

# Route Optimization for Delivery Businesses

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# Abstract

In this report, we take on the role of a local delivery business that would like to minimize costs associated with delivering a product to their customers, located in the Edmonton area. The day-to-day operating decisions faced by this business are primarily logistics-related and can influence the profitability of the company.

For instance, questions like:

- What route should our delivery trucks take?
- How does the size of truck rented (and the amount of product that can be delivered in a single trip) impact the optimal route?
- Is there a benefit in renting an additional location to store product?
- Should we rent an additional truck?
- How much do these decisions impact our delivery costs?

can help the business understand how they can manage their delivery expenses effectively and have a lot of value for the business, especially as the business expands and attracts more and more customers. We explore utilizing integer programming (IP) optimization techniques to answer these valuable questions.

We first begin by presenting a mathematical model of problem, in the form of an integer program. We define the problem inputs, decision variables, objective function, as well as constraints, for several cases of the problem:

- Symmetric and asymmetric distance matrices
- Satisfying customer demand using a single delivery route, as well as multiple routes

We pick 52 random Edmonton addresses to solve our problem instance on. We utilize two techniques to obtain a distance matrix (a necessary input to our problem):

- Estimate the distance matrix from the GPS coordinates (lat, lng) of the 52 locations
- Retrieve an accurate (driving profile) distance matrix from Google Maps

We formulated our problem in Python, and utilize several solvers throughout the project to solve the problem (ie. coin-or-branch and cut, GLPK, SCIP, and Gurobi), through the use of two freely available Python connectors (PuLP and PySCIPOpt). For our base case of 50 customers, a single truck and warehouse, and a truck capacity of 50, we obtained a delivery cost of \$ 252.28.

We present a visual representation of the solutions, along with the obtained optimal objective function value, and also perform sensitivity analysis on several of the inputs:

- Varying truck capacity between 50 and 30 deliveries
- Examining the impact of an additional warehouse
- Having two delivery trucks available instead of one

The results of these scenarios were analyzed, and we found that the truck capacity had the largest impact on the delivery cost, decreasing the optimal route cost to \$ 250.570.

# Introduction

The motivation behind this project was to model how a small business could utilize data driven decision making. With advances in technology and available data, businesses have the ability to make better more highly informed decisions, rather than operating on “gut-feeling”. While many areas of an online grocers’ business could benefit from data driven decision making (directed marketing to give an example), we opted to focus our model on the logistical side of the business. This approach presented a clear idea of which factors that drive costs and which variables we have under our control.

# Background

An online grocery company (Company Co.) has recently begun operating in the Edmonton market. Company Co. allows customers to order their food and grocery products online from the comfort of their homes, with convenient delivery all the way to the door. Most of the customer base are repeat customers, requiring weekly deliveries. For most customers, the exact delivery day is not important, as long as their order is delivered within a 5-day window every week. Each delivery is composed the product(s) ordered by the customer and a small flyer, placed in a standard-size, branded package (a cardboard-based box). The boxes are shipped by a driver working directly for Company Co. using leased vehicles.

The difficulty faced by Company Co. revolves around scheduling deliveries and route-planning. Ideally, they would like to generate a pre-planned route for their driver every day, so that distribution expenses are minimized, while ensuring that all orders for the week are fulfilled. They pay a fixed monthly price for every vehicle leased, and thus would like to use the least number of trucks possible, while also keeping driver overtime under control. Currently Company Co. has 200 customers and deliver 5 times per week, the largest number of deliveries required in one day is 50. This report will focus on a sample of 50 customers, which represents the largest number of deliveries Company Co. would make in one day. The addresses of 50 customers and the company warehouse have been plotted on a map of Edmonton in figure 1 below.

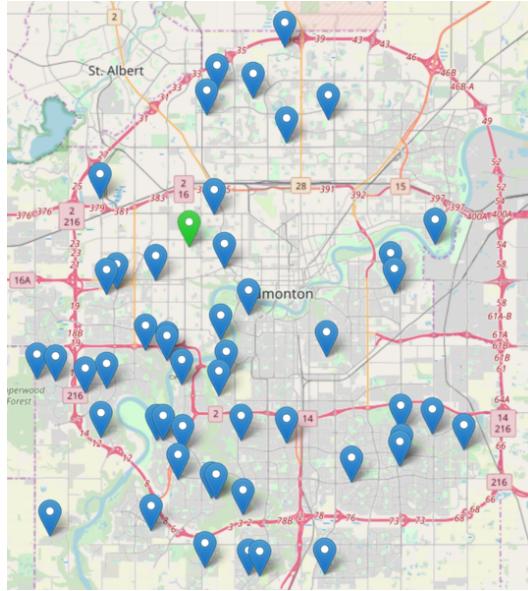


Figure 1 - Map of customer address sample (blue) and warehouse (green)

The truck that Company Co. is currently using has a capacity of 50 boxes (equivalent to 50 customer orders) and uses roughly 2.5 liters of fuel per 10 km of city driving. As the lease of this truck will expire soon Company Co. wants to know if they would be better off leasing 2 smaller trucks with a capacity of 30 boxes each. The driver is paid an hourly wage of \$25. Company Co. would like to optimize their delivery route(s), such that they incur minimum costs for deliveries.

## Model Formulation

The aim of the problem model is to optimize the delivery operations of Company Co. The model relates the primary delivery costs: driver hourly wage and fuel costs (stated in terms of the cost per km) with decision variables for each possible step of the delivery route. The model also allows Company Co. to analyse the effect of using more than one truck with varying truck capacity, as well as using an additional warehouse.

This gives the model the ability to not only plan day to day operations, but also provides decision making input for how many trucks to rent and drivers to hire. Additionally, the model could suggest how many warehouses Company Co. should have to ensure every truck has a realistic carrying capacity; i.e. it might not be realistic to have one truck making 50 deliveries to 50 different locations in one day.

## Assumptions and simplifications

To keep the problem manageable in terms of complexity we assume that delivery routes can be planned without taking the production schedule into account; all orders are prepped the day/night before. The model also does not take into consideration the customers preference for which day of the week, or time of day, that delivery is made. In the future Company Co. could expand the model with more constraints to include these features, but for now they are left out.

The costs for travelling each distance are calculated based on distance travelled in kilometers assuming good road and traffic conditions, such as:

- All roads are dry and flat,
- There is negligible traffic, and
- There are no roadblocks.

The delivery truck(s) are leased by Company Co at a fixed rate, i.e. the distance driven by each truck does not increase the cost of the lease.

## Solution Format

The analysis will calculate, based on the number and locations of the destinations for delivery, the optimal travel path or the travel path which will incur the lowest costs. In simpler terms, say there are 50 locations chosen in random that the company must deliver to without neglecting a single location per day. Upon choosing the number of trucks, the carrying capacity for each truck, and the number of warehouses used, the optimal path can be calculated.

# Problem Formulation

The problem which Company Co. faces share many similarities with what's known as a traveling salesman problem (TSP). TSPs are a form of network problem where each node of the network only can be visited once, resembling the path of a traveling salesman visiting different cities.

Both binary and integer variables were utilized in the analysis (in the case of cutting planes method, the variables were initially declared as continuous, and later converted to binary/integer). Binary variables can only be assigned a value of either 1 or 0, while integer variables can be assigned any integer in the range specified. They are further categorized into two types: inputs and decision variables.

## Inputs

Inputs are variables that are provided to the solver as constants. They are predetermined for a given instance of the problem.

$n_c$ : number of customers

This variable indicates the total number of delivery locations that is chosen for analysis. For example,  $n = 50$  means that there is a total of 50 locations, or customers, that Company Co. must make deliveries to.

$n_w$  : number of warehouses

This variable indicates the number of warehouses available that the trucks could start from. It could also serve as a location where the trucks could stop by and restock to make further deliveries.

$D$ : distance matrix

This is a  $(n_c + n_w) \times (n_c + n_w)$  matrix indicating the distance between any pair of locations based on their indices.  $n_c + n_w$  is the total number of locations available for the analysis. For example:

$d_{i,j}$  : the distance from node i (warehouse or customer) to node j (warehouse or customer)

We used two distance matrices in our analysis (see next section for more details):

- 1) Approximation using GPS coordinates (symmetric)
- 2) One obtained from Google Maps Distance Matrix API (asymmetric) with 'driving' mode, which returns distance calculations using the road network (see 'Solutions' section for more details)

$t$ : number of trucks

This variable indicates the number of trucks being utilized to make sure every single location, or customer, is covered in the solution.

**c:** truck capacity

This is the carrying capacity of each truck being utilized that is equal to the number of locations, or customers, inputted. This, however, does not mean that  $c = n_c$ . For example,  $n_c$  could be 50 and  $c$  could be 30, meaning that even though there are 50 locations that Company Co. must make deliveries to, each of their trucks could only carry enough to deliver to 30 of those 50 locations.

**$c_f$ :** Cost of fuel coefficient

This is a constant indicating the cost of fuel per kilometer of distance travelled by a truck. It is here assumed that a truck with capacity for 50 boxes uses 2.5 liters of fuel per 10km, whilst a truck with capacity for 30 boxes uses 2.2 liters of fuel per 10 km. The cost of fuel is estimated to be \$1.25 per liter. This gives us:

$$c_{f50} = \frac{2.5 * 1.25}{10} = 0.3125 \left( \frac{\$}{km} \right)$$

$$c_{f30} = \frac{2.2 * 1.25}{10} = 0.275 \left( \frac{\$}{km} \right)$$

**$c_w$ :** Cost of wage coefficient

This is a constant indicating the cost of a driver's hourly wage, but in order to make it proportional to distance travelled we express it per km. Here we assume that city traffic allows the truck to travel at an average speed of 30km per hour. With the driver being paid a wage of being \$25 per hour this gives us:

$$c_w = \frac{25}{30} = 0.833 \left( \frac{\$}{km} \right)$$

## Decision Variables

Decision variables are variables that the solver is allowed to vary within the range allowed by the constraints to find an optimal solution. The solution the solver comes up with will be composed of the values for the decision variables, as well as the objective function value.

**$x_{i,j}$ :** whether path from node i to node j is taken (binary)

These binary variables indicate which path the truck should choose to make the delivery. The subscripts i and j are indices of the pair of locations on the which path the truck is taking. For example, if  $x_{1,2} = 1$ , then the path from location #1 to location #2 is chosen to be a part of the final delivery path for one of the total number of trucks being utilized by Company Co.

$L_i$ : node order (integer between 1 and  $\min(n_c, c)$ )

These integer variables indicate where location  $i$  is found in the sequence of locations that is being used in the analysis, with the first customer visited corresponding to  $L_i = 1$ .

Note: this decision variable is only utilized in the multiple-path formulation.

## Objective function

We define our objective function as a cost minimization, where the total length of the minimum distance route is multiplied by a constant factor, resulting in an estimate of the cost of the route, including labour and fuel costs.

Define our locations as two sets:

$w$ : **set of warehouses**  $\{1, \dots, n_w\}$   
 $c$ : **set of customers**  $\{1, \dots, n_c\}$

The objective function is:

$$\text{minimize: } z = \sum_{i \in \{w,c\}} \sum_{\substack{j \in \{w,c\} \\ i \neq j}} (c_f + c_w) \cdot d_{i,j} \cdot x_{i,j}$$

This minimizes the total cost incurred by the business to make the delivery, based on the costs of fuel and labour.

## Constraints

### Case 1: Single Path

The first formulation generates a solution using only a single path. This implies that the truck capacity, must be bigger or equal to the number of customers:  $c \geq n_c$

In addition, for this case, the following must be true as well:

- Number of warehouses,  $n_w = 1$
- Number of trucks,  $t = 1$

### Two Connections Per Node Constraint

There are two versions of this constraint, one for symmetric and one for asymmetric distance matrices:

Table 1: Symmetric and Asymmetric Constraints for the Single Path Formulation

Symmetric	Asymmetric
$\sum_{\substack{j \in \{w,c\} \\ i \neq j}} x_{i,j} + \sum_{\substack{j \in \{w,c\} \\ i \neq j}} x_{j,i} = 2 \quad \text{for } \forall i \in \{w, c\}$	$\sum_{\substack{j \in \{w,c\} \\ i \neq j}} x_{i,j} = 1 \quad \text{for } \forall i \in \{w, c\}$
	$\sum_{\substack{j \in \{w,c\} \\ i \neq j}} x_{j,i} = 1 \quad \text{for } \forall i \in \{w, c\}$

The symmetric formulation allows us to use fewer constraints. We use this problem formulation to solve distance matrix (1).

The asymmetric distance matrix requires double the number of constraints. This ensures that for each location, we have one path to and one path from that location. This formulation is required to accurately solve distance matrix (2).

Attempting to solve an asymmetric distance matrix with the symmetric problem formulation would result in an artificially low objective function value, as the optimal solution could contain some locations with 2 paths going to the location, or 2 paths coming from the location.

### Subtour Elimination Constraint

A common obstacle in this type of problem is to eliminate subtours, where the solution involves every node being visited once, but not in one closed loop. This renders an infeasible solution to the problem and constraints must be in place to eliminate subtours from forming. A visualization of a subtour compared to a closed loop is presented in figure 2 below:

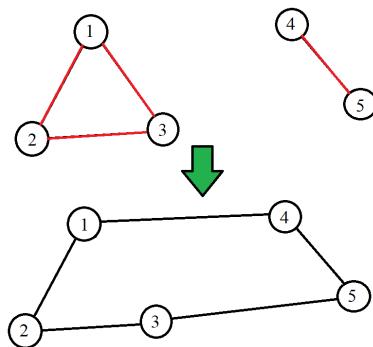


Figure 2 - Subtour visualization

### Subtour elimination approach

Our initial understanding of linear programming led us into method of adding one constraint for each possible subtour, in retrospect this turned out to be a version of the Miller-Tucker-Zemlin (MTZ) formulation. It became apparent that as the number of customers ( $n$ ) is increased, the number of constraints that are required to fully describe the problem and guarantee an optimal solution increases very quickly, much faster than  $n$ . This is known as an ‘NP-hard’ problem.

$$\sum_{\substack{i,j \in S \\ i \neq j}} x_{i,j} \leq |S| - 1 \quad \text{for } \forall S \subseteq \{w, c\}; S \neq \emptyset; |S| > 1$$

This says that every proper subset of the full set of locations (warehouses & customers) can be at most one less than the number of locations in the subset (ignoring the empty set and sets of size 1). If this constraint is violated, then we have subtour.

### Subtour Elimination Improvement: Cutting Planes

It quickly proved infeasible to compute a solution for more than 20 customers using the MTZ formulation. We then utilized PySCIPOpt to selectively add constraints, as subtours are found in the current solution, until a solution with no subtours was found. For more information, see [15].

### Case 2: Multiple Paths

The multiple path formulation is required to solve a problem where at least one of the following conditions is true:

- 1) Truck capacity is less than the number of customers:  $c < n_c$
- 2) More than one truck is used to make the deliveries:  $t > 1$
- 3) More than one warehouse is available:  $n_w > 1$

### Two Connections Per Node Constraint

To address point (3), we reformulate the constraint used in case (1) such that  $i$  does not include  $\{w\}$ :

Table 2: Symmetric and Asymmetric Constraints for the Multiple Paths Formulation

Symmetric	Asymmetric
$\sum_{\substack{j \in \{w,c\} \\ i \neq j}} x_{i,j} + \sum_{\substack{j \in \{w,c\} \\ i \neq j}} x_{j,i} = 2 \quad \text{for } \forall i \in \{c\}$	$\sum_{\substack{j \in \{w,c\} \\ i \neq j}} x_{i,j} = 1 \quad \text{for } \forall i \in \{c\}$
	$\sum_{\substack{j \in \{w,c\} \\ i \neq j}} x_{j,i} = 1 \quad \text{for } \forall i \in \{c\}$

This ensures that each customer location still requires two edges to be connected to it. However, this doesn’t require warehouses to be connected by two edges. This gives the

formulation more flexibility because not all warehouses are required to be in a path, and a warehouse may be used for more than a single path (if it is optimal).

### Start/End at Warehouse Constraint

We define an input variable, which indicates how many total paths are required to solve the problem:

$$\text{paths: } \max(\text{ceil}\left(\frac{n_c}{c}\right), t)$$

This ensures that we have enough paths to cover all customers, given that the maximum number of customers visited in a single path can be  $c$ . It also allows us to use more than the minimum number of paths required, if more trucks are available.

Since we removed  $\{w\}$  from the previous constraint, we need an additional constraint to ensure that each route starts and ends at a warehouse:

$$\sum_{i \in \{w\}} \sum_{\substack{j \in \{c\} \\ i \neq j}} x_{j,i} = \text{paths}$$

Reformulating the constraint in this way allows any of the warehouses to be used. Using this constraint, it is even possible for the path to start at one warehouse and end at another, if this results in a smaller total distance travelled than starting and ending at the same warehouse.

### Node Order Constraint

We use a constraint utilizing the node order,  $L_i$ , specifying that  $L_i$  must increase with each customer visited. This allows us to limit the maximum length of a single path:

$$L_i - L_j + n_c \cdot x_{i,j} \leq n_c - 1 \quad \text{for all } i, j \in \{c\}$$

# Data Set

## Addresses

We picked a random sample of 50 Edmonton addresses from the City of Edmonton's online Property Assessment Data dataset [2]. We also picked two warehouse locations in industrial areas: one in the northwest side of Edmonton, and one on the southeast side:

The addresses came with GPS coordinates, which are listed in Appendix 1. We utilized Leaflet[3] to plot the data points on an interactive map, using the openstreetmap.org standard tiles[4] (see figure 3). The code for this is provided in Appendix 2. We initially prepared our data set in an Excel file, and then imported it into .csv (comma-separated value) format, so that it could be imported into our solver (see next section).



Figure 3 - Addresses and both warehouses

## Distance Matrix Approximation

We initially generated an approximation of the distance matrix based on straight-line distance between locations:

$$d_{i,j} = \sqrt{\left(110.574 \text{ km} \times (\text{lat}_i - \text{lat}_j)\right)^2 + \left(111.320 \text{ km} \times \cos\left(\frac{\text{lat}_i + \text{lat}_j}{2}\right) \times (\text{lng}_i - \text{lng}_j)\right)^2}$$

We utilized an Excel spreadsheet to calculate this matrix. The result is provided in Appendix 3.

## MapBox Distance Matrix

We initially attempted to use the MapBox Matrix API to retrieve our distance matrix [5]. We used the ‘mapbox/driving’ profile to retrieve estimates of travel times and distances between each pair of locations. This API has a limitation because it allows a maximum of 25 addresses per request (625 matrix elements), with the option to specify either any or all of those addresses as the source and destination addresses.

This meant we needed to make many requests to their API to retrieve the entire distance matrix of  $52 * 52$  (max 2 warehouses, 50 customers). This is 2704 elements, which is much higher than 625 ( $25 * 25$  = maximum number that can be returned in a single request). For this reason, we had to split up the distance matrix into multiple segments, and rebuild the distance matrix from the segments:

Table 3: 5 x 5 Segmentation of the Distance Matrix

	1-12	13-24	25-36	37-48	49-52
1-12	1	6	11	16	21
13-24	2	7	12	17	22
25-36	3	8	13	18	23
37-48	4	9	14	19	24
49-52	5	10	15	20	25

We utilized a short Python script to load the locations from the dataset file (csv format), split up the locations into sets of 12, retrieve the distance & time matrices in 25 requests, and save the results in csv. The code for this is provided in Appendix 6.

We found the MapBox matrix to be highly asymmetric and to not produce reliable results, and we used Google Maps instead (see next section). The MapBox distance matrix is provided in Appendix 4.

The MapBox API has the following endpoint for retrieving a distance matrix:

```
https://api.mapbox.com/directions-matrix/v1/mapbox/driving/53.512735,-113.423675;53.572226,-113.58381;53.45332914,-113.5832276;53.45903088,-113.4195745;53.5459037,-113.5493732;53.534394,-113.6363747;53.56959423,-113.5568043;53.44479748,-113.5553688;53.41155502,-113.4750256;53.46937759,-113.5031153?destinations=0;1;2;3;4;5;6;7;8;9&sources=0;1;2;3;4;5;6;7;8;9&annotations=duration,distance&access_token=API_KEY
```

## Google Maps Distance Matrix

We used Google Map’s Distance Matrix API to retrieve an estimate of the distance matrix for our 52 locations [7]. This API has a limitation and can return a maximum of 100 matrix elements per request. This required us to split up the distance matrix into 36 requests:

**Table 4: 6 x 6 Segmentation of the Distance Matrix**

	1-10	11-20	21-30	31-40	41-50	51-52
1-10	<b>1</b>	<b>7</b>	<b>13</b>	<b>19</b>	<b>25</b>	<b>31</b>
11-20	<b>2</b>	<b>8</b>	<b>14</b>	<b>20</b>	<b>26</b>	<b>32</b>
21-30	<b>3</b>	<b>9</b>	<b>15</b>	<b>21</b>	<b>27</b>	<b>33</b>
31-40	<b>4</b>	<b>10</b>	<b>16</b>	<b>22</b>	<b>28</b>	<b>34</b>
41-50	<b>5</b>	<b>11</b>	<b>17</b>	<b>23</b>	<b>29</b>	<b>35</b>
51-52	<b>6</b>	<b>12</b>	<b>18</b>	<b>24</b>	<b>30</b>	<b>36</b>

We used a short python script to load the data set (in csv format), split up the locations into sets of 10, and perform the request for every combination of sets. The code for this is provided in Appendix 7. The distance matrix obtained is provided in Appendix 5.

The requests performed to the Distance Matrix API are of the following format:

```
https://maps.googleapis.com/maps/api/distancematrix/json?origins=53.512735,-
113.423675|53.572226,-113.58381|53.45332914,-113.5832276|53.45903088,-113.4195745|53.5459037,-
113.5493732|53.534394,-113.6363747|53.56959423,-113.5568043|53.44479748,-
113.5553688|53.41155502,-113.4750256|53.46937759,-113.5031153&destinations=53.512735,-
113.423675|53.572226,-113.58381|53.45332914,-113.5832276|53.45903088,-113.4195745|53.5459037,-
113.5493732|53.534394,-113.6363747|53.56959423,-113.5568043|53.44479748,-
113.5553688|53.41155502,-113.4750256|53.46937759,-113.5031153
```

This is different than the MapBox endpoint, because here the origins and destinations parameters both accept a vector of GPS (lat,lng) coordinates.

## Solving the Problem

To solve a problem with 50 customers and 2 warehouses requires a distance matrix that is  $52 * 52 = 2704$  elements. A minimum of  $2704 - 52 = 2652$   $x_{i,j}$  decision variables are required. Due to the difficulty in manually inputting this many decision variables (and constraints), we decided to use a programmatic approach:

- Develop a simple Python program that could read our dataset.csv
- Create a linear integer programming (LIP) model
- Add the  $x_{i,j}$  decision variables dynamically, based on the size of the data set
- Add the necessary constraints
- Use a Python connector to a MIP solver to pass the problem formulation and retrieve the solution
- Add additional constraints if necessary and resolve (cutting planes method)
- Provide optimal objective function value
- Save optimal solution  $x_{i,j}$  and  $L_i$  (if applicable) decision variables to a .csv file

## Utilizing Python

We decided to write our program in Python (an open-source programming language with a similar syntax to MATLAB – see reference [7]). This allowed us to read in our data set, dynamically generate the problem formulation, pass it to a solver, and plot the resulting output.

## Solvers Used

We attempted several solvers in obtaining the optimal solution:

- Cbc: coin-or-branch and cut: part of the Coin-Or project (see reference [8])
- GLPK: GNU Linear Programming Kit (see reference [9])
- Gurobi: commercial solver with academic license available (see reference [10])
- SCIP Optimization Suite (see reference [11])
- Held-Karp: a python implementation of the Held-Karp dynamic programming algorithm. We initially attempted this solver using publicly available Python code (see reference [16]), but due to poor performance, we did not include it in our analysis

These solvers had to be installed as separate applications on the computer that we ran our solver. In order to pass the problem formulation from Python to these programs, use utilized Python connectors (see next section).

## Connectors

The solvers we attempted to use were written in C/C++ (for high performance) and were provided in native assembly format (executable). In order to pass the problem formulation from our Python program to these solvers, we utilized a Python connector. We used the following:

- PuLP: a flexible connector that works with multiple solvers (Cbc, Gurobi, GLPK). See [12] for more details on PuLP.
- PySCIPOpt: connector made for the SCIP Optimization Suite, with support for cutting planes method (see [13]).

## Programmatic Problem Formulation

The connector libraries above have a slightly different syntax for defining the problem model. We provide a brief summary of how the problem is formulated using these connectors:

Table 5: Formulation for the PuLP Solver

Imports	<code>import pulp</code>
Define model	<code>z = pulp.LpProblem('EngM540', pulp.LpMinimize)</code>
Decision variables	<code>x[i,j] = pulp.LpVariable('x' + str(i) + ' ' + str(j), 0, 1, pulp.LpInteger)</code> <code>l[i] = pulp.LpVariable('l' + str(i), 1, min(n,c), pulp.LpInteger)</code>
Objective function	<code>z += pulp.lpSum([d[i][j] * x[i,j] for i in range(n+w) for j in list(range(i)) + list(range(i+1,n+w))])</code>
Constraints	<code>for i in range(w, n+w):</code> <code>    z += pulp.lpSum([x[i,j] for j in range(n+w) if i != j]) == 1</code> <code>    z += pulp.lpSum([x[j,i] for j in range(n+w) if i != j]) == 1</code> <code>for i in range(w, n+w):</code> <code>    for j in range(w, n+w):</code> <code>        if i!=j:</code> <code>            z += pulp.lpSum([l[i], -1*l[j], n*x[i,j], -n+1]) &lt;= 0</code> <code>z += pulp.lpSum([x[i,j] for i in range(w) for j in range(w, n+w) if i != j]) == paths</code>
Solving	<code>status = z.solve() # Coin-OR CBC</code> <code>status = z.solve(pulp.GLPK()) # GLPK</code> <code>status = z.solve(pulp.GUROBI_CMD()) # Gurobi commercial solver</code>
Accessing Solution	<code>pulp.value(x[i,j])</code> <code>pulp.value(l[i])</code> <code>z.objective.value()</code>

Our code for PySCIPOpt is based on the example code provided with this library [14].

Table 6: Formulation for the PySCIPOpt

Imports	<code>import pyscipopt</code>
Define model	<code>model = Model("EngM540")</code>
Decision variables	<code>x[i,j] = model.addVar(ub=1, name="x(%s,%s)"%(i,j))</code> <code>l[i] = model.addVar(ub=min(c,n),lb=1, name="l(%s)"%(i))</code>
Objective function	<code>model.setObjective(quicksum(d[i,j]*x[i,j] for (i,j) in x), "minimize")</code>
Constraints	<code>for i in range(w, n+w):</code> <code>    model.addCons(quicksum(x[j,i] for j in range(n+w) if j != i) == 1, "In(%s)"%i)</code> <code>    model.addCons(quicksum(x[i,j] for j in range(n+w) if j != i) == 1, "Out(%s)"%i)</code> <code>for i in range(w, n+w):</code> <code>    for j in range(w, n+w):</code> <code>        if i!=j:</code> <code>            model.addCons(l[i] - l[j] + n*x[i,j] &lt;= n-1, "Li(%s,%s)"%(i,j))</code> <code>z += pulp.lpSum([x[i,j] for i in range(w) for j in range(w, n+w) if i != j]) == paths</code>
Solving	<code>model.optimize()</code>
Cutting Planes 1 one-time	<code>model.freeTransform()</code> <code>model.chgVarType(x[i,j], "B") # binary</code> <code>model.chgVarType(l[i], "I") # integer</code> <code>model.optimize()</code>

Cutting Planes 2 repeat	<pre>model.freeTransform() model.addCons(quicksum(x[i,j] for i in S for j in S if j!=i) &lt;= len(S)-1) model.optimize()</pre>
Accessing Solution	<pre>model.getVal(x[i,j]) model.getVal(l[i]) model.getObjVal()</pre>

When solving case (1) of the formulation, the cutting planes code above is used to eliminate subtours as they come up in the solution, one at a time, until no more subtours remain.

In addition, the Gurobi solver (with PuLP connector) also implements cutting planes under-the-hood, but there is no control over that process, unlike when using PySCIPOpt. The full code for the program we wrote is provided in Appendix 8.

## Comparison

The solvers we used did not perform the same, and not all of them were able to find an optimal solution for our base case (50 customers, a single truck & warehouse, and a truck capacity of 50). Generally, the cbc and GLPK solvers performed the worst and did not scale for problem sizes containing 50 customers:

- Coin-or-branch and cut (cbc): the default solver utilized by the PuLP connector. This solver took unreasonably long for problem instances containing more than 25 customers
- GLPK: this solver performed faster than cbc for instances of the problem containing  $\sim 10$  customers or less, but was significantly slower for larger problem instances

The cutting planes method along with the SCIP solver (utilized via the PySCIPOpt connector), and the Gurobi solver (utilized via the PuLP connector) performed the best:

- Both SCIP and Gurobi were able to find solutions for problem sizes containing 50 customers
- Gurobi usually found a solution faster than SCIP

## Solution Visualization

A simple GUI was developed using the matplotlib library (see [15]), which allowed us to quickly run several different scenarios and examine the effect on the optimal solution. In some cases, we were performing trial and error to determine which permutations of inputs were solvable using the algorithm selected (some would run for over a few hours, with no way of the % progress completed as far). The GUI is shown in figure 4 below:

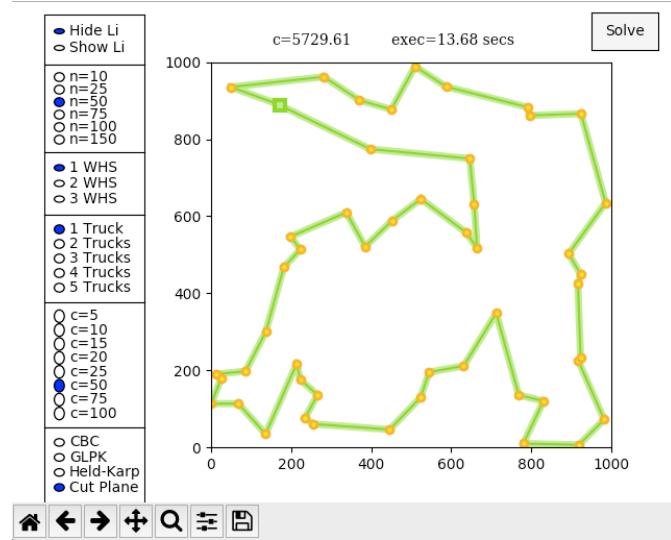


Figure 4 – Graphical user interface for the solver

The program initially solved the problem on a randomly generated dataset of the size selected in the interface but was later modified to import the dataset.csv file.

## Solutions

### Approximate Distance Matrix (GPS)

We first solved the problem by using the GPS coordinates of every location to compute the straight-line distance, in km. This gave us the following solution:

Parameters	$n_c = 50$ $n_w = 1$ $t = 1$ $c = 50$
Optimal route distance	<b>128.089 km</b>
Optimal route cost	<b>\$ 146.73</b>

Here, we utilized the symmetric version of the problem formulation, as this approach always yields a symmetric distance matrix. This produces the following solution:



Figure 5 – Problem solution using approximation of  $D$ ,  $n_c=50$ ,  $c=50$ ,  $t=1$ ,  $wh=1$

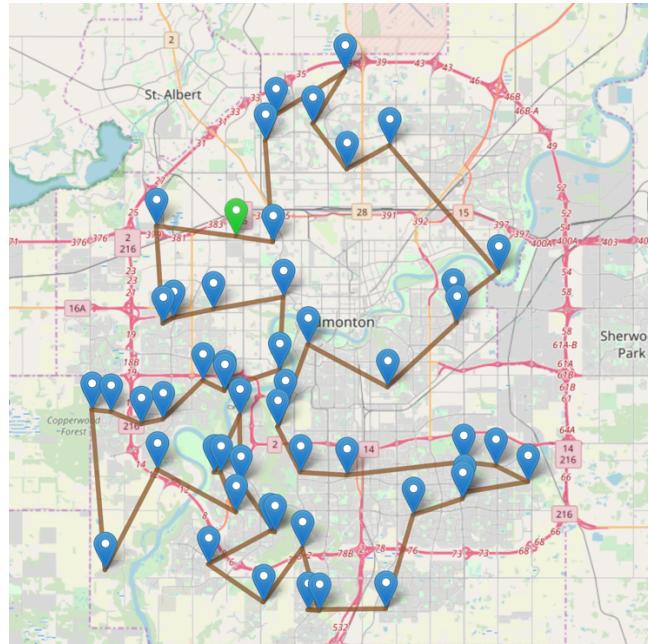
### Accurate Distance Matrix (Google Maps)

Then, we solved the problem using a distance matrix that we retrieved from Google Maps (see ‘Dataset’ section for more details). The result is provided below:

**Table 7: Google Maps Distance Matrix**

Parameters	$n_c = 50$ $n_w = 1$ $t = 1$ $c = 50$
Optimal route distance	<b>220.24 km</b>
Optimal route cost	<b>\$ 252.28</b>

This yields the following path:



*Figure 6 – Problem solution using Google Maps D,  $n_c=50$ ,  $c=50$ ,  $t=1$ ,  $wh=1$*

## Sensitivity Analysis

In this section, we solve the problem formulation for different combinations of inputs and compare the objective function values to see how sensitive the objective function is to the input variables.

### Capacity = 30

The solution where the truck capacity is reduced from 50 to 30 is provided below. This implication of this change is that the truck now has to take two paths, returning to the warehouse a single time to pick up more product. Note that our formulation will allow both paths to have a length between 20 and 30, depending on what results in the shortest route.

Table 8: Optimal route distance and cost for capacity = 30

Parameters	$n_c = 50$ $n_w = 1$ $t = 1$ $c = 30$
Optimal route distance	<b>226.147 km</b>
Optimal route cost	\$ 250.570

Compared to the base case (where  $c=50$ ), we see that:

The optimal route distance increases by **5.154 km** (which is expected, as now 2 trips are required instead of one), and the optimal route cost decreased by **\$ 1.71** (due to the lower fuel cost  $c_f$  for  $c=30$  compared to  $c=50$ ). The optimal route is shown in figure 7.

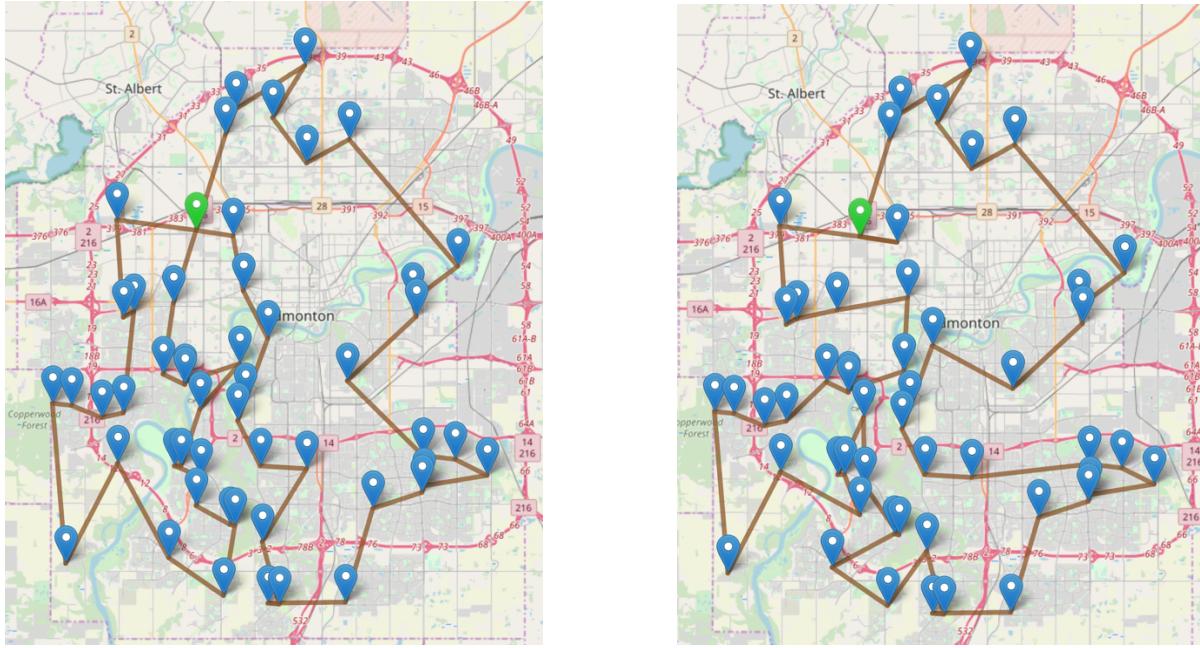


Figure 7 – Problem solution using Google Maps D, LEFT:  $n_c=50$ ,  $c=30$ ,  $t=1$ ,  $wh=1$ ; RIGHT:  $n_c=50$ ,  $c=50$ ,  $t=2$ ,  $wh=1$

## Trucks = 2

Next, the problem is solved for the case where  $t = 2$ . This implies that two paths must be utilized, but without any limitation placed on the lengths of the paths. So, the length of each path could be anywhere between 1 and 49.

Table 9: Optimal route distance and cost with two trucks

Parameters	$n_c = 50$ $n_w = 1$ $t = 2$ $c = 50$
Optimal route distance	<b>222.469 km</b>
Optimal route cost	<b>\$ 254.838</b>

We see that this solution is better than  $c=30$ , but worse than the base case of  $t = 1$  &  $c = 50$ . This is expected, because this version of the problem is a less constrained version of the case where  $c=30$ .

Compared to the base case, the optimal route distance is **2.233 km** longer, while the cost is **\$ 2.59** higher. See figure 7 above for a visualization. Here, one route contains a single customer, while the other route contains 49 customers.

## Warehouses = 2

Next, the problem is solved when there are two warehouses instead of one. The formulation gives more flexibility to the route, allowing it start/end at either warehouse to be consistent with the constraints. We obtained the following solution:

Table 10: Optimal route distance and cost for having two warehouses

Parameters	$n_c = 50$ $n_w = 2$ $t = 1$ $c = 50$
Optimal route distance	<b>219.787 km</b>
Optimal route cost	<b>\$ 251.766</b>

As expected, the optimal distance and cost are better than the base case with  $w = 1$ , as this is a less constrained version of the problem.

This solution is **0.449 km shorter** than the route with  $n_w = 1$ , and **\$0.514 cheaper**. This is shown in figure 8. The solution is interesting, as the optimal path begins at one of the warehouses, and ends at the other.

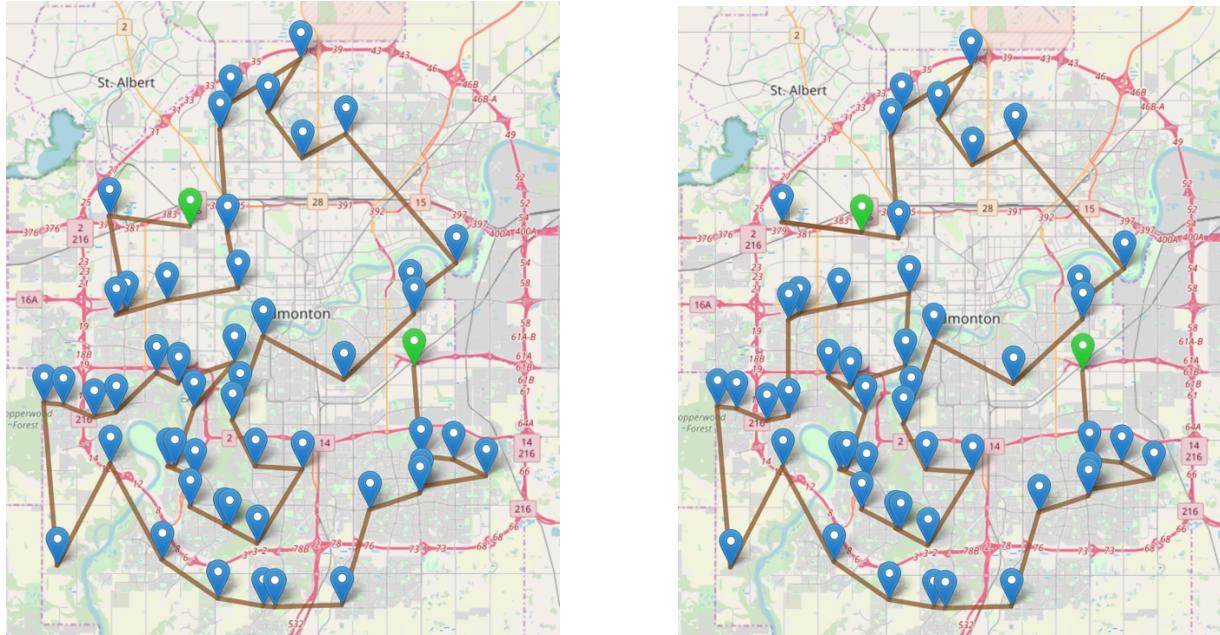


Figure 8 – Problem solution using Google Maps D, LEFT:  $n_c=50$ ,  $c=50$ ,  $t=1$ ,  $wh=2$ ; RIGHT:  $n_c=50$ ,  $c=50$ ,  $t=2$ ,  $wh=2$

## Warehouses = 2, $t = 2$

In this case, we require exactly 2 paths, to ensure that two trucks are used, but leave the solver to determine the length of each route taken by the truck (from 1 to 49). We obtain the following solution:

Table 11: Optimal route distance and cost for two warehouses and two trucks

Parameters	$n_c = 50$ $n_w = 2$ $t = 2$ $c = 50$
Optimal route distance	<b>221.103 km</b>
Optimal route cost	<b>\$ 253.273</b>

Compared to the version with  $w=2$  and  $t=1$ , this route is **1.316 km** longer and **\$1.507** more expensive. See figure 8 for a visual view of the paths taken. The optimal routes involve one of the trucks going to a single stop, while the other truck has a route with 49 customers. This may not be ideal, in terms of labour scheduling, and we present the case with a limit on a single truck's capacity of 30 next.

## Warehouses = 2, c = 30

In this case, we also require exactly 2 paths, to ensure that two trucks are used, but place a stricter constraint on the length of each route (from 20 to 30). We obtain the following solution:

Table 12: Optimal route distance and cost for two warehouses and capacity = 30

Parameters	$n_c = 50$ $n_w = 2$ $t = 1$ $c = 30$
Optimal route distance	<b>222.163 km</b>
Optimal route cost	<b>\$ 246.16</b>

Compared to the version with  $w=2$ ,  $t=1$  and  $c=50$ , this route is **2.376 km** longer and **\$ 5.61** cheaper. It is also longer and less expensive than the case with  $w = 2$ ,  $t = 2$  and  $c = 50$ . See figure 9 below for a visualization of this solution:



Figure 9 – Problem solution using Google Maps D, with  $n_c=50$ ,  $c=30$ ,  $t=1$ ,  $wh=2$

Here, we see that one of the paths begins and ends at warehouse #2, while the other utilizes both warehouses.

## Summary

A summary of the solutions we obtained is provided below:

Table 13: Summary of optimal route distances and costs for all scenarios under consideration

<b>n</b>	<b>w</b>	<b>t</b>	<b>c</b>	<b>Optimal route distance (km)</b>	<b>Optimal route cost (\$)</b>
50	1	1	50	220.240	252.280
50	1	2	50	222.469	254.838
50	1	1	30	226.147	250.570
50	2	1	50	219.787	251.766
50	2	2	50	221.103	253.273
50	2	1	30	222.163	246.156

The results are somewhat surprising. Due to having a fairly large number of customers (50), the impact of adding an additional warehouse on the objective function value are insignificant (around 0.39% reduction in the optimal route cost). We see a similar situation for the truck capacity and number of trucks. Reducing truck capacity to 30 has the largest impact on

the optimal objective function value (decreasing it by around 0.68% - while the optimal distance is slightly higher, the optimal cost is actually lower, as the increase in distance is offset by the reduction in fuel cost due to having a lighter load).

This result logically makes sense. Due to the large number of customers per route (50 or 30), and the fact that the warehouse is fairly close to some customers (and not outside the city), the additional trip to the warehouse required for the case of  $n_c=30$  or  $t=2$ , as it can be done in an optimal way (ie. between a pair of customers). We would expect, though, that as the number of customers per trip is decreased (say to 25 or 20), we would see a greater impact resulting from an additional warehouse.

## Conclusions

Integer programming provides a valuable management tools for making complicated decisions. In this report, we explored the optimization problem associated with finding an optimal delivery route, which revolved around find a sequence of visiting customers that minimizes the total distance travelled. We expressed our objective function as a cost minimization problem by making an assumption about how labour and fuel costs are related to the distance travelled.

We found that the way we formulated our problem and the solver we used had a huge impact on our ability to find an optimal solution. For instance, a simplified version of the formulation can be used if the distance matrix is symmetric, and if only a single path is required to fulfil customer demand (if a single truck has sufficient capacity for all products). We found that the only solvers that were able to reliably find an optimal solution for an asymmetric distance matrix, with more than one path were the SCIP and Gurobi solvers.

We expressed our solution as an optimal distance and cost, and compared it to several scenarios which used (i) a smaller truck with lower truck capacity, (ii) an additional truck, and (iii) an additional warehouse. We found that lowering truck capacity increased the total distance travelled, but decreased the total cost incurred to make the deliveries (due to the lower fuel cost associated with a small truck).

As we've shown, for a business where daily operating expenses are composed primarily of logistics costs, this type of analysis is invaluable: it can help the business to better manage its delivery expenses, and understand the monetary impact of strategic business decisions (such as truck size, number of warehouses, and number of trucks).

Some areas that could further be improved upon in our analysis are:

- Utilizing a time matrix in addition to a distance matrix, which would find an optimal route which minimizes trip time (these are provided by MapBox and Google Maps, in addition to the distance matrix  $D$  that we utilized)
- Incorporate truck rental costs into the objective function
- Explore overtime cost of labour for long routes

## References

- [1] <https://developers.google.com/maps/documentation/distance-matrix/>
- [2] <https://data.edmonton.ca/City-Administration/Property-Assessment-Data-2012-2017-/qj6axuwt/data>
- [3] <https://leafletjs.com/>
- [4] [https://wiki.openstreetmap.org/wiki/Standard\\_tile\\_layer](https://wiki.openstreetmap.org/wiki/Standard_tile_layer)
- [5] <https://www.mapbox.com/help/define-matrix-api/>
- [6] <https://developers.google.com/maps/documentation/distance-matrix/start>
- [7] <https://www.python.org/>
- [8] <https://projects.coin-or.org/Cbc>
- [9] <https://www.gnu.org/software/glpk/>
- [10] <http://www.gurobi.com/>
- [11] <https://scip.zib.de/>
- [12] <https://pythonhosted.org/PuLP/>
- [13] <https://github.com/SCIP-Interfaces/PySCIPOpt>
- [14] <https://github.com/SCIP-Interfaces/PySCIPOpt/tree/master/examples/finished>
- [15] <http://www.math.uwaterloo.ca/tsp/methods/dfj/index.html>
- [16] <https://github.com/CarlEkerot/held-karp>

## Appendix 1: Dataset

Location	Address	lat	lng
Warehouse 1	11921 152 St NW EDMONTON AB T5V 1E3	53.572226	-113.58381
Warehouse 2	5810 76 Ave NW EDMONTON AB T6B 0A6	53.512735	-113.423675
Customer 1	1912 TOMLINSON WAY NW EDMONTON AB T6R 2R5	53.45332914	-113.5832276
Customer 2	4922 27A AVENUE NW EDMONTON AB T6L 6B3	53.45903088	-113.4195745
Customer 3	131211 104 AVENUE NW EDMONTON AB	53.5459037	-113.5493732
Customer 4	18219 98A AVENUE NW EDMONTON AB T5T 3L5	53.534394	-113.6363747
Customer 5	11716 135A STREET NW EDMONTON AB T5M 1L5	53.56959423	-113.5568043
Customer 6	4416 MCCLUNG COURT NW EDMONTON AB T6R0M9	53.44479748	-113.5553688
Customer 7	9011 23 AVENUE SW EDMONTON AB T6X0Z9	53.41155502	-113.4750256
Customer 8	3528 105B STREET NW EDMONTON AB T6J 2L1	53.46937759	-113.5031153
Customer 9	747 HETU LANE NW EDMONTON AB T6R 2W9	53.4703923	-113.59925
Customer 10	6007 101A AVENUE NW EDMONTON AB T6A 0L9	53.54195069	-113.4261944
Customer 11	7020 95 STREET NW EDMONTON AB T6E 3E5	53.5072696	-113.4736968
Customer 12	18019 105A STREET NW EDMONTON AB T5X6J8	53.64312767	-113.5045585
Customer 13	14923 87 STREET NW EDMONTON AB T5E 5T4	53.61122946	-113.472363
Customer 14	6220 127 STREET NW EDMONTON AB T6H 3W9	53.49884402	-113.5474969
Customer 15	821 FORBES CLOSE NW EDMONTON AB T6R 2P4	53.4702743	-113.5944371
Customer 16	4906 31 AVENUE NW EDMONTON AB T6L 5H6	53.46191648	-113.4179429
Customer 17	14020 151 AVENUE NW EDMONTON AB T6V1T6	53.61308148	-113.5622736
Customer 18	16255 135 STREET NW EDMONTON AB T6V 0G3	53.624123	-113.5549965
Customer 19	815 WILDWOOD CRESCENT NW EDMONTON AB T6T0M2	53.46654863	-113.3717636
Customer 20	16126 100A AVENUE NW EDMONTON AB	53.54055386	-113.6001564
Customer 21	8928 116 STREET NW EDMONTON AB T6G 1P8	53.5256586	-113.531231
Customer 22	828 CHAHLEY WAY NW EDMONTON AB T6M0C7	53.4718784	-113.6405512
Customer 23	11939 20 AVENUE SW EDMONTON AB T6W 0E1	53.41135954	-113.5311719
Customer 24	21330 61 AVENUE NW EDMONTON AB T6M0K1	53.49736349	-113.6879737
Customer 25	12608 52B AVENUE NW EDMONTON AB T6H 0R4	53.49015719	-113.5535897
Customer 26	3523 38A AVENUE NW EDMONTON AB T6L 6N9	53.47320515	-113.3952815
Customer 27	5808 181 STREET NW EDMONTON AB T6M 1V7	53.49346792	-113.6362668
Customer 28	2218 STAN WATERS AVENUE NW EDMONTON AB T5E5Y8	53.60113978	-113.5031571
Customer 29	2003 AINSLIE LINK SW EDMONTON AB T6W 2M1	53.43066709	-113.6033058
Customer 30	7328 157 STREET NW EDMONTON AB T5R 1Z9	53.50564961	-113.5920701
Customer 31	103 CARLSON CLOSE NW EDMONTON AB T6R 2J8	53.465949	-113.5799035
Customer 32	525 CALLAGHAN POINTE SW EDMONTON AB T6W0G4	53.4107573	-113.5228052
Customer 33	3134 PAISLEY ROAD SW EDMONTON AB	53.41437039	-113.5639131
Customer 34	39 PATRICIA CRESCENT NW EDMONTON AB T5R 5N7	53.51022434	-113.6077606
Customer 35	925 GOODWIN WAY NW EDMONTON AB T5T6X8	53.496531	-113.674332
Customer 36	15104 57 AVENUE NW EDMONTON AB T6H 5B9	53.49497049	-113.5806122
Customer 37	911 117 STREET NW EDMONTON AB T6J 6Z7	53.43789767	-113.5351194
Customer 38	15820 119 STREET NW EDMONTON AB T5X 2P5	53.62070042	-113.5277118
Customer 39	20721 5 AVENUE SW EDMONTON AB T6M 2P4	53.42815457	-113.678483
Customer 40	8012 22 AVENUE NW EDMONTON AB T6K 1Z3	53.45194556	-113.4554235
Customer 41	17916 99A AVENUE NW EDMONTON AB T5T 3R1	53.5372012	-113.6291644
Customer 42	13312 79 AVENUE NW EDMONTON AB T5R 3G5	53.51450263	-113.5517854
Customer 43	3616 117B STREET NW EDMONTON AB T6J 1W2	53.47057706	-113.5366202
Customer 44	5708 95 AVENUE NW EDMONTON AB T6B 1A5	53.53500161	-113.4232647
Customer 45	18445 122 AVENUE NW EDMONTON AB T5V 1R4	53.576407	-113.6409895
Customer 46	3211 103 AVENUE NW EDMONTON AB T5W 0A4	53.55671498	-113.3930178
Customer 47	19011 56 AVENUE NW EDMONTON AB T6M 2L4	53.4913377	-113.6519364
Customer 48	7412 157 STREET NW EDMONTON AB T5R 1Z9	53.50701963	-113.5919666
Customer 49	3909 MACNEIL BAY NW EDMONTON AB T6R0H5	53.4449942	-113.558756
Customer 50	5309 39B AVENUE NW EDMONTON AB T6L 1R9	53.4747778	-113.4188405

## Appendix 2: Location Visualization Code

```

<!DOCTYPE html>
<html>
<head>
<title>Page Title</title>
<link rel="stylesheet" href="https://unpkg.com/leaflet@1.3.4/dist/leaflet.css" />
<style>
#mapid { height: 700px; }
</style>
</head>
<body>
<div id="mapid"></div>
<script src="https://unpkg.com/leaflet@1.3.4/dist/leaflet.js"></script>
<script>
  map = new L.Map('mapid');
  var osmUrl='https://{s}.tile.openstreetmap.org/{z}/{x}/{y}.png';
  var osmAttrib='Map data © <a href="https://openstreetmap.org">OpenStreetMap</a> contributors';
  var osm = new L.TileLayer(osmUrl, {minZoom: 8, maxZoom: 12, attribution: osmAttrib});

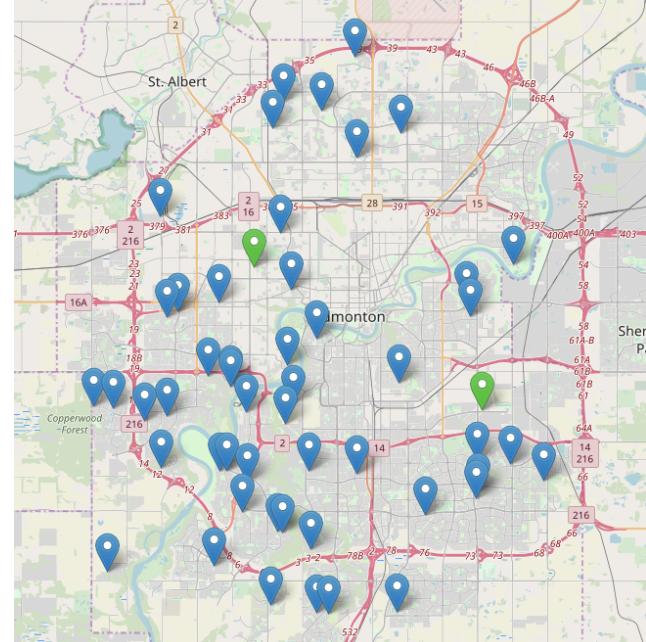
  map.setView(new L.LatLng(53.51670635,-113.372475),11);
  map.addLayer(osm);

  var whIcon = L.icon({ iconUrl: 'marker-icon-wh.png', shadowUrl: 'marker-shadow.png' });

  // warehouses
  L.marker([53.512735,-113.423675], {icon: whIcon}).addTo(map);
  L.marker([53.572226,-113.583810], {icon: whIcon}).addTo(map);

  // customers
  L.marker([53.45332914,-113.5832276]).addTo(map);
  L.marker([53.45903088,-113.4195745]).addTo(map);
  L.marker([53.5459037,-113.5493732]).addTo(map);
  L.marker([53.534394,-113.6363747]).addTo(map);
  L.marker([53.56959423,-113.5568043]).addTo(map);
  L.marker([53.44479748,-113.5553688]).addTo(map);
  L.marker([53.41155502,-113.4750256]).addTo(map);
  L.marker([53.46937759,-113.5031153]).addTo(map);
  L.marker([53.4703923,-113.59925]).addTo(map);
  L.marker([53.54195069,-113.4261944]).addTo(map);
  L.marker([53.5072696,-113.4736968]).addTo(map);
  L.marker([53.64312767,-113.5045585]).addTo(map);
  L.marker([53.61122946,-113.472363]).addTo(map);
  L.marker([53.49884402,-113.5474969]).addTo(map);
  L.marker([53.4702743,-113.5944371]).addTo(map);
  L.marker([53.46191648,-113.4179429]).addTo(map);
  L.marker([53.61308148,-113.5622736]).addTo(map);
  L.marker([53.624123,-113.5549965]).addTo(map);
  L.marker([53.46654863,-113.3717636]).addTo(map);
  L.marker([53.54055386,-113.6001564]).addTo(map);
  L.marker([53.5256586,-113.531231]).addTo(map);
  L.marker([53.4718784,-113.6405512]).addTo(map);
  L.marker([53.41135954,-113.5311719]).addTo(map);
  L.marker([53.49736349,-113.6879737]).addTo(map);
  L.marker([53.49015719,-113.5535897]).addTo(map);
  L.marker([53.47320515,-113.3952815]).addTo(map);
  L.marker([53.49346792,-113.6362668]).addTo(map);
  L.marker([53.60113978,-113.5031571]).addTo(map);
  L.marker([53.43066709,-113.6033058]).addTo(map);
  L.marker([53.50564961,-113.5920701]).addTo(map);
  L.marker([53.465949,-113.5799035]).addTo(map);
  L.marker([53.4107573,-113.5228052]).addTo(map);
  L.marker([53.41437039,-113.5639131]).addTo(map);
  L.marker([53.51022434,-113.6077606]).addTo(map);
  L.marker([53.496531,-113.674332]).addTo(map);
  L.marker([53.49497049,-113.5806122]).addTo(map);
  L.marker([53.43789767,-113.5351194]).addTo(map);
  L.marker([53.62070042,-113.5277118]).addTo(map);
  L.marker([53.42815457,-113.678483]).addTo(map);
  L.marker([53.45194556,-113.4554235]).addTo(map);
  L.marker([53.5372012,-113.6291644]).addTo(map);
  L.marker([53.51450263,-113.5517854]).addTo(map);
  L.marker([53.47057706,-113.5366202]).addTo(map);
  L.marker([53.53500161,-113.4232647]).addTo(map);
  L.marker([53.576407,-113.6409895]).addTo(map);
  L.marker([53.55671498,-113.3930178]).addTo(map);
  L.marker([53.4913377,-113.6519364]).addTo(map);
  L.marker([53.50701963,-113.5919666]).addTo(map);
  L.marker([53.4449942,-113.558756]).addTo(map);
  L.marker([53.4747778,-113.4188405]).addTo(map);
</script>
</body>
</html>

```







Appendix 5: Order-Merchandise Matrix (n)

		Warehouse 2		Warehouse 1			
Warehouse 1		Warehouse 2		Warehouse 1		Customer	
Customer	Order ID	Warehouse 1	Warehouse 2	Warehouse 1	Warehouse 2	Customer	Order ID
Customer 1	10001	10000	10000	10000	10000	Customer 1	10001
Customer 2	10002	20000	20000	20000	20000	Customer 2	10002
Customer 3	10003	30000	30000	30000	30000	Customer 3	10003
Customer 4	10004	40000	40000	40000	40000	Customer 4	10004
Customer 5	10005	50000	50000	50000	50000	Customer 5	10005
Customer 6	10006	60000	60000	60000	60000	Customer 6	10006
Customer 7	10007	70000	70000	70000	70000	Customer 7	10007
Customer 8	10008	80000	80000	80000	80000	Customer 8	10008
Customer 9	10009	90000	90000	90000	90000	Customer 9	10009
Customer 10	10010	100000	100000	100000	100000	Customer 10	10010
Customer 11	10011	110000	110000	110000	110000	Customer 11	10011
Customer 12	10012	120000	120000	120000	120000	Customer 12	10012
Customer 13	10013	130000	130000	130000	130000	Customer 13	10013
Customer 14	10014	140000	140000	140000	140000	Customer 14	10014
Customer 15	10015	150000	150000	150000	150000	Customer 15	10015
Customer 16	10016	160000	160000	160000	160000	Customer 16	10016
Customer 17	10017	170000	170000	170000	170000	Customer 17	10017
Customer 18	10018	180000	180000	180000	180000	Customer 18	10018
Customer 19	10019	190000	190000	190000	190000	Customer 19	10019
Customer 20	10020	200000	200000	200000	200000	Customer 20	10020
Customer 21	10021	210000	210000	210000	210000	Customer 21	10021
Customer 22	10022	220000	220000	220000	220000	Customer 22	10022
Customer 23	10023	230000	230000	230000	230000	Customer 23	10023
Customer 24	10024	240000	240000	240000	240000	Customer 24	10024
Customer 25	10025	250000	250000	250000	250000	Customer 25	10025
Customer 26	10026	260000	260000	260000	260000	Customer 26	10026
Customer 27	10027	270000	270000	270000	270000	Customer 27	10027
Customer 28	10028	280000	280000	280000	280000	Customer 28	10028
Customer 29	10029	290000	290000	290000	290000	Customer 29	10029
Customer 30	10030	300000	300000	300000	300000	Customer 30	10030
Customer 31	10031	310000	310000	310000	310000	Customer 31	10031
Customer 32	10032	320000	320000	320000	320000	Customer 32	10032
Customer 33	10033	330000	330000	330000	330000	Customer 33	10033
Customer 34	10034	340000	340000	340000	340000	Customer 34	10034
Customer 35	10035	350000	350000	350000	350000	Customer 35	10035
Customer 36	10036	360000	360000	360000	360000	Customer 36	10036
Customer 37	10037	370000	370000	370000	370000	Customer 37	10037
Customer 38	10038	380000	380000	380000	380000	Customer 38	10038
Customer 39	10039	390000	390000	390000	390000	Customer 39	10039
Customer 40	10040	400000	400000	400000	400000	Customer 40	10040
Customer 41	10041	410000	410000	410000	410000	Customer 41	10041
Customer 42	10042	420000	420000	420000	420000	Customer 42	10042
Customer 43	10043	430000	430000	430000	430000	Customer 43	10043
Customer 44	10044	440000	440000	440000	440000	Customer 44	10044
Customer 45	10045	450000	450000	450000	450000	Customer 45	10045
Customer 46	10046	460000	460000	460000	460000	Customer 46	10046
Customer 47	10047	470000	470000	470000	470000	Customer 47	10047
Customer 48	10048	480000	480000	480000	480000	Customer 48	10048
Customer 49	10049	490000	490000	490000	490000	Customer 49	10049
Customer 50	10050	500000	500000	500000	500000	Customer 50	10050

## Appendix 6: Code for Retrieving MapBox Distance Matrix

```

import json
import requests
import csv
import numpy

coords = numpy.empty([52, 2])

with open('coords.csv') as csv_file:
    csv_reader = csv.reader(csv_file, delimiter=',')
    for idx, row in enumerate(csv_reader):
        coords[idx,:] = row

indexes = numpy.empty([6, 2])
indexes[0,:] = [0,11]
indexes[1,:] = [12,23]
indexes[2,:] = [24,35]
indexes[3,:] = [36,47]
indexes[4,:] = [48,51]
indexes[5,:] = [52,55]

dd = numpy.empty([52,52])
dt = numpy.empty([52,52])

for s in range(5):
    for d in range(5):
        min_s = indexes[s,0]
        min_d = indexes[d,0]
        if s < d:
            min_d = indexes[d,0]-12
        elif s > d:
            min_s = indexes[s,0]-12
        s_l = list(range(int(indexes[s,0]-min_s), int(indexes[s+1,0]-min_s)))
        d_l = list(range(int(indexes[d,0]-min_d), int(indexes[d+1,0]-min_d)))
        s_s = ';'.join([str(i) for i in s_l])
        d_s = ';'.join([str(i) for i in d_l])
        c_s = None
        c_l = None
        if s==d:
            c_l = coords[int(indexes[s,0]):int(indexes[s+1,0]),:]
        else:
            c_l = coords[int(indexes[s,0]):int(indexes[s+1,0]),:]
            c_l = numpy.append(c_l, coords[int(indexes[d,0]):int(indexes[d+1,0]),:], axis=0)
        c_s = ';'.join('.'.join(str(x) for x in y) for y in c_l)

        url = "https://api.mapbox.com/directions-matrix/v1/mapbox/driving/" + c_s + "?destinations="
        + d_s + "&sources=" + s_s + "&annotations=duration,distance&access_token=API_KEY"
        print("Calling url: " + url)
        response = requests.get(url)
        json_data = json.loads(response.text)
        if json_data['code'] != "Ok":
            print("Error calling API: " + str(s) + " d: " + str(d))
            dd[int(indexes[s,0]):int(indexes[s+1,0]), int(indexes[d,0]):int(indexes[d+1,0])] =
            json_data['distances']
            dt[int(indexes[s,0]):int(indexes[s+1,0]), int(indexes[d,0]):int(indexes[d+1,0])] =
            json_data['durations']

numpy.savetxt("d_dist.csv", dd, delimiter=",")
numpy.savetxt("d_time.csv", dt, delimiter=",")

```

## Appendix 7: Code for Retrieving Google Maps Distance Matrix

```
import json
import requests
import csv
import numpy

coords = numpy.empty([52, 2])

with open('coords.csv') as csv_file:
    csv_reader = csv.reader(csv_file, delimiter=',')
    for idx, row in enumerate(csv_reader):
        coords[idx,:] = row

indexes = numpy.empty([7, 2])
indexes[0,:] = [0,9]
indexes[1,:] = [10,19]
indexes[2,:] = [20,29]
indexes[3,:] = [30,39]
indexes[4,:] = [40,49]
indexes[5,:] = [50,51]
indexes[6,:] = [52,55]

dd = numpy.empty([52,52])
dt = numpy.empty([52,52])

for s in range(6):
    for d in range(6):
        s_s = None
        s_l = coords[int(indexes[s,0]):int(indexes[s+1,0]),:]
        d_s = None
        d_l = coords[int(indexes[d,0]):int(indexes[d+1,0]),:]

        s_s = '||'.join('||'.join(str(x) for x in y) for y in s_l)
        d_s = '||'.join('||'.join(str(x) for x in y) for y in d_l)

        url = "https://maps.googleapis.com/maps/api/distancematrix/json?origins=" + s_s +
        "&destinations=" + d_s + "&key=API_KEY"
        print("Calling Url: " + url)
        response = requests.get(url)
        json_data = json.loads(response.text)

        distances = numpy.empty([int(indexes[s+1,0]-indexes[s,0]), int(indexes[d+1,0]-indexes[d,0])])
        times = numpy.empty([int(indexes[s+1,0]-indexes[s,0]), int(indexes[d+1,0]-indexes[d,0])])
        rows = json_data['rows']
        for i in range(len(rows)):
            row = rows[i]
            elements = row['elements']
            for j in range(len(elements)):
                element = elements[j]
                if element['status'] != 'OK':
                    print('Error: i: ' + str(i) + ' j: ' + str(j))
                distances[i,j] = element['distance']['value']
                times[i,j] = element['duration']['value']
        dd[int(indexes[s,0]):int(indexes[s+1,0]), int(indexes[d,0]):int(indexes[d+1,0])] = distances
        dt[int(indexes[s,0]):int(indexes[s+1,0]), int(indexes[d,0]):int(indexes[d+1,0])] = times

numpy.savetxt("d_dist.csv", dd, delimiter=",")
numpy.savetxt("d_time.csv", dt, delimiter=",")
```

## Appendix 8: Solver Interface Code

```
import numpy as np
import matplotlib.pyplot as plt
from matplotlib.widgets import RadioButtons
import random
from matplotlib.widgets import Button
from matplotlib.text import Text
import pulp
import math
import time

import networkx
from pycipopt import Model, quicksum, SCIP_PARAMSETTING
import itertools
import csv

loc_x = []
loc_y = []
n = 50
c = 50
loc_size = 1000
marker_size = 5
trucks = 2
solver = "gurobi"
li = [0] * n
warehouses = 1
lines_x = []
lines_y = []
obj_value = ""
exec_value = ""
model = None
x = None

min_loc_x = None
min_loc_y = None
max_loc_x = None
max_loc_y = None

distances = [[0 for x in range(n+warehouses)] for y in range(n+warehouses)]
distances2 = {}

def generate_data(n,whs):
    #global loc_x,loc_y,
    global obj_value,exec_value,distances,distances2
    global min_loc_x,min_loc_y,max_loc_x,max_loc_y
    distances = [[0 for x in range(n+whs)] for y in range(n+whs)]
    distances2 = {}

    with open('distances_lwh.csv') as csv_file:
        csv_reader = csv.reader(csv_file, delimiter=',')
        for idx, row in enumerate(csv_reader):
            for i in range(len(row)):
                distances2[idx,i] = float(row[i])
                distances[idx][i] = float(row[i])

    with open('coords_lwh.csv') as csv_file:
        csv_reader = csv.reader(csv_file, delimiter=',')
        for row in csv_reader:
            lng = float(row[0])
            lat = float(row[1])
            loc_x.append(lng)
            loc_y.append(lat)

    min_loc_x = min(loc_x)
    min_loc_y = min(loc_y)
    max_loc_x = max(loc_x)
    max_loc_y = max(loc_y)
    for i in range(len(loc_x)):
        loc_x[i] = (loc_x[i] - min_loc_x) / (max_loc_x - min_loc_x) * 1000
```

```

        for i in range(len(loc_y)):
            loc_y[i] = (loc_y[i] - min_loc_y) / (max_loc_y - min_loc_y) * 1000
            print('lng: ' + str(loc_x[i]) + ' lat: ' + str(loc_y[i]))

    obj_value = ""
    exec_value = ""

def plot_data(ax, loc_x, loc_y, warehouses):
    l1, = ax.plot(loc_x[warehouses:], loc_y[warehouses:], linestyle='None', marker='o',
    markersize=marker_size, antialiased=True, markeredgecolor='#F5A623',
    markerfacecolor='#F8E71C', markeredgewidth=2)
    l2, = ax.plot(loc_x[0:warehouses], loc_y[0:warehouses], linestyle='None', marker='s',
    markersize=marker_size+2, antialiased=True, markeredgecolor='#7ED321',
    markerfacecolor='#B8E986', markeredgewidth=3)

fig, ax = plt.subplots()

generate_data(n,warehouses)
plot_data(ax, loc_x, loc_y, warehouses)

plt.axis([0, 1000, 0, 1000])
plt.subplots_adjust(left=0.3)

# Radio Buttons - Li
rax = plt.axes([0.05, 0.875, 0.15, 0.1])
radioli = RadioButtons(rax, ('Hide Li', 'Show Li'))

def lifunc(label):
    global li, loc_x, loc_y, n, warehouses, fig, ax, obj_value, exec_value

    if label=="Show Li":
        for idx, val in enumerate(li):
            x = loc_x[idx+warehouses]
            y = loc_y[idx+warehouses]
            # ax.text(x+15, y-15, "Li=" + str(int(val)), family="sans-serif",
            horizontalalignment='left', verticalalignment='top')
            ax.text(x+15, y-15, "i=" + str(int(val)), family="sans-serif",
            horizontalalignment='left', verticalalignment='top')
        fig.canvas.draw()
    if label=="Hide Li":
        ax.clear()
        ax.set_xlim(0,1000)
        ax.set_ylim(0,1000)

        ax.plot(lines_x, lines_y, color='#B8E986', markeredgewidth=50, markersize=50,
        linewidth=5)
        ax.plot(lines_x, lines_y, color='#7ED321')

        ax.text(350, 1075, obj_value, family="serif", horizontalalignment='right',
        verticalalignment='top')
        ax.text(450, 1075, exec_value, family="serif", horizontalalignment='left',
        verticalalignment='top')

    plot_data(ax, loc_x, loc_y, warehouses)
    fig.canvas.draw()

radioli.on_clicked(lifunc)

# Radio Buttons - n
rax = plt.axes([0.05, 0.7, 0.15, 0.175])
radio = RadioButtons(rax, ('n=10', 'n=25', 'n=50', 'n=75', 'n=100', 'n=150'))

def nfunc(label):
    global loc_x, loc_y, n, warehouses, ax, li
    s = label.split('=')
    n = int(s[1])
    generate_data(n,warehouses)
    ax.clear()

```

```

ax.set_xlim(0,1000)
ax.set_ylim(0,1000)
plot_data(ax, loc_x, loc_y, warehouses)
li = []
#l1, = ax.plot(loc_x[1:], loc_y[1:], linestyle='None', marker='o', markersize=marker_size,
antialiased=True, markeredgewidth=2, markeredgecolor="#F5A623", markerfacecolor="#F8E71C", markeredgewidth=2)
#l2, = ax.plot(loc_x[0], loc_y[0], linestyle='None', marker='s', markersize=marker_size+2,
antialiased=True, markeredgewidth=3, markeredgecolor="#7ED321", markerfacecolor="#B8E986", markeredgewidth=3)
plt.draw()
radio.on_clicked(nfunc)
#
# Radio Buttons - warehouses
rax = plt.axes([0.05, 0.575, 0.15, 0.125])
radiowh = RadioButtons(rax, ('1 WHS', '2 WHS', '3 WHS'))

def whfunc(label):
    global warehouses, n, ax, loc_x, loc_y, fig
    s = label.split(" ")
    warehouses = int(s[0])
    ax.clear()
    ax.set_xlim(0,1000)
    ax.set_ylim(0,1000)
    generate_data(n,warehouses)
    plot_data(ax, loc_x, loc_y, warehouses)
    fig.canvas.draw()
radiowh.on_clicked(whfunc)

# Radio Buttons - trucks
rax = plt.axes([0.05, 0.4, 0.15, 0.175])
radio2 = RadioButtons(rax, ('1 Truck', '2 Trucks', '3 Trucks', '4 Trucks', '5 Trucks'))

def trucksfunc(label):
    global trucks
    s = label.split(" ")
    trucks = int(s[0])
radio2.on_clicked(trucksfunc)

# Radio Buttons - truck capacity
rax = plt.axes([0.05, 0.15, 0.15, 0.25])
radio4 = RadioButtons(rax, ('c=5', 'c=10', 'c=15', 'c=20', 'c=25', 'c=50', 'c=75', 'c=100'))

def cfunc(label):
    global c
    s = label.split('=')
    c = int(s[1])
radio4.on_clicked(cfunc)

# Radio Buttons - solver
rax = plt.axes([0.05, 0.0, 0.15, 0.15])
radio3 = RadioButtons(rax, ('CBC', 'GLPK', 'Held-Karp', 'Cut Plane'))

def solverfunc(label):
    global solver
    solver = label.lower()
radio3.on_clicked(solverfunc)

# Plot connecting lines
def plot_data_lines(lines_x,lines_y):
    ax.plot(lines_x, lines_y, color="#B8E986", markeredgewidth=50, markersize=50, linewidth=5)
    ax.plot(lines_x, lines_y, color="#7ED321")

def addcut(cut_edges,model,x,warehouses):
    invalid = False #ADDED
    G = networkx.Graph()
    G.add_edges_from(cut_edges)
    Components = list(networkx.connected_components(G))
    if len(Components) == 1:
        return False

    for S in Components:

```

```

invalid_path = True
for warehouse in range(0,warehouses):
    if warehouse in S:
        invalid_path = False
        break
if invalid_path:
    invalid=True
    break

if not invalid:
    return False

model.freeTransform()

for S in Components:
    invalid_path = True
    for warehouse in range(0,warehouses):
        if warehouse in S:
            invalid_path = False
            break
    if invalid_path:
        model.addCons(quicksum(x[i,j] for i in S for j in S if j!=i) <= len(S)-1)
        print("cut: len(%s) <= %s" % (S,len(S)-1))

return True

def held_karp(dists):
    """
    Implementation of Held-Karp, an algorithm that solves the Traveling
    Salesman Problem using dynamic programming with memoization.

    Parameters:
        dists: distance matrix

    Returns:
        A tuple, (cost, path).
    """
    n = len(dists)

    C = {}

    for k in range(1, n):
        C[(1 << k, k)] = (dists[0][k], 0)

    for subset_size in range(2, n):
        for subset in itertools.combinations(range(1, n), subset_size):
            # Set bits for all nodes in this subset
            bits = 0
            for bit in subset:
                bits |= 1 << bit

            # Find the lowest cost to get to this subset
            for k in subset:
                prev = bits & ~(1 << k)

                res = []
                for m in subset:
                    if m == 0 or m == k:
                        continue
                    res.append((C[(prev, m)][0] + dists[m][k], m))
                C[(bits, k)] = min(res)

    bits = (2**n - 1) - 1

    res = []
    for k in range(1, n):
        res.append((C[(bits, k)][0] + dists[k][0], k))
    opt, parent = min(res)

    path = []
    for i in range(n - 1):

```

```

        path.append(parent)
        new_bits = bits & ~(1 << parent)
        _, Parent = C[(bits, parent)]
        bits = new_bits

    path.append(0)

    return opt, list(reversed(path))

def solve(event):
    global n, trucks, solver, li, ax, warehouses, loc_x, loc_y, lines_x, lines_y, obj_value,
    exec_value
    global distances, distances2
    print("solving...")

    ax.clear()
    ax.set_xlim(0,1000)
    ax.set_ylim(0,1000)
    plot_data(ax, loc_x, loc_y, warehouses)
    ax.text(400, 1075, "solving...", family="serif", horizontalalignment='left',
    verticalalignment='top')
    plt.draw()
    fig.canvas.draw()

    start_time = time.time()

    # Calculate constraint for Li
    total_l = 0
    total_c = 0.0
    paths = 0
    slack = False
    while total_c < n or paths < trucks:
        c1 = min(c,n)
        total_c += c1
        total_l += c1*(c1+1)/2
        paths += 1
    if total_c > n:
        slack = True

    if solver=="cbc" or solver=="glpk" or solver=="gurobi":

        # Objective function
        z = pulp.LpProblem('Test', pulp.LpMinimize)

        # Generate decision variables
        x = {}
        y = {}
        variables = []
        l = {}
        s = {}
        for i in range(n+warehouses):
            for j in range(n+warehouses):
                if i==j:
                    continue
                x[i,j] = pulp.LpVariable('x_' + str(i) + '_' + str(j), 0, 1, pulp.LpInteger)
        if i >= warehouses:
            l[i] = pulp.LpVariable('l_' + str(i), 1, min(n,c), pulp.LpInteger)

        # Objective function
        z += pulp.lpSum([distances[i][j] * x[i,j] for i in range(n+warehouses) for j in
list(range(i)) + list(range(i+1,n+warehouses))])

        # Constraints
        constraintSeq = []
        constraintTrucks = []
        for i in range(n+warehouses):
            if i>=warehouses:
                constraintSeq.append(l[i])

        constraintFrom = []

```

```

constraintTo = []
for j in range(n+warehouses):
    if i==j:
        continue
    if i>=warehouses and j>=warehouses:
        z += pulp.lpSum([l[i], -1*l[j], n*x[i,j], -n+1]) <= 0

    if i>=warehouses:
        constraintFrom.append(x[i,j])
        constraintTo.append(x[j,i])
    if i<warehouses:
        constraintTrucks.append(x[j,i])

if i>=warehouses:
    z += pulp.lpSum(constraintFrom) == 1 # paths from location
    z += pulp.lpSum(constraintTo) == 1 # paths to location
if i==warehouses and (paths > 1 or warehouses>1):
    z += pulp.lpSum(constraintTrucks) == paths # paths to warehouse

if not slack:
    z += pulp.lpSum(constraintSeq) == total_1
else:
    z += pulp.lpSum(constraintSeq) <= total_1

# Solve
if solver=="cbc":
    status = z.solve()
if solver=="glpk":
    status = z.solve(pulp.GLPK())
if solver=="gurobi":
    status = z.solve(pulp.GUROBI_CMD())

# should be 'Optimal'
if pulp.LpStatus[status]!="Optimal":
    print("RESULT: ".pulp.LpStatus[status])

print("Objective function value: "+str(z.objective.value()))

# Print variables & save path
lines_x = []
lines_y = []
li = [0] * n
for i in range(n+warehouses):
    if i>=warehouses:
        li[i-warehouses] = pulp.value(l[i])
    for j in range(n+warehouses):
        if i==j:
            continue
        if pulp.value(x[i,j]) == 1:
            lines_x.append(loc_x[i])
            lines_x.append(loc_x[j])
            lines_y.append(loc_y[i])
            lines_y.append(loc_y[j])
            lines_x.append(np.nan)
            lines_y.append(np.nan)

obj_value = "c=" + str(round(z.objective.value(),2))

elif solver=="cut plane":
    model = Model("tsp")
    model.hideOutput()
    x = {}
    l = {}
    for i in range(n+warehouses):
        for j in range(n+warehouses):
            if i != j:
                x[i,j] = model.addVar(ub=1, name="x(%s,%s)"%(i,j))
    if (paths > 1 or warehouses > 1) and i >= warehouses:
        l[i] = model.addVar(ub=min(c,n),lb=1, name="l(%s)"%(i))

if paths == 1 and warehouses == 1:

```

```

# SYMMETRIC DISTANCE MATRIX ONLY
#for i in range(n+warehouses):
    #model.addCons(quicksum(x[j,i] for j in range(n+warehouses) if j != i) + \
    #               quicksum(x[i,j] for j in range(n+warehouses) if j != i) == 2,
"Degree(%s)"%i)

# ASYMMETRIC DISTANCE MATRIX
for i in range(n+warehouses):
    model.addCons(quicksum(x[j,i] for j in range(n+warehouses) if j != i) == 1,
"In(%s)"%i)
    model.addCons(quicksum(x[i,j] for j in range(n+warehouses) if j != i) == 1,
"Out(%s)"%i)

else:
    for i in range(warehouses, n+warehouses):
        model.addCons(quicksum(x[j,i] for j in range(n+warehouses) if j != i) == 1,
"In(%s)"%i)
        model.addCons(quicksum(x[i,j] for j in range(n+warehouses) if j != i) == 1,
"Out(%s)"%i)

    for i in range(warehouses, n+warehouses):
        for j in range(warehouses, n+warehouses):
            if i!=j:
                model.addCons(l[i] -l[j] +n*x[i,j] <= n-1, "Li(%s,%s)"%(i,j))

model.addCons(quicksum(x[j,i] for i in range(warehouses) for j in range(n+warehouses)
if i!=j) == paths, "Paths(%s)"%paths)

if not slack:
    model.addCons(quicksum(l[i] for i in range(warehouses,n+warehouses)) == total_l,
"TotalL")
else:
    model.addCons(quicksum(l[i] for i in range(warehouses,n+warehouses)) <= total_l,
"TotalL")

model.setObjective(quicksum(distances2[i,j]*x[i,j] for (i,j) in x), "minimize")

EPS = 1.e-6
isMIP = False
model.setPresolve(SCIP_PARAMSETTING.OFF)

while True:
    model.optimize()
    #edges = []
    lines_x = []
    lines_y = []
    edges = []
    li = [0] * n
    for (i,j) in x:
        # i=j already skipped
        if model.getVal(x[i,j]) > EPS:
            #edges.append( (i,j) )
            lines_x.append(loc_x[i])
            lines_x.append(loc_x[j])
            lines_y.append(loc_y[i])
            lines_y.append(loc_y[j])
            lines_x.append(np.nan)
            lines_y.append(np.nan)
            edges.append( (i,j) )
    if paths>1 or warehouses>1:
        for i in range(warehouses, n+warehouses):
            li[i-warehouses] = int(model.getVal(l[i]))

obj_value = "c=" + str(round(model.getObjVal(),2))

ax.clear()
ax.set_xlim(0,1000)
ax.set_ylim(0,1000)

plot_data_lines(lines_x,lines_y)
plot_data(ax, loc_x, loc_y, warehouses)

```

```

    ax.text(400, 1075, "solving...", family="serif", horizontalalignment='left',
verticalalignment='top')

    fig.canvas.draw()

    if addcut(edges,model,x,warehouses) == False:
        if isMIP:      # integer variables, components connected: solution found
            break
        model.freeTransform()
        for (i,j) in x:      # all components connected, switch to integer model
            model.chgVarType(x[i,j], "B")
        if paths > 1 or warehouses > 1:
            for i in range(warehouses,n+warehouses):
                model.chgVarType(l[i], "I")
        isMIP = True

    sol_li = [0] * (n+warehouses)
    sol_xij = {}

    print('solved.')

elif solver == 'held-karp':
    li = [0] * n
    opt, path = held_karp(distances)
    print(path)
    obj_value = "c=" + str(round(opt,2))
    x = [[0 for x in range(n+warehouses)] for y in range(n+warehouses)]
    for idx, val in enumerate(path):
        if idx < (len(path)-1):
            x[val][path[idx+1]] = 1;
        elif idx == (len(path)-1):
            x[val][path[0]] = 1;

    for i in range(n+warehouses):
        for j in range(n+warehouses):
            if x[i][j] == 1:
                #edges.append( (i,j) )
                lines_x.append(loc_x[i])
                lines_x.append(loc_x[j])
                lines_y.append(loc_y[i])
                lines_y.append(loc_y[j])
                lines_x.append(np.nan)
                lines_y.append(np.nan)
                #edges.append( (i,j) )

# Print computation time

time2 = time.time() - start_time
exec_value = time2
units = 'secs'
if time2 > 60:
    time2 /= 60
    units = 'mins'
if time2 > 60:
    time2 /= 60
    units = 'hours'

time2 = round(time2,2)

exec_value = "exec=" + str(time2) + " " + units

print("--- " + str(time2) + " " + units + " ---")

# Redraw points
ax.clear()
ax.set_xlim(0,1000)
ax.set_ylim(0,1000)

plot_data_lines(lines_x,lines_y)

```

```
plot_data(ax, loc_x, loc_y, warehouses)

ax.text(350, 1075, obj_value, family="serif", horizontalalignment='right',
verticalalignment='top')
ax.text(450, 1075, exec_value, family="serif", horizontalalignment='left',
verticalalignment='top')
fig.canvas.draw()

axsolve = plt.axes([0.87, 0.905, 0.1, 0.075])
bsolve = Button(axesolve, 'Solve')
bsolve.on_clicked(solve)

plt.show()
```