Ire installed on the *simulated* trash site and allows another device (my computer) to receive data through internet.

Figure 6 Detection sensor installation

source: https://create.arduino.cc/projecthub/Technovation/smart-garbage-monitoring-system-using-arduino-101-3b813c?ref=search&ref_id=smart%20trash&offset=2

5.2 Selection of trashcan

In order to further reduce fuel consumption, I can first determine the exigency of a can to be picked as the first thing the program does every day before moving on to running algorithm. As a result, the driver does not need to visit every trashcan every day, if certain cans are not so urgent to be processed.

To this end, I use the data recorded by detection sensors to calculate what is called urgency degree to determine the necessity of a bin to be processed today.
Then comes to calculation of urgency degree: if it exceeds a predetermined threshold, I mark the can as necessary to be processed today, otherwise don't and leave it until the next day's examination comes. The urgency degree is calculated using equation below (figure 7):

$$Urgency\ Degree = 0.4 \times Time + 0.6 \times Height$$

Figure 7 Determination of a bin's pickup today

The figure above demonstrates 3 trashcans' necessity of being picked up today with premise that the threshold is 61.2.

Therefore, the overall process in this step can be summarized in the flowchart below.

5.3 Selection of route

Generally, in singling out the optimal route, there are 7 steps involved: 1) creating classes for storing bins' information; 2) creating all possible routes; 3) calculating satisfaction and total distance of each route; 4) storing each route's information in another class; 5) running AHP; 6) output the optimal route; 7) output the analysis of results. The flowchart describing the overall process is demonstrated in figure 8.

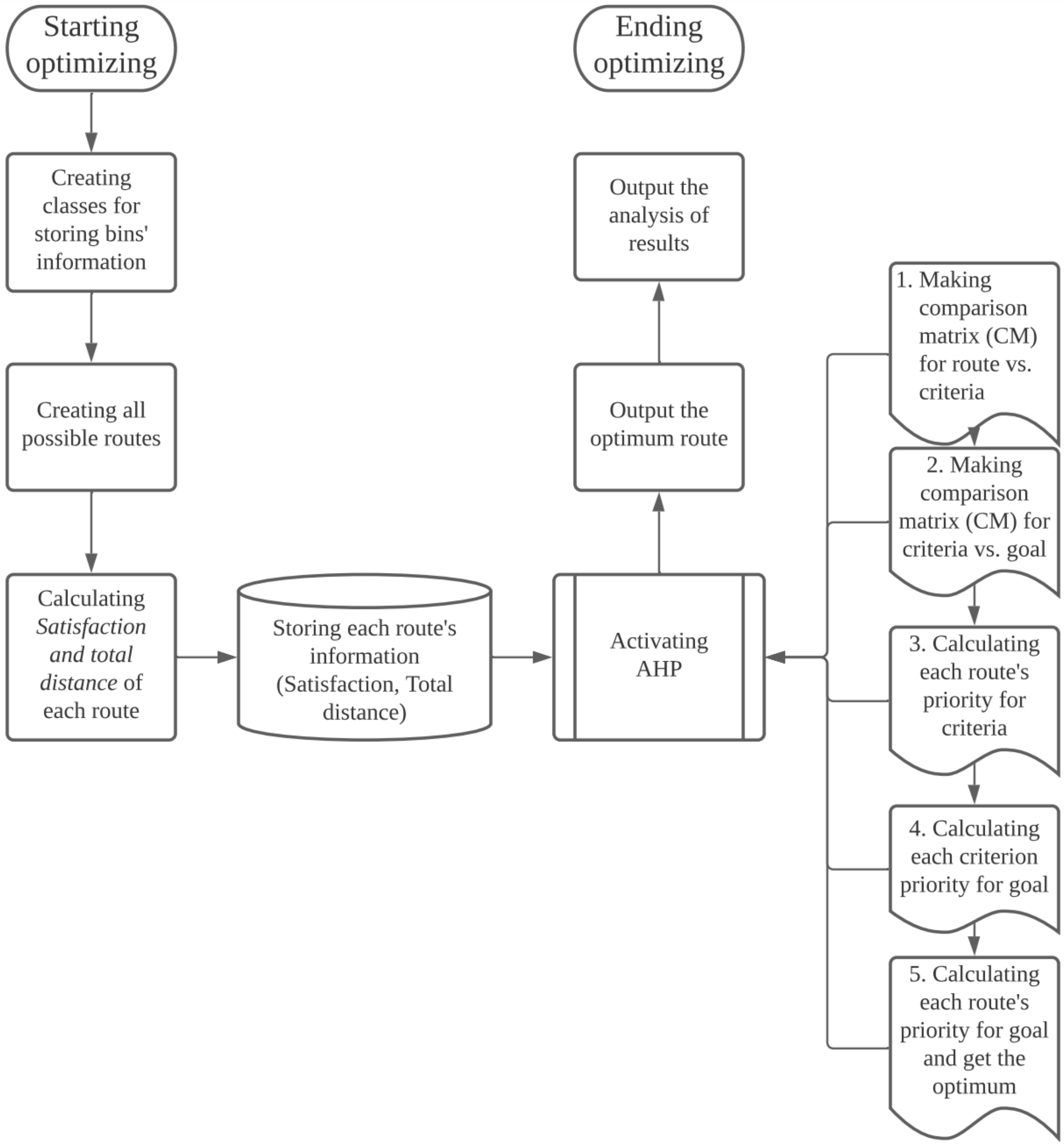

Figure 8 Flowchart of core algorithm

5.3.1 Producing the initial pool

After knowing trashcans necessary to be processed today, I then have to generate the pool, or all possible routes starting from one trashcan, travelling through all other trashcans, to the final one. Since it is assumed that every two cans have at least one path connecting, I can say every can is connected to all the other ones. As such, permutation is most suitable for producing the pool. For instance, in the case of dealing with 5 waste bins, I can create a list that stores the sequence of visit; namely, [1, 2, 3, 5, 4] means starting from site 1, I sequentially go to site 2, 3, 5, and eventually 4. Thus, I just need to produce all, conclusive variants of this list so that I can have a complete pool of candidates (for now).

$$\binom{n}{k} = \frac{n(n-1)\cdots(n-k+1)}{k(k-1)\cdots 1},$$

.

5.3.2 Completing the pool

Now, holding the pool, I need to create variants further, since every two cans may have more than just one path. Hence, if, say, I are creating variants for a particular sequence list [1, 2, 3, 4, 5], where site 2 and 3 have 3 paths between them, then I can create in total of 3 variants for this sequence list. These variants differ from the original one in total travelled distance, which is one of the factors I consider when deciding the optimal route. I add new variants created from this process to the initial pool. At this point, the pool is completely conclusive and ready for the next step.

5.3.3 Forming new factor

It is inappropriate to directly take time and height as criteria, since what I are comparing is routes. So, when comparing 2 routes, there is no meaning to compare their time and height. Instead, I can combine the two factors into one more suitable acting as a criterion--Satisfaction. Specifically, in dealing with the case, and the case only, of determining sequence of trashcan to be processed, I know, in fact, the best sequence in the first place when detection sensors record each can's information. Clearly, I want trashcans that are most urgent to get processed to be prioritized, so I can create a standard model according to this fact, where the model is the best sequence starting from the most urgent trashcan to the least. Then, I evaluate the difference between the standard model with each of the routes in the pool. The more they are alike, the higher the satisfaction is.

5.3.4 Running AHP

Now I have two criteria when determining the optimal route: satisfaction and total distance. Since our goal is to single out the optimal route among the pool, this is a decision problem. I can construct the problem on 3 levels: objective, criterion, alternative. Therefore, in short, our goal is to determine the best alternative considering all criteria that best meet the objective, as can be shown from figure 9 below.

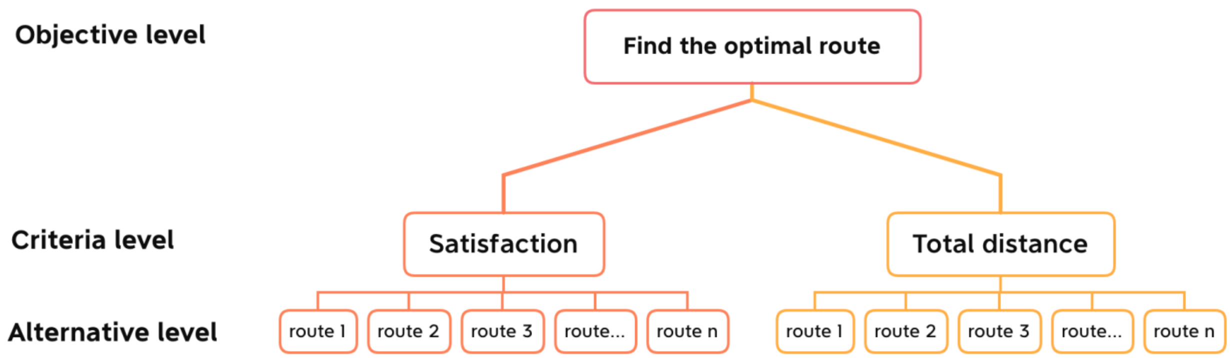

Figure 9 Hierarchy tree

Analytical Hierarchy Process (AHP) is a perfect solution to coping with such problem. AHP consists of 3 steps: construct the hierarchy tree; create comparison matrix (CM) between objective and criteria and between criteria and alternatives; calculate comparison matrix between objective and alternative.

Now that I have built the hierarchy tree, I need to make CM. First of all, objective vs. criteria CM. I have to compare the importance of each criterion under objective, using AHP fundamental scale as figure 10 shown below.

The Fundamental Scale for Pairwise Comparisons		
Intensity of Importance	**Definition**	**Explanation**
1	Equal importance	Two elements contribute equally to the objective
3	Moderate importance	Experience and judgment moderately favor one element over another
5	Strong importance	Experience and judgment strongly favor one element over another
7	Very strong importance	One element is favored very strongly over another; its dominance is demonstrated in practice
9	Extreme importance	The evidence favoring one element over another is of the highest possible order of affirmation
Intensities of 2, 4, 6, and 8 can be used to express intermediate values. Intensities of 1.1, 1.2, 1.3, etc. can be used for elements that are very close in importance.		

Figure 10 AHP fundamental scale

source: https://en.wikipedia.org/wiki/Analytic_hierarchy_process_%E2%80%93_leader_example

Since the project's primary goal is to reduce CO_2 emission (goal 1), followed by reduction in likelihood of residents facing unpleasant odor produced by kitchen waste (goal 2), I assign 7 to

the importance of goal 1 and 1 to that of goal 2. So, goal 1's importance is very strong compared to goal 2's. Then, applying linear algebra, I can calculate priorities of each criterion against the objective. The higher the priority, the more important its corresponding criterion is.
Secondly, I create criteria vs. alternatives CM. Every alternative has to be examined in each of criteria. Then, again, I can calculate priorities.
Finally, I combine the two kinds of CMs to get the objective vs. alternative CM and calculate each alternative's priority. The alternative with highest priority is the one I are looking for.
The process of the core algorithm can be summarized into one flowchart below.
Ultimately, I can find the optimal path. Note, however, AHP holds a maximum capacity of routes to be 100, so, when the total candidates exceed 100, I have to make AHP several times, getting Local optimums. Then I process all Local optimums into AHP again to find the Global optimum.

5.3.5 Analysis of results
Calculation of fuel consumption
The average fuel consumption by pickup truck, in meters per liter, is 2.8 mpg, or 1190.4 meters per liter (APTA, 2019). So, I can divide the total distance of a route by this average to get average fuel consumption during this route.

$$Fuel\ consumption\ (liters) = \frac{total\ distance\ (meters)}{1190.4\ (meters/liter)}$$

Calculation of CO2 emission
CO2 emission is gained by multiplying the total liters of fuel burned during the route by the average CO2 in one liter. The average CO2 emission per gallon of gasoline is 2347.697 grams (Statista, accessed: Sep 7, 2021).

$$Petrol\ consumption(liters) \ = \frac{total\ distance\ (meters)}{1190.4\ \ (meters\ /\ liter)}$$

$$CO_2\ emission\ =\ petrol\ consumption\ \times 2392\ CO_2\ \ (grams\ /\ liter)$$

Notes about China's residential abodes
Note, the apartments in China is estimated to 6.45 millions (EPA, accessed: Sep 7, 2021) and I divide it by 5 since I are taking 5 apartments at a time to analyze optimal route amongst them.

5.3.6 Example of algorithm running in real case

I use an example to illustrate the whole process described above. First of all, I chose 5 apartments, JY, YG, BJ, JK, MW in my district, measured the distance between each two of them, and stored them into a chart.

Table 1 Distance between every 2 apartments

Distance (km)	JY (0)	YG (1)	BJ (2)	JK (3)	MW (4)
JY (0)	-	(2, 1.9, 4.3)	(2.3, 2.2, 3)	(3.6, 4.1, 4.3)	(4,5,5.1)
YG (1)	-	-	0.35	(6, 7.2, 7.4)	(3.1, 3.5, 3.9)
BJ (2)	-	-	-	3.9	(3.3, 3.4, 3.5)
JK (3)	-	-	-	-	(3.5, 3.7, 5.4)

Since every pair of sites is reversible, meaning disregarding order of the 2 sites, the table does not repeat the distance list given 2 sites when order is reversed.
Next, I give random numbers to a trash site's time and height, ranging from 0 to 48 (hrs) and - to 120 (cm) respectively and then calculate their urgency degrees.

Table 2 Urgency degree of each trashcan

Distance (km)	JY (0)	YG (1)	BJ (2)	JK (3)	MW (4)
UD	67	71	82.3	93.2	79

Unfortunately, today driver needs to go to every one of trashcans. So, I start generating the initial pool in total of 5 * 4 * 3 * 2 * 1 = 120 routes. Then, according to number of paths between each two trash sites, I produce variants and gain the ultimate pool of routes, waiting for the next move.

Processing the pool into AHP, I can finally get the optimal route with its information outputted.

5.4 Viewer display

The driver will receive the calculated optimal route on his cell phone in a form of map, just as the figure 11 shows. Using Google map, I first notified all the community points as blue to form a map. Then, after getting the optimal route, I gained the order of the trashcans to be visited so I could use arrow with different color pointing from one site to another to inform the drivers.

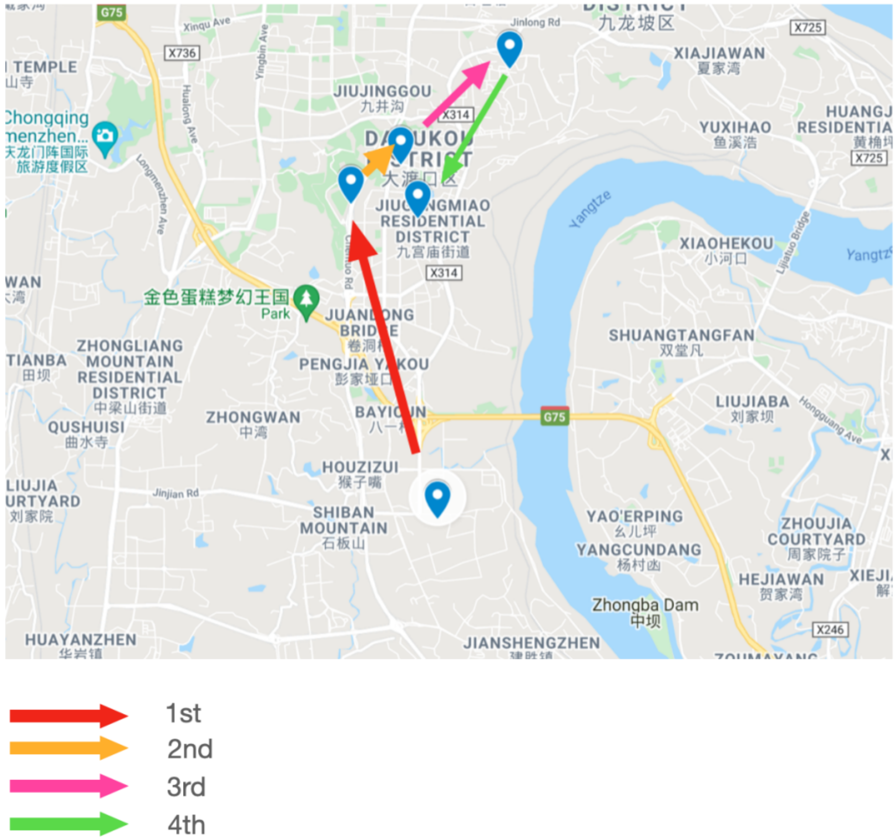

Figure 11 Display route to drivers

Starting from the red arrow, the end will be where the green arrow directs toward.

6 Analysis of results

6.1 Overall statistics about total distance and driving time

I had set up 4 experiments with selection of 5 abodes each time and run the program. For each trial, I found its statistical variance, as the boxplot shown below.
Figure 12 analyzes statistics of routes' total driving distances.

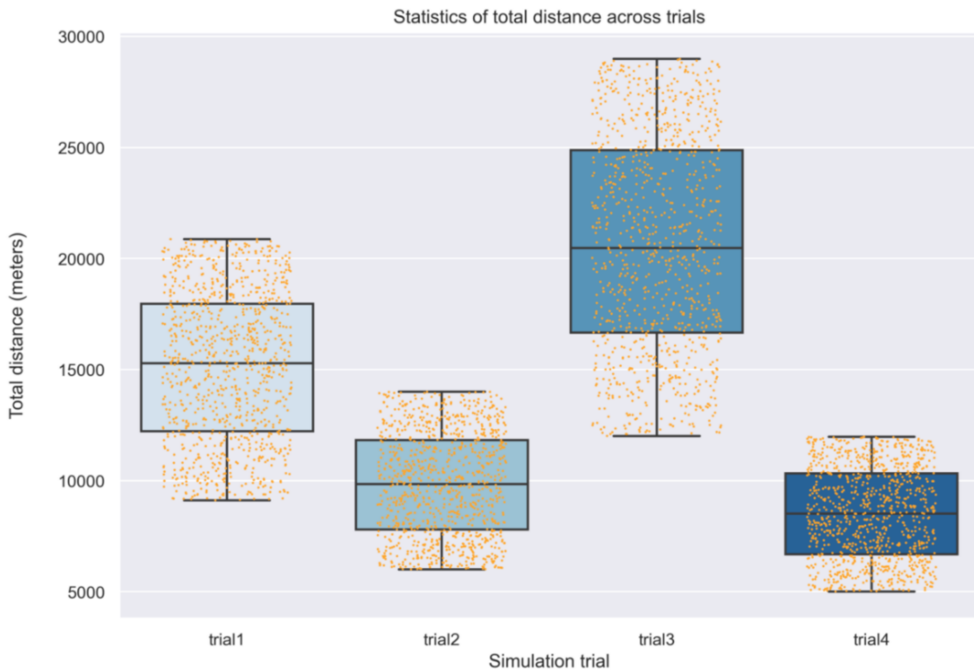

Figure 12 Analysis of driving distance

According to figure 12, there are great variances in the distances among the four trials, given that each trial considers different neighborhoods.

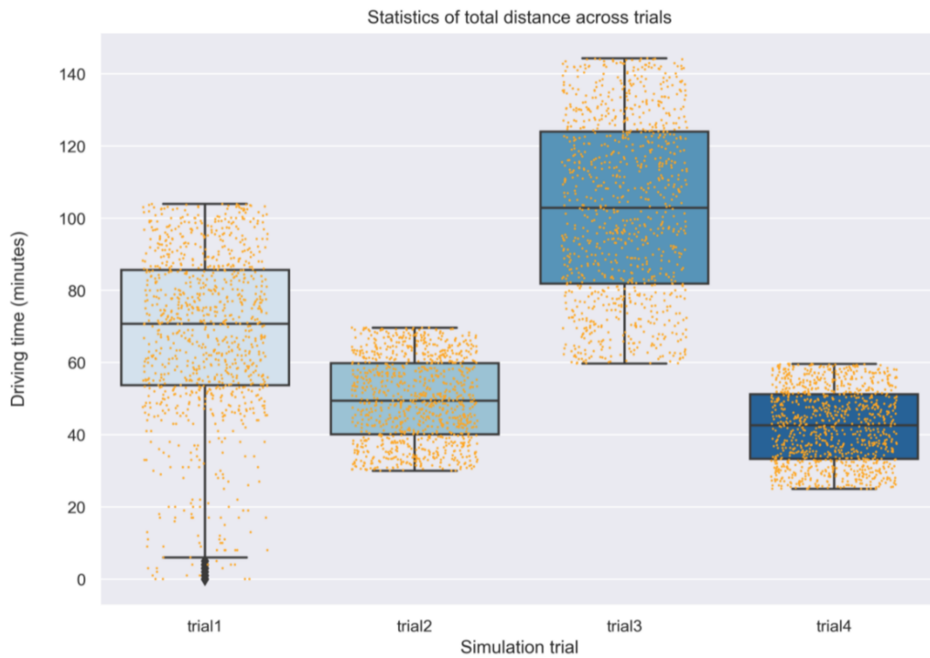

Figure 13 Analysis of driving time

Figure 13 analyzes statistics of routes' total driving time. The trial 1 clearly shows more widespread data points compare to others.

6.2 Statistics about optimal, average, and worst routes

Note: here I assume the speed of pickup truck is constant and equal to 7.5 mph, or 201 meters per minute. (This unit is chosen for convenience in the program's calculation) ((G.S., H.C., S., Jones, and E., 2016)

6.2.1 Total distance

Figure 14 analyzes the optimal and average route in each trial regarding their total travelled distance. Note that in order to better show the performance of the program, I conducted 15 more trials, in total of 20 trials during the following analysis.

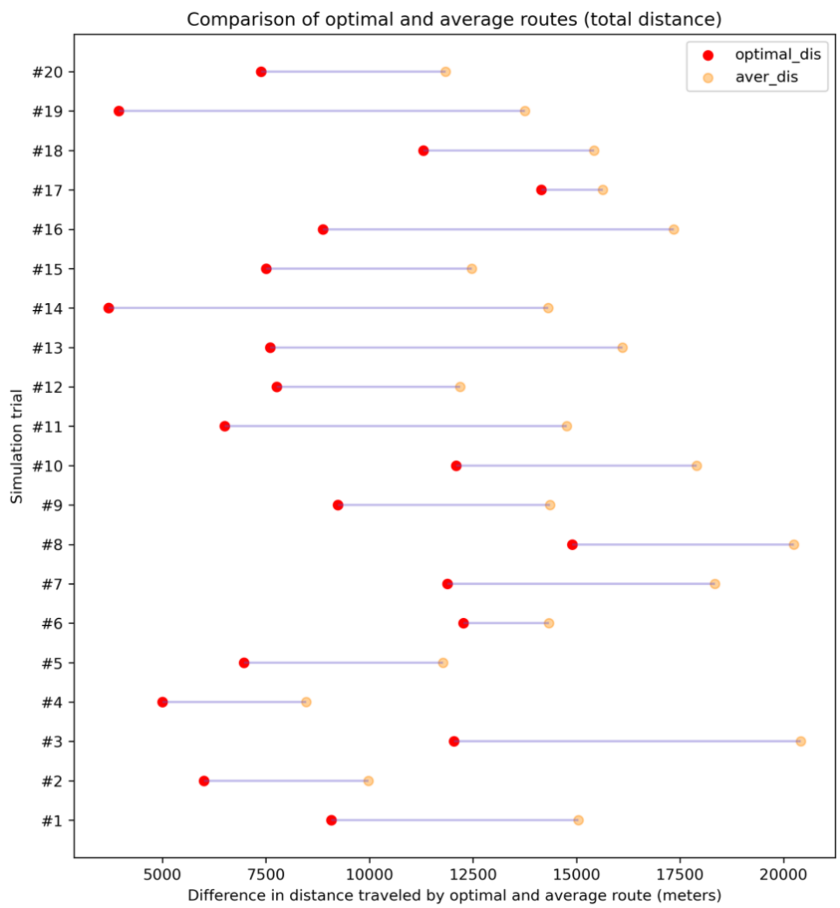

Figure 13 Analysis of the program's result related to driving distance

The relatively transparent purple line connecting the optimal distance and average distance is their difference. Therefore, according to figure 16, for all of the trials, the optimal distance is always much shorter than the average distance. Note that the optimal distance is not always the shortest one since distance is only one of the two factors we need to consider.

6.2.2 Fuel consumption

Figure 14 analyzes the reduction in fuel consumption using optimal and average route in each trial.

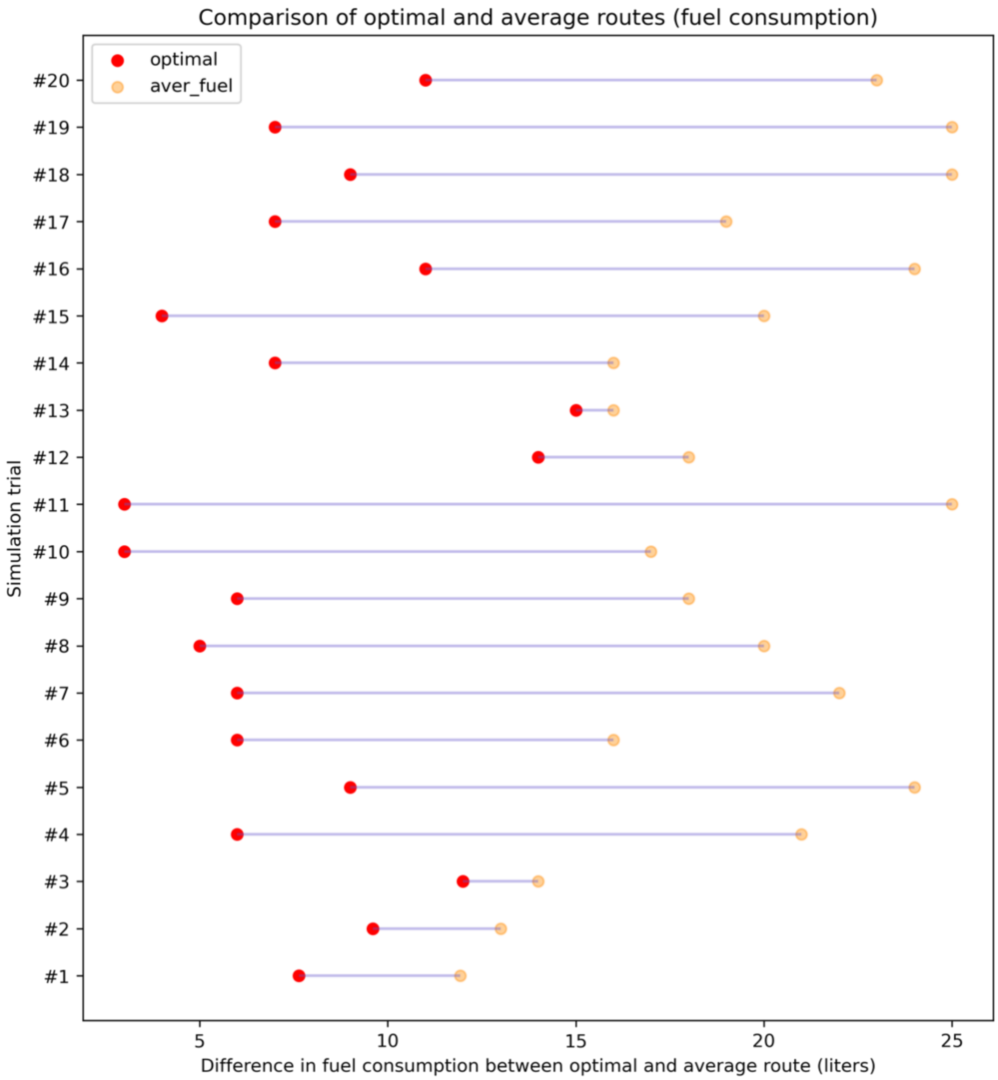

Figure 14 Analysis of routes' fuel consumptions

According to figure 14, for most of the trials being conducted, the optimal route can save greater than 10 liters fuels per pickup day. Only in 1 trial did the difference between optimal one's fuel consumption and the average's not exceed 5 liters.

6.2.3 CO2 emission

Figure 15 analyzes the CO2 emission of the optimal route in comparison to the average route and their difference, assuming the program lasts for one year and covers all China's residential area, as described in 5.3.5. Note that for sake of clarity of the graph, I only included four trials out of 20 trials I have simulated.

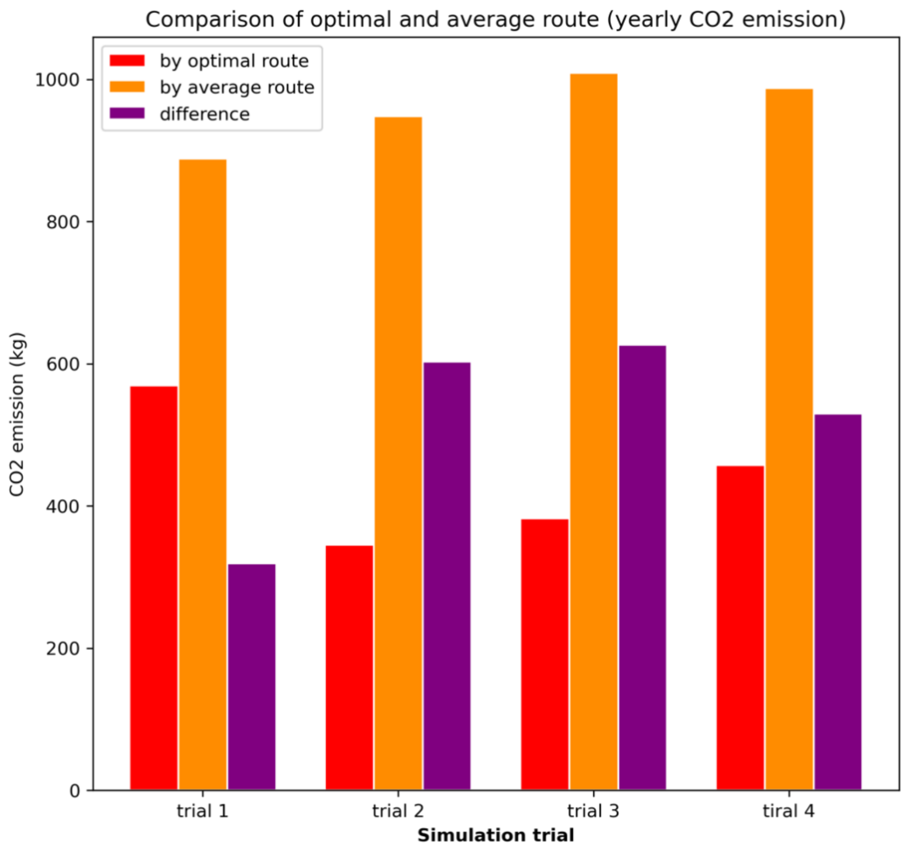

Figure 15 Analysis of reduction in CO2 emission

According to the figure, the CO2 emissions by optimal routes are significantly less than average route routes, and the mean reduction of CO2 emissions by optimal route compared to the average route (as shown by those purple bars) is approximately 425 kg per year.

7. Reference

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