Group Number: Team 2

Assignment Title: Assignment 3

Course Code: RSM8423

Instructor Name: Andre Cire

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CaBi Truck Inventory Rebalancing

ASSIGNMENT 3

TEAM 2

Table of Content

Executive Summary

Capital Bikeshare (CaBi) is a bicycle sharing system that serves Washington, D.C., Arlington County, Virginia, and the city of Alexandria, Virginia. Currently there are 1,670 bicycles operating from 189 stations. A member could pick-up and return bikes at any designated hub. Since each hub has limited space to store bikes, CaBi is facing the problem of spatial imbalance of the bike inventory over time. We expect the target result will provide a tour design that helps CaBi rearrange the bike inventory in an efficient and effective way. This report will include a model based on single-truck transportation and a model considering additional trucks in the transportation process.

For the single-truck model, we obtained a tour design with a total travel distance of 23.33KM. We further discover that a 6% increase on the truck capacity will reduce the total travel distance by 12%. It is mainly because of some rotation routes for the truck to pick-up excess inventory to satisfy demands. A slightly larger capacity will help the truck to remove some rotation routes. The single-truck model is designed to be simple for tractability, indicating some theoretical assumptions have been made. The cost is calculated based on the distance while the travelling time may not be consistent with the distance. The model also did not consider the operating time at each hub, which may lead to an infeasible solution. The sequential transportation system means an incremental risk of delay at each stop for reasons such as accidents on the road or longer operation time.

Due to the constraint of the computation power, the same methodology adopted in the single-truck model is unable to expand to the multi-truck model. The problem is preprocessed by separating demands into four different clusters. The clustering has been done by two different approaches. First, the model leverages the existing package to perform k-means and agglomerative clustering. A map generated based on the relative distance among hubs is also used to perform visual clustering. After the subgraphs are obtained, they are solved as individual single-truck models. Both methods yield the similar result with a total distance of 61.3 KM. The model also indicates that a 16.67% increase on the truck capacity will improve the travel distance by a 4.84% reduction.

Part 1. Single Truck Inventory Rebalancing

1-1 Results of the Single-Truck Inventory Model

The summary of the optimization model is summarized in **Appendix A.** The following assumptions were made upon modeling the system (also reflected in the constraints section of Appendix A):

- Each hub is only visited once on the tour
- The start and finish of the tour is at the Central Depot
- All tours are done at the start of each period (4 hour blocks per day) and is possible to be completed within the period time frame
- Capacity of the truck is 30 bicycles
- The defined distances are indeed the distance that the truck travels (i.e. there are no blockages that makes the truck to make a detour)
- The trucks do not detour to fill gas (i.e. they are already full of gas or gas stations are on the tour pathways - no detour needed)
- Trucks are fully functioning and bicycles are all in good condition

The results of the model as listed in **Appendix B** shows that the optimal path for the truck is to travel: 1 → 5 → 11 → 3 → 6 → 10 → 7 → 4 → 2 → 9 → 12 → 8 → 1. This results in the most optimized solution with the total cost of 23.33KM total distance travelled.

1-2 Potential investment in a greater capacity truck

Current situation, the 30 bicycles capacity serves as a constraint. Once the truck loads up some vacant bikes, it needs to drop-off some of them to a hub with negative demand, to make room for another batch. By investing in a larger capacity truck, CaBi could be more flexible in route planning to achieve lower mileage. Given the current demands, if the new truck's capacity is over 55 bicycles (sum of the number of bicycles needed to be picked up across all hubs), we see that the limitation of having to generate the tours between positive and negative demands is not needed; optimal route will simply be based on finding the shortest distances between hubs (i.e. The truck could pick up all the vacant bicycles at once and relocate them all in one trip). It would have the most flexible route with lowest mileage.

Nevertheless, the operating cost of the old, small capacity truck is mileage times fuel cost per mile. A new, large capacity truck would lower the mileage, fuel cost per mile could increase, and it requires an up-front cash expense. There is a trade-off between the increased cost of getting/maintaining the new truck vs. saved cost by potentially travelling shorter distances. Thus, we need to answer the following questions:

- Would lower mileage compensate for the additional fuel consumption?
- If so, would the net present value of the saving cover the cash investment in the truck's usable lifespan?

For initial insights, we simulate to see if the investment is indeed worth it. By running a model where there is no capacity constraints, the resulting optimal model as shown in **Appendix C** outputs a slightly different route 1 → 5 → 6 → 3 → 11 → 12 → 9 → 2 → 4 → 7 → 10 → 8 → 1. The optimized cost is 20.26KM which is just 3 KM less than keeping the current truck capacity while the truck capacity only surpassed 30 in timestamp 4 (31 bicycles) and timestamp 9 (32 bicycles). If the 3 kilometers saving per day multiplied by the incremental saving cost per kilometer multiplied by the lifespan of the new truck, is greater than the cost of upgrading to a truck with capacity greater than 32, this investment would be justified. Unfortunately, we do not have knowledge on the operating cost per kilometer, nor the period that the executives would like to consider for return on investment. However, assuming that the provided demand data is representative of the average demand of CaBi, and that required increase in capacity is low (1-2 trucks) with low savings (3KM), we do not believe that a larger capacity truck is needed at the moment.

1-3 Interesting Model Result

One interesting yet expected insight is that in most cases, the optimized route tends to rotate between loading bicycle hubs and dropping bicycle hubs. From a practical point of view, this seems very efficient as it allows a full leverage of the truck capacity. For instance, if we were to visit all the loading bicycle hubs first, the truck capacity would have had to be 55. However, by flipping back and forth between positive and negative, we are able to maintain the truck capacity to under 30.

1-4 Advantages & Disadvantages

This model has the advantage of finding feasible routes optimized for distance, while meeting the capacity constraints that we have. It is simple to implement and easy to understand what pathways a truck could take to make efficient use of its capacity and fuel.

However, one of the biggest fallbacks is that it is not necessarily optimized for the realistic total cost. There are many components that are missing as part of costs and constraints that could provide a greater analysis of cost scenarios. Some examples are as follows, which will also be addressed in next section:

- How much is the operating cost of the trucks? What is the cost per distance travelled, maintenance and insurance cost?
- What is the time constraint? When exactly do all tours need to be finished at the start of each period?
- How much is the cost per time? Is it cheaper to have two drivers work 6 hours each vs. one driver working 12 hours?

Another disadvantage of this approach is that there are many unrealistic assumptions as discussed in the next section. For example, hub 1 could be closer to hub 2 compared to hub 3, but hub 3 might experience much lighter traffic. Our results might be different if the model was based on traveling time rather than distance.

1-5 Realisticness of the Assumptions

While the model is simple and easy to understand, it may be too simple in a realistic setting. Revisiting our model assumptions from 1-1, this model does not account for any uncertainty in the changing environment. What if a detour is needed that is much longer than the shortest path (e.g. gas station is not nearby, road is blocked due to construction, etc.)? What if the truck breaks down in the middle of the tour? What if some of the bicycles that were picked up are broken and we need new bicycles to fill up the demand in certain hubs? Assuming that these uncertainties will never happen is too strong of an assumption. Thus, the model results should only be used as a directional input to the logistic decision where further judgements need to be made to adjust for uncertainty factors.

1-6 Useful Additional Data

As noted in part 1-2, knowing the operating costs of the trucks would enable comparison of potential investment in a truck with greater capacity. If the operating costs are known for current and potential upgraded trucks, we can run a model for each truck and compare the results where the objective function now becomes the total operating and investment cost (i.e. distance x fuel cost per distance + maintenance costs + investment cost, etc.).

Another data that would be useful would be time of operation as mentioned in 1-3. In a realistic setting, there are time constraints tied to distance travelled. Currently, we have 4 hour periods in which a truck completes a tour - we need to assess whether this whole tour is indeed possible within that single period. We also need to know exactly when the pick-up/drop-off needs to be done (is it the first hour of each period?). Currently, the total distance travelled is under 25KM, which will be around 30 minutes of travel time + loading/dropping off time and is feasible at maximum 2 hours. However, if this model is to be applied to a greater number of hubs, the tours may not be possible within the 4 hours (or first hour - based on the requirement) where time constraint is needed to potentially signal for a need for additional trucks. If the information is available, it could be incorporated to the model by adding a time-constraint by knowing the time it takes a truck to travel a given distance (distance x time), load/drop bicycle (+ loading and dropping time), and restricting it to 4 hours (or less than 4 if needed earlier). Furthermore, as mentioned in 1-3, if we know the time cost, we could also add labour cost per time (is it different depending on time period?) to the objective function to fully understand cost structure.

Lastly, in an advanced model, we may incorporate uncertainty components by including safety distance based on the nature of the path (i.e. if there is a path that is on a highway that is frequently blocked due to incidents and requires a detour, we may add additional distances to the shortest path distance). We can also perform dynamic programming by incorporating live traffic conditions or truck/bicycle conditions into the model to adjust the tour based on unexpected events that arise during the tour.

Part 2. Multi Truck Inventory Rebalancing

2-1 Overview of the Model Approach

In the multi-truck inventory model, there are a total of 41 hubs and 4 potential trucks that could be performing tours each period. In order to generate an optimized model, the first step was to first generate a list of feasible tours in subsets of hubs. This included clustering the hubs into subsets based on distance and running a single-truck optimization model to find feasible tours. The hub clustering was performed both through KMeans and Agglomerative clustering algorithms and through visual search on a graph representing distance among hubs shown in **Appendix F**. The graph for manual clustering was generated by using the relative distances of all the hubs. Then, we model to find the optimal solution by picking 4 (or less) tours that visit and meet the demand of all the hubs.

2-2 Pre-generating TSP Tours

With 41 hubs available, there are essentially 2.2e+12 (2^41 - 1) potential combinations of subsets which are computationally too heavy to compute. Instead, we leverage simple heuristics to narrow down the potential cluster of hubs based on the shortest distance. We made key assumptions as follows:

- We want to avoid any extremely long tours as they are not realistic to be completed within the time period. The objective of the optimization system is therefore minimizing the maximum travel distance among trucks. Therefore we set a maximum tour length of 15 hubs.
- Other assumptions from the single-truck model still apply.

The key steps we have performed to first pre-generate TSP tours are as follows:

1. We perform the clustering procedure to generate subgraphs for optimization. We tried some clustering technologies such as k-means and agglomerative based on the distance. Both algorithms look at the distance between hubs and create clusters or tours based on the minimum or shortest distance. For both clustering algorithms, we used a loop to create different numbers of subgraphs. For example, for K-Means we created K clusters or subgraphs where K is from 2 to 11. This allowed for different combinations and using both algorithms allowed for double the amount of potential tours. Additionally, it was assumed that all tours began at Hub 1 or Node 0 and therefore were always set as 1. We also tried graphical technology to generate a map based on the relative distance between each hub. This was then used to manually create clusters to solve the problem.
2. Run the single-truck optimization model on the clusters of hubs found in the previous step to find feasible and optimized tours based on demand. This is because not all tours are feasible given the capacity and demand constraints given. See **Appendix G** for results.

3. The potential tours that were created are listed in **Appendix D**. We first created a list of tours based on the distance matrix provided and then that list of tours was filtered to not include tours with more than 15 hubs. Finally, the net demand, which is the sum of all the demand in the hubs for a given tour, was calculated and net demand greater than 30 and less than -30, respectively were removed. This is because of the capacity constraint we had not allowing for a truck to have more than 30 bikes.

In **Appendix D**, we can observe the list of generated TSP tours. It is worth noting that not all the tours are feasible even after conducting clustering and filtering them out. Additionally, the clusters created visually were added to the final dataframe that included all the potential tours.

Note that the result of the final list of pre-generated tours above is created specifically for the one period of data provided. In order to use this model for other periods which have different demand, we will keep the same list of clusters that we have identified in step 1, but rerun step 2 and 3 to generate optimal tours given subset hubs that work for the given demand of the new period.

As for the visual search approach, clusters are constructed based mainly on the relative distances between hubs shown in **Appendix F**. Another criteria considered when selecting tours is whether all the demands within each tour are satisfiable using one truck. This implies we need to have a balanced number of surplus and shortage hubs within each tour.

2-3 Choosing the Optimal Tours

For the visual clustering method based on distance and demand feasibility, several different combinations of tours have been tested and optimal construction formed: (total distance)

- Truck 1: 1 → 15 → 17 → 5 → 14 → 33 → 6 → 30 → 34 → 3 → 36 → 1 (13.24)
- Truck 2: 1 → 8 → 21 → 25 → 20 → 35 → 27 → 22 → 41 → 11 → 23 → 13 → 1 (22.26)
- Truck 3: 1 → 29 → 7 → 10 → 38 → 37 → 9 → 26 → 12 → 24 → 39 → 1 (17.25)
- Truck 4: 1 → 31 → 4 → 19 → 32 → 2 → 28 → 18 → 40 → 16 → 1 (8.55)

Using the pre-generated tours from the previous section with the tours selected from the visual clustering, we generated an optimized model that selects the 4 (or less) tours that the trucks should choose to take while minimizing distance costs. The results are outlined in **Appendix G**, where we see the optimal solution for the given period yields total distance cost of around 62 where all 4 trucks are operating as follows:

- Truck 1: 1 → 15 → 17 → 5 → 14 → 33 → 6 → 30 → 34 → 3 → 36 → 1 (13.24)
- Truck 2: 1 → 8 → 21 → 25 → 20 → 35 → 27 → 22 → 41 → 11 → 23 → 13 → 1 (22.26)
- Truck 3: 1 → 29 → 7 → 10 → 38 → 37 → 9 → 26 → 12 → 24 → 39 → 1 (17.25)
- Truck 4: 1 → 31 → 4 → 19 → 32 → 2 → 28 → 18 → 40 → 16 → 1 (8.55)

From our results we recognized that even after clustering and creating over 108 different combinations, the clusters created visually and not by clustering methods provided the optimal results. What this implies is that the clustering methods could not create the correct combinations of tours that would allow for a feasible solution. Additionally, from our analysis, we found that when the algorithm does pick tours from the clustering, it leads to situations where a truck can overlap in two hubs. While this may be a viable method, it can lead to issues with the model double counting the demand for one hub leading to an inaccurate optimal solution. Therefore, from our analysis, it seems that the best method given the limitations we have on computing power is using the visual clustering approach. If we had the computing power to create every combination of tours possible, this would not be an issue, however due to the sheer amount of possibilities, the solution we have is logical and easy to explain to management.

2-4 Potential investment in a Greater Capacity and Trucks

During this section, the upper bound of the truck capacity is removed and we are trying to test how it would affect the optimal result. We reach a similar conclusion as part I, which is that increasing the capacity of the trucks would enable a more flexible routing flow arrangement, thus decreasing the total distance of each tour. However, again, we need to consider the trade-off between the additional fuel and equipment upgrade cost when increasing the capacity.

For the visual search and algorithmic clustering methods, the results are summarized below and details are shown in **Appendix H**:

- Truck 1: 1 → 15 → 17 → 5 → 33 → 14→ 6 → 30 → 34 → 3 → 36 → 1 (12.19)
- Truck 2: 1 → 8 → 21 → 23 → 25 → 35 → 27→ 20 → 22 → 41 → 11 → 13 → 1 (19.28)
- Truck 3: 1 → 29 → 7 → 38 → 37 → 9 → 24 → 39 → 12 → 26 → 10 → 1 (16.58)
- Truck 4: 1 → 31 → 4 → 19 → 40 → 18 → 28 → 2 → 32 → 16 → 1 (8.38)

However, it should be noted that without the capacity constraint it is possible for one truck to complete the entire tour by itself. However, what we demonstrate is that by removing the constraint, the original tour will have lower distances as well. As CaBi has already invested in 4 trucks, not using all of them is a waste of capital.

Additionally, from our algorithmic clustering approach, if we hire more trucks the method can reach an optimal solution, however we have shown through the visual clustering approach that it is possible to reach all the demand with 4 trucks. Additionally, extra trucks will lead to more capital expenditure and operating expenses. The additional time saved may not be worth it depending on the total cost needed to buy and train a new truck and driver.

Finally, from our observations the issue with distance has more to do with the central hub being node 0 (hub 1), when according to **Appendix F** node 9 (hub 10) or node 7 (hub8) should be the central hub. This is because they are in the middle of all the hubs and would lead to much lower distances when the trucks are returning.

2-5 Interesting Model Result

According to the optimal solution, trucks will be travelling along their set route daily, each route would have different demand. Because of the uneven demand distribution among hubs, each route requires different optimal capacity per truck. CaBi could buy trucks that have suitable capacity to its designated route in order to minimize costs and the initial investment.

The optimal solution is based on 4 trucks (4 route) operations. Operating with more trucks would reduce the daily travelling distance for each truck on average, thus increasing its usable life-spin. Operating with fewer trucks would reduce overhead costs, also shorter life-spin per truck allows CaBi to upgrade its fleet more frequently, newer vehicles are more likely to have better cost efficiency and less likely to break down, which will significantly disrupt CaBi's operation.

Finally, we notice that when we remove the capacity constraint, by increasing the capacity of all trucks to 35, we allow for lower total distance for Truck 1, 3, and 4. The Truck 2 tour will be minimized when capacity is 54. This means that by increasing the capacity by 16.67%, we are able to reduce total distance overall by 4.84%. Increasing the capacity for 54 is not worth it, and it would be better to just buy another truck.

2-6 Advantages & Disadvantages

The advantages to this model is to be able to use computationally-lighter methods to find an optimal route that the available trucks can take to minimize total cost, measured in distance travelled. Additionally, the visual clustering method is more tractable as it provides an easy way to understand how the clusters are formed based on relative distance and demands required of each hub.

There are also limitations restricted by computational power and limited data available. Firstly, we have used different clustering methods to pre-generate feasible candidate tours that the trucks can take vs. all 2e+12 combinations. While we aim to generate 'the' optimal solution, this heuristic method does not guarantee an optimal solution. Moreover, similar to our discussions in the Single-Truck Inventory model, there is missing data for the key factors like time constraints and operation costs that should ideally be embedded in the model.

In this application, the major limitation we are facing is the computational power. There are over 2 billion possible combinations for trucks' travel routes, which makes our mission of selecting a route that minimizes the overall distance of trucks unattainable.

2-7 Realisticness of the Assumptions

Similar to the discussions outlined in 1-5 for single-truck, the same applies for this model as well. In particular, there are even more uncertain factors because now we have four vehicles vs. one, which means room for more variability in uncertainty and environment. Additionally, clustering is not the best method available, due to the lack of data available.

2-8 Any additional data that would be useful?

The same additional data outlined in 1-6 for single-truck would be beneficial here as well. For instance, if we have exact information on things like travel time and load/drop time, etc, we may be able to generate conditions that resemble the following:

- The average distance between the hubs is around 3.8KM. This means, when visiting across 12 hubs, it requires around 42KM of travel. When we make conservative assumptions to consider 42KM distance as around 40 minutes of driving without any blockage (at 60KM/H), loading/drop-off of bicycles taking (15 minutes each = 15x12 = 3hr), it results in around 3 hours and 40 minutes per round. With a slack time needed to account for any potential uncertain events, it seems to appear that it is safe to have each truck visit less than 12 hubs on average.

Appendix

Appendix A: Single-Truck Optimization Model

In the model below, we define the following:

- In the given period, we see that there are 12 hubs (**n = 12**)
- **i, j** = Hubs: 1,2,…,n where 1 represents the central depot
- **t** = timesteps: 1, 2, ..,n in each period (n steps required to visit n hubs)

Parameters: Constant data values used as inputs to the model		
Model	**Python Code**	**Description**
d_{ij}	hubsdistance[(i,j)]	Distance from hub i to j in km
b_j	requiredbike[j]	Required bikes for Hub j

Variables: Values we aim to generate with the model			
Model	**Python Code**	**Variable Type**	**Description**
$x_{i,j,t}$	xvar[(i,j,t)]	Binary, $x_{i,j,t} = \{0, 1\}$	1 if truck moved from hub i to hub j in time t, 0 otherwise
c_t	cvar[t]	Integer, $0 \leq c_t \leq 30$	Capacity of Truck (number of bikes in the truck) at beginning of time t, C_1=0

Objective Function: Minimize Total Distance Travelled

- $\sum_{t=1}^{n} \sum_{j=1}^{n} \sum_{i=1}^{n} d_{ij} x_{ijt}$

Constraints: Variables are subject to the following constraints

1. Every hub j = 1,…,n is visited just once
   - Sum of all inflows to each hub = 1
     - » $\sum_{i=1}^{n} \sum_{t=1}^{n} x_{ijt} = 1, \qquad j = 1, ..., n$
2. Conversation of Flow
   - If there was inflow to hub j in time t, there is a corresponding outflow from hub j the next period
     - » $\sum_{i=1}^{n} x_{ijt} = \sum_{k=1}^{n} x_{jk\,t+1}, \qquad j = 1, ..., n, \; t = 1,..,n - 1$
3. Truck starts from and ends at the Central Depot (i = 1)
   - At t =1, the only outflow is from Central Depot
     - » $\sum_{j=1}^{n} x_{1j1} = 1,$

» $\sum_{j=1}^{n} x_{ij1} = 0, \qquad i = 2, ..., n$

- At t = n (12 for this case), the only inflow is to Central Depot
  - » $\sum_{i=1}^{n} x_{i1,n} = 1,$
  - » $\sum_{i=1}^{n} x_{ij,n} = 0, \qquad j = 2, ..., n$

4. Capacity of the Truck is maximum 30 bikes
   - At begging of the day, the truck carries 0 bikes
     - » $c_1 = 0$
     - » $0 \le c_t \le 30, \qquad t = 1, ..., n$
   - Capacity of trucks at each period changes based on the bike demand of the hub it visited in the previous period.
     - » $c_{t+1} = c_t + \sum_{i=1}^{n}\sum_{j=1}^{n} b_j x_{ijt}, \qquad t = 1, ..., n-1$

Final Model:

Minimize Total Distance

$$\sum_{t=1}^{n}\sum_{j=1}^{n}\sum_{i=1}^{n} d_{ij} x_{ijt}$$

Subject to:

- $\sum_{i=1}^{n}\sum_{t=1}^{n} x_{ijt} = 1, \qquad j = 1, ..., n$
- $\sum_{i=1}^{n} x_{ijt} = \sum_{k=1}^{n} x_{jk\,t+1}, \qquad j = 1, ..., n, \ t = 1,.., n-1$
- $\sum_{j=1}^{n} x_{1j1} = 1,$
- $\sum_{j=1}^{n} x_{ij1} = 0, \qquad i = 2, ..., n$
- $\sum_{i=1}^{n} x_{i1n} = 1,$
- $\sum_{i=1}^{n} x_{ijn} = 0, \qquad j = 2, ..., n$
- $c_1 = 0$
- $0 \le c_t \le 30, \qquad t = 1, ..., n$
- $c_{t+1} = c_t + \sum_{i=1}^{n}\sum_{j=1}^{n} b_j x_{ijt}, \qquad t = 1, ..., n-1$
- $x_{ijt} \in \{0, 1\}, \qquad i, j = 1, ..., n, \ t = 1, ..., n$

- $c_t \in integer, \qquad t = 1, \ldots, n$

Appendix B: Model Results

```
Timestep 1: Hub 1 to Hub 5
            truck capacity: 0.0
            distance travelled: 0.31
Timestep 2: Hub 5 to Hub 11
            truck capacity: 10.0
            distance travelled: 4.38162
Timestep 3: Hub 11 to Hub 3
            truck capacity: 2.0
            distance travelled: 4.12802
Timestep 4: Hub 3 to Hub 6
            truck capacity: 14.0
            distance travelled: 0.779001
Timestep 5: Hub 6 to Hub 10
            truck capacity: 23.0
            distance travelled: 3.432
Timestep 6: Hub 10 to Hub 7
            truck capacity: 16.0
            distance travelled: 0.533349
Timestep 7: Hub 7 to Hub 4
            truck capacity: 3.0
            distance travelled: 0.736384
Timestep 8: Hub 4 to Hub 2
            truck capacity: 18.0
            distance travelled: 1.01701
Timestep 9: Hub 2 to Hub 9
            truck capacity: 27.0
            distance travelled: 2.50202
Timestep 10: Hub 9 to Hub 12
            truck capacity: 19.0
            distance travelled: 1.67627
Timestep 11: Hub 12 to Hub 8
            truck capacity: 12.0
            distance travelled: 1.8244
Timestep 12: Hub 8 to Hub 1
            truck capacity: 3.0
            distance travelled: 2.01384
```

Appendix C: Model Results with no Truck Capacity Constraint

```
Timestep 1: Hub 1 to Hub 5
            truck capacity: 0.0
            distance travelled: 0.31
Timestep 2: Hub 5 to Hub 6
            truck capacity: 10.0
            distance travelled: 1.654
Timestep 3: Hub 6 to Hub 3
            truck capacity: 19.0
            distance travelled: 0.779001
Timestep 4: Hub 3 to Hub 11
            truck capacity: 31.0
            distance travelled: 4.12802
Timestep 5: Hub 11 to Hub 12
            truck capacity: 23.0
            distance travelled: 3.1018
Timestep 6: Hub 12 to Hub 9
            truck capacity: 16.0
            distance travelled: 1.67627
Timestep 7: Hub 9 to Hub 2
            truck capacity: 8.0
            distance travelled: 2.50202
Timestep 8: Hub 2 to Hub 4
            truck capacity: 17.0
            distance travelled: 1.01701
Timestep 9: Hub 4 to Hub 7
            truck capacity: 32.0
            distance travelled: 0.736384
Timestep 10: Hub 7 to Hub 10
            truck capacity: 19.0
            distance travelled: 0.533349
Timestep 11: Hub 10 to Hub 8
            truck capacity: 12.0
            distance travelled: 1.8106
Timestep 12: Hub 8 to Hub 1
            truck capacity: 3.0
            distance travelled: 2.01384
```

Appendix D: Pre-generated TSP Tours

Clustering

	0	1	2	3	4	5	6	7	8	9	...	31	32	33	34	35	36	37	38	39	40
1	1	1	1	1	1	1	1	1	1	1	...	1	1	1	0	1	1	1	0	1	0
2	0	0	0	0	0	0	0	0	0	0	...	0	0	0	1	0	0	0	1	0	1
1	0	1	0	1	0	0	1	1	1	1	...	1	0	0	0	1	1	1	0	1	0
2	0	0	0	0	0	0	0	0	0	0	...	0	0	0	1	0	0	0	1	0	1
3	1	0	1	0	1	1	0	0	0	0	...	0	1	1	0	0	0	0	0	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
6	0	0	0	0	0	0	0	0	0	0	...	0	0	0	1	0	0	0	1	0	0
7	0	1	0	0	0	0	0	0	0	0	...	1	0	0	0	0	0	0	0	1	0
8	0	0	0	0	0	0	0	1	0	0	...	0	0	0	0	0	0	0	0	0	0
9	1	0	0	0	1	0	0	0	0	0	...	0	1	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	1	0	0	1	...	0	0	0	0	0	0	0	0	0	0

108 rows × 41 columns

Clustering After Filtering Out Net Demand >30 and <-30

	0	1	2	3	4	5	6	7	8	9	...	33	34	35	36	37	38	39	40	num_hubs_visited	net_demand
0	1	0	1	0	1	1	0	0	0	0	...	1	0	0	0	0	0	0	0	8.0	-11.0
1	1	0	0	0	0	0	0	1	1	0	...	0	0	1	1	1	0	0	0	13.0	8.0
2	1	0	1	0	1	1	0	0	0	0	...	1	0	0	0	0	0	0	0	8.0	-11.0
3	1	1	0	1	0	0	1	0	0	1	...	0	0	0	0	0	0	1	0	15.0	9.0
4	1	0	0	0	0	0	0	1	1	0	...	0	0	1	1	1	0	0	0	13.0	8.0
5	1	1	0	1	0	0	1	0	0	1	...	0	0	0	0	0	0	1	0	15.0	9.0
6	1	0	1	0	1	1	0	0	0	0	...	1	0	0	0	0	0	0	0	8.0	-11.0
7	1	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	1	3.0	-27.0
8	1	1	0	1	0	0	1	0	0	1	...	0	0	0	0	0	0	1	0	15.0	9.0
9	1	0	1	0	1	1	0	0	0	0	...	1	0	0	0	0	0	0	0	8.0	-11.0
10	1	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	1	3.0	-27.0
11	1	0	1	0	1	1	0	0	0	0	...	1	0	0	0	0	0	0	0	8.0	-11.0
12	1	1	0	1	0	0	1	0	0	1	...	0	0	0	0	0	0	1	0	15.0	9.0
13	1	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	1	3.0	-27.0

14	1	0	0	0	0	0	0	0	1	0	...	0	0	0	1	1	0	0	0	4.0	-19.0
15	1	1	0	1	0	0	1	0	0	1	...	0	0	0	0	0	0	1	0	15.0	9.0
16	1	0	0	0	1	0	0	0	0	0	...	0	0	0	0	0	0	0	0	4.0	2.0
17	1	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	1	3.0	-27.0
18	1	0	0	0	0	0	0	0	1	0	...	0	0	0	1	1	0	0	0	4.0	-19.0
19	1	0	1	0	0	1	0	0	0	0	...	1	0	0	0	0	0	0	0	5.0	-27.0
20	1	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	1	3.0	-27.0
21	1	0	0	0	0	0	0	0	1	0	...	0	0	0	1	1	0	0	0	4.0	-19.0
22	1	0	1	0	0	1	0	0	0	0	...	1	0	0	0	0	0	0	0	5.0	-27.0
23	1	0	0	0	1	0	0	0	0	0	...	0	0	0	0	0	0	0	0	4.0	2.0
24	1	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	1	3.0	-27.0
25	1	0	0	0	0	0	0	0	0	0	...	0	1	0	0	0	1	0	0	5.0	-24.0
26	1	0	0	0	0	0	0	0	1	0	...	0	0	0	1	1	0	0	0	4.0	-19.0
27	1	0	1	0	0	1	0	0	0	0	...	1	0	0	0	0	0	0	0	5.0	-27.0
28	1	0	0	0	1	0	0	0	0	0	...	0	0	0	0	0	0	0	0	4.0	2.0
29	1	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	2.0	-23.0
30	1	0	1	0	1	1	0	1	0	0	...	1	0	1	0	0	0	0	0	16.0	26.0
31	1	0	1	0	1	1	0	0	0	0	...	1	0	0	0	0	0	0	0	8.0	-11.0
32	1	0	0	0	0	0	0	1	0	0	...	0	0	1	0	0	0	0	0	10.0	13.0
33	1	0	1	0	1	1	0	0	0	0	...	1	0	0	0	0	0	0	0	8.0	-11.0
34	1	1	0	1	0	0	1	0	0	1	...	0	0	0	0	0	0	1	0	15.0	9.0
35	1	0	0	0	0	0	0	1	1	1	...	0	0	0	1	1	0	0	0	7.0	-11.0
36	1	0	1	0	0	1	0	0	0	0	...	1	0	0	0	0	0	0	0	5.0	-27.0

37	1	1	0	1	0	0	1	0	0	0	...	0	0	0	0	0	0	1	0	13.0	22.0
38	1	0	0	0	0	0	0	0	0	0	...	0	0	1	0	0	0	0	0	8.0	-3.0
39	1	0	0	0	1	0	0	0	0	0	...	0	0	0	0	0	0	0	0	5.0	-3.0
40	1	0	0	0	1	0	0	0	0	0	...	0	0	0	0	0	0	0	0	4.0	2.0
41	1	0	0	0	0	0	0	1	1	0	...	0	0	0	1	0	0	0	0	9.0	23.0
42	1	0	1	0	0	1	0	0	0	0	...	1	0	0	0	0	0	0	0	5.0	-27.0
43	1	0	0	0	1	0	0	0	0	0	...	0	0	0	0	0	0	0	0	5.0	-3.0
44	1	1	0	1	0	0	0	0	0	0	...	0	0	0	0	0	0	1	0	12.0	13.0
45	1	0	1	0	0	1	0	0	0	0	...	1	0	0	0	0	0	0	0	5.0	-27.0
46	1	0	0	0	0	0	1	0	1	1	...	0	0	0	1	1	0	0	0	6.0	-18.0
47	1	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	1	3.0	-27.0
48	1	0	1	0	0	1	0	0	0	0	...	1	0	0	0	0	0	0	0	5.0	-27.0
49	1	0	0	0	0	0	0	0	1	0	...	0	0	0	1	1	0	0	0	4.0	-19.0
50	1	0	0	0	1	0	0	0	0	0	...	0	0	0	0	0	0	0	0	4.0	2.0
51	1	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	1	3.0	-27.0
52	1	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	1	3.0	-27.0
53	1	0	0	0	0	0	0	0	1	0	...	0	0	0	1	1	0	0	0	4.0	-19.0
54	1	0	1	0	0	1	0	0	0	0	...	1	0	0	0	0	0	0	0	5.0	-27.0
55	1	0	0	0	1	0	0	0	0	0	...	0	0	0	0	0	0	0	0	4.0	2.0
56	1	0	0	0	0	0	1	0	0	1	...	0	0	0	0	0	0	0	0	4.0	-18.0

Final Dataframe After Removing Infeasible Routes (Manually Created Tours Also Added)

	0	1	2	3	4	5	6	7	8	9	...	33	34	35	36	37	38	39	40	distance	optimal
0	1.0	0	1	0	1	1	0	0	0	0	...	1	0	0	0	0	0	0	0	5.486013	Optimal
1	1.0	0	0	0	0	0	0	1	1	0	...	0	0	1	1	1	0	0	0	16.724421	Optimal
2	1.0	0	1	0	1	1	0	0	0	0	...	1	0	0	0	0	0	0	0	5.486013	Optimal
3	1.0	1	0	1	0	0	1	0	0	1	...	0	0	0	0	0	0	1	0	10.006788	Optimal
4	1.0	0	0	0	0	0	0	1	1	0	...	0	0	1	1	1	0	0	0	16.724421	Optimal
5	1.0	1	0	1	0	0	1	0	0	1	...	0	0	0	0	0	0	1	0	10.006788	Optimal
6	1.0	0	1	0	1	1	0	0	0	0	...	1	0	0	0	0	0	0	0	5.486013	Optimal
7	1.0	1	0	1	0	0	1	0	0	1	...	0	0	0	0	0	0	1	0	10.006788	Optimal
8	1.0	0	1	0	1	1	0	0	0	0	...	1	0	0	0	0	0	0	0	5.486013	Optimal
9	1.0	0	1	0	1	1	0	0	0	0	...	1	0	0	0	0	0	0	0	5.486013	Optimal
10	1.0	1	0	1	0	0	1	0	0	1	...	0	0	0	0	0	0	1	0	10.006788	Optimal
11	1.0	1	0	1	0	0	1	0	0	1	...	0	0	0	0	0	0	1	0	10.006788	Optimal
12	1.0	0	0	0	1	0	0	0	0	0	...	0	0	0	0	0	0	0	0	1.980002	Optimal
13	1.0	0	0	0	1	0	0	0	0	0	...	0	0	0	0	0	0	0	0	1.980002	Optimal
14	1.0	0	0	0	1	0	0	0	0	0	...	0	0	0	0	0	0	0	0	1.980002	Optimal
15	1.0	0	1	0	1	1	0	0	0	0	...	1	0	0	0	0	0	0	0	5.486013	Optimal
16	1.0	0	0	0	0	0	0	1	0	0	...	0	0	1	0	0	0	0	0	15.059641	Optimal
17	1.0	0	1	0	1	1	0	0	0	0	...	1	0	0	0	0	0	0	0	5.486013	Optimal
18	1.0	1	0	1	0	0	1	0	0	1	...	0	0	0	0	0	0	1	0	10.006788	Optimal
19	1.0	0	0	0	0	0	0	1	1	1	...	0	0	0	1	1	0	0	0	8.881142	Optimal
20	1.0	0	0	0	0	0	0	0	0	0	...	0	0	1	0	0	0	0	0	14.305265	Optimal
21	1.0	0	0	0	1	0	0	0	0	0	...	0	0	0	0	0	0	0	0	3.584019	Optimal
22	1.0	0	0	0	1	0	0	0	0	0	...	0	0	0	0	0	0	0	0	1.980002	Optimal
23	1.0	0	0	0	1	0	0	0	0	0	...	0	0	0	0	0	0	0	0	3.584019	Optimal
24	1.0	1	0	1	0	0	0	0	0	0	...	0	0	0	0	0	0	1	0	8.551583	Optimal
25	1.0	0	0	0	1	0	0	0	0	0	...	0	0	0	0	0	0	0	0	1.980002	Optimal
26	1.0	0	0	0	1	0	0	0	0	0	...	0	0	0	0	0	0	0	0	1.980002	Optimal
27	1.0	0	1	0	1	1	0	0	0	0	...	1	0	1	0	0	0	0	0	13.242277	NaN
28	1.0	0	0	0	0	0	0	1	0	0	...	0	1	0	0	0	0	0	1	22.267285	NaN
29	1.0	0	0	0	0	0	1	0	1	1	...	0	0	0	1	1	1	0	0	17.251826	NaN
30	1.0	1	0	1	0	0	0	0	0	0	...	0	0	0	0	0	0	1	0	8.551562	NaN

31 rows × 43 columns

Appendix E: Multi-Truck Optimization Model

Modeling

In the model below, we define the following:

- In the given period, we see that there are 4 trucks – 4 possible tours
- **i** = tours: 1, …, N where we explore n potential tours
- **j** = Hubs: 1,2,…,J where 1 represents the central depot

Parameters: Constant data values used as inputs to the model		
Model	**Python Code**	**Description**
c_i	final_df.loc[i,"distance"]	Dataframe that contains distance cost for each tour

Variables: Values we aim to generate with the model			
Model	**Python Code**	**Variable Type**	**Description**
x_i	xvar[i]	Binary, $x_i = \{0, 1\}$	1 if tour i is selected, 0 otherwise

Objective Function: Minimize Total Distance Travelled

- $\sum_{i=1}^{N} c_i x_i$

Constraints: Variables are subject to the following constraints

5. All locations are covered by some tour
   - $\sum_{i=1}^{N} a_{ij} x_i = 1, \quad all\ j$
6. Vehicle Availability – 4 trucks
   - $\sum_{i=1}^{n} x_i \leq 4$

Final Initial Model:

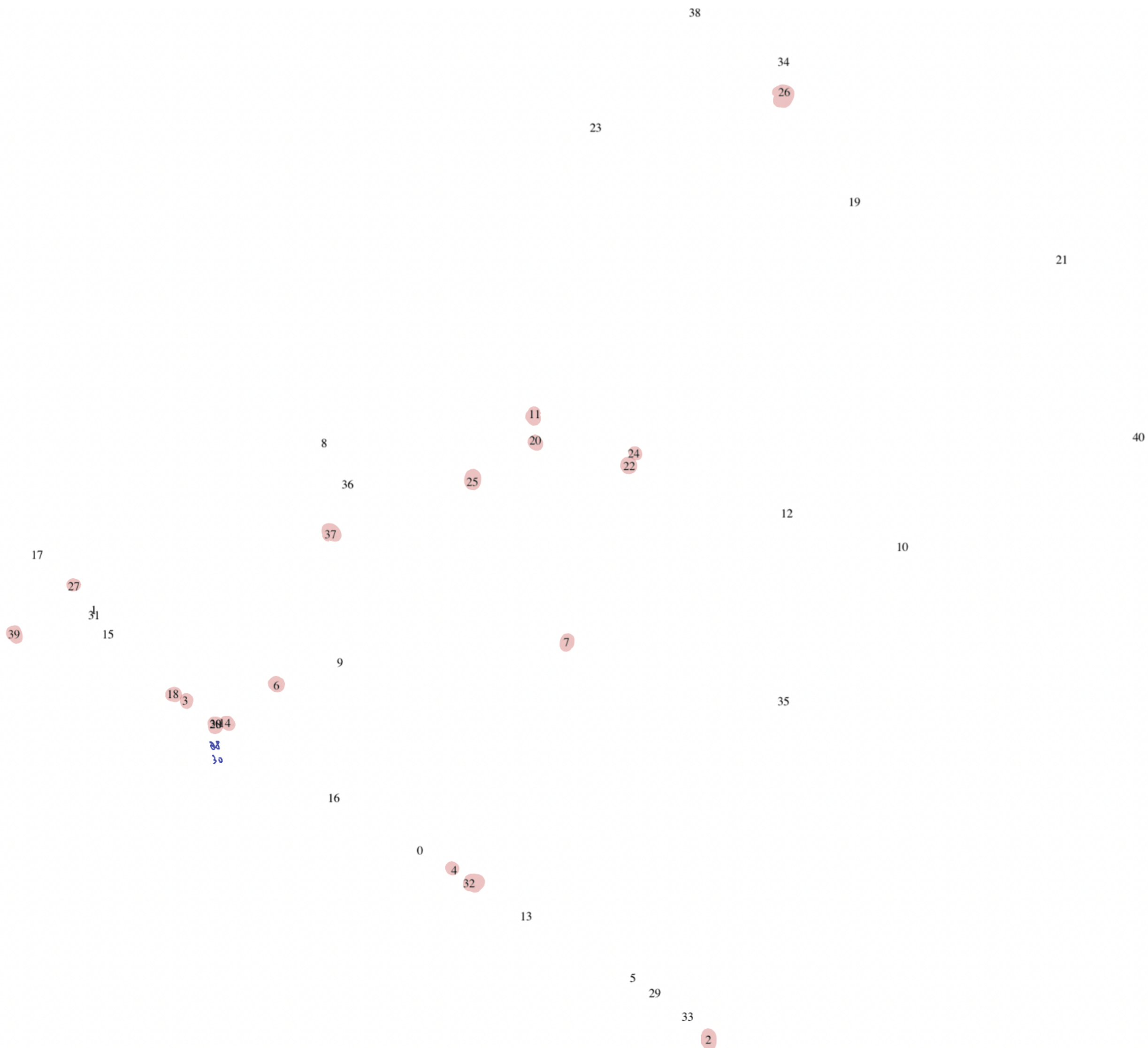
Minimize Total Distance

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

Subject to:

- $\sum_{i=1}^{N} a_{ij} x_i = 1, \quad for\ all\ j$
- $\sum_{i=1}^{n} x_i \leq 4$
- $x_i \in \{0, 1\},\ for\ all\ i$
- $a_{ij} \in \{0, 1\}$, for all i,j

Appendix F: Hubs Relative Location Graph



Note:

- *hubs labels are one-unit down than the actual labelling because of indexing in python (i.e. hub 0 is hub 1)*
- *hub with surplus bikes are colored in read for easier visual searching*

Appendix G: Optimized Tour Results

Result for Clustering approach in output & plot:

```
Tour 27 Distance:  13.242276999999998
Tour 28 Distance:  22.267284999999998
Tour 29 Distance:  17.251826000000005
Tour 30 Distance:  8.5515624
```

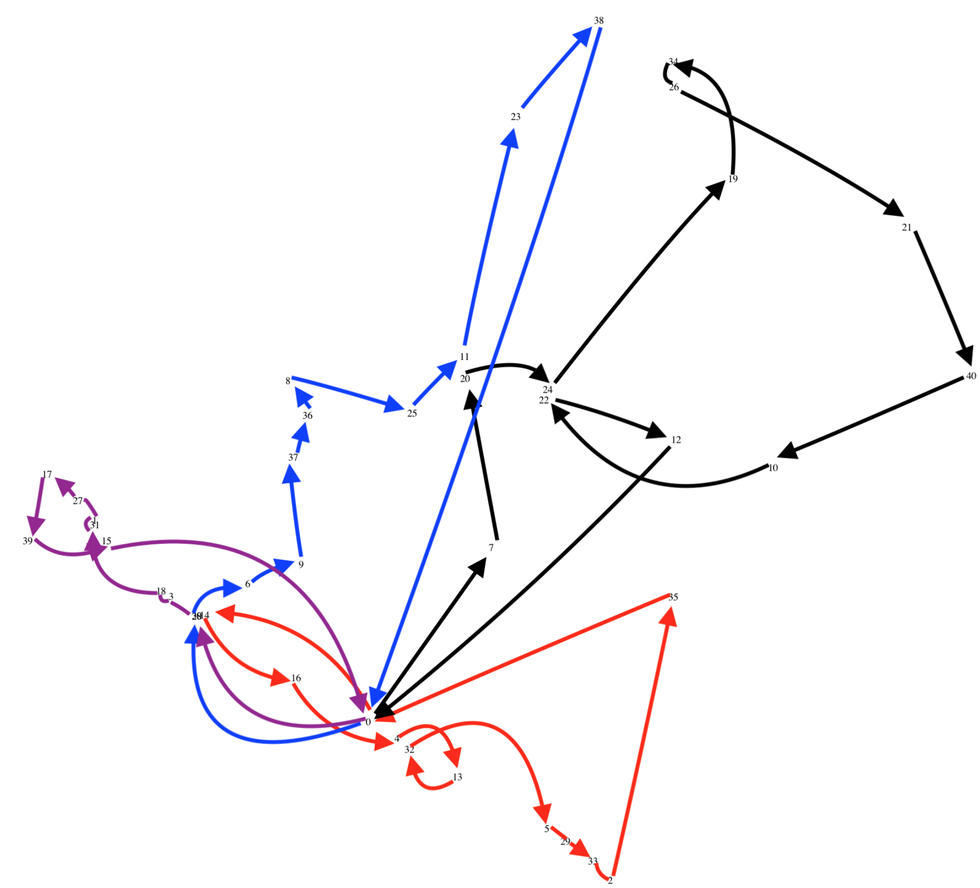
Result for visual search clustering approach in output & plot:

```
Status: Optimal
Total distance: 13.242276999999998
Timestep 1: Hub 1 to Hub 15
            truck capacity: 0.0
            distance travelled: 1.832
Timestep 2: Hub 15 to Hub 17
            truck capacity: 15.0
            distance travelled: 1.03
Timestep 3: Hub 17 to Hub 5
            truck capacity: 10.0
            distance travelled: 1.11201
Timestep 4: Hub 5 to Hub 14
            truck capacity: 19.0
            distance travelled: 0.680001
Timestep 5: Hub 14 to Hub 33
            truck capacity: 11.0
            distance travelled: 0.522
Timestep 6: Hub 33 to Hub 6
            truck capacity: 26.0
            distance travelled: 1.496
Timestep 7: Hub 6 to Hub 30
            truck capacity: 17.0
            distance travelled: 0.212002
Timestep 8: Hub 30 to Hub 34
            truck capacity: 10.0
            distance travelled: 0.321006
Timestep 9: Hub 34 to Hub 3
            truck capacity: 5.0
            distance travelled: 0.246008
Timestep 10: Hub 3 to Hub 36
            truck capacity: 13.0
            distance travelled: 2.68509
Timestep 11: Hub 36 to Hub 1
            truck capacity: 3.0
            distance travelled: 3.10616
```

```
Status: Optimal
Total distance: 22.267284999999998
Timestep 1: Hub 1 to Hub 8
            truck capacity: 0.0
            distance travelled: 2.01384
Timestep 2: Hub 8 to Hub 21
            truck capacity: 9.0
            distance travelled: 1.61819
Timestep 3: Hub 21 to Hub 25
            truck capacity: 19.0
            distance travelled: 0.798164
Timestep 4: Hub 25 to Hub 20
            truck capacity: 29.0
            distance travelled: 2.65061
Timestep 5: Hub 20 to Hub 35
            truck capacity: 16.0
            distance travelled: 1.24611
Timestep 6: Hub 35 to Hub 27
            truck capacity: 11.0
            distance travelled: 0.239201
Timestep 7: Hub 27 to Hub 22
            truck capacity: 26.0
            distance travelled: 2.56611
Timestep 8: Hub 22 to Hub 41
            truck capacity: 21.0
            distance travelled: 1.53492
Timestep 9: Hub 41 to Hub 11
            truck capacity: 13.0
            distance travelled: 2.06626
Timestep 10: Hub 11 to Hub 23
            truck capacity: 3.0
            distance travelled: 2.27184
Timestep 11: Hub 23 to Hub 13
            truck capacity: 18.0
            distance travelled: 1.31981
Timestep 12: Hub 13 to Hub 1
            truck capacity: 8.0
            distance travelled: 3.94223
```

```
Status: Optimal
Total distance: 17.251826000000005
Timestep 1: Hub 1 to Hub 29
            truck capacity: 0.0
            distance travelled: 1.906
Timestep 2: Hub 29 to Hub 7
            truck capacity: 12.0
            distance travelled: 0.556094
Timestep 3: Hub 7 to Hub 10
            truck capacity: 21.0
            distance travelled: 0.533349
Timestep 4: Hub 10 to Hub 38
            truck capacity: 13.0
            distance travelled: 1.01556
Timestep 5: Hub 38 to Hub 37
            truck capacity: 28.0
            distance travelled: 0.417809
Timestep 6: Hub 37 to Hub 9
            truck capacity: 18.0
            distance travelled: 0.379301
Timestep 7: Hub 9 to Hub 26
            truck capacity: 8.0
            distance travelled: 1.20965
Timestep 8: Hub 26 to Hub 12
            truck capacity: 15.0
            distance travelled: 0.727633
Timestep 9: Hub 12 to Hub 24
            truck capacity: 21.0
            distance travelled: 2.32248
Timestep 10: Hub 24 to Hub 39
            truck capacity: 12.0
            distance travelled: 1.20097
Timestep 11: Hub 39 to Hub 1
            truck capacity: 5.0
            distance travelled: 6.98298
```

```
Status: Optimal
Total distance: 8.5515624
Timestep 1: Hub 1 to Hub 31
            truck capacity: 0.0
            distance travelled: 1.903
Timestep 2: Hub 31 to Hub 4
            truck capacity: 5.0
            distance travelled: 0.303015
Timestep 3: Hub 4 to Hub 19
            truck capacity: 10.0
            distance travelled: 0.108005
Timestep 4: Hub 19 to Hub 32
            truck capacity: 22.0
            distance travelled: 0.865009
Timestep 5: Hub 32 to Hub 2
            truck capacity: 10.0
            distance travelled: 0.0440114
Timestep 6: Hub 2 to Hub 28
            truck capacity: 3.0
            distance travelled: 0.238
Timestep 7: Hub 28 to Hub 18
            truck capacity: 12.0
            distance travelled: 0.366005
Timestep 8: Hub 18 to Hub 40
            truck capacity: 0.0
            distance travelled: 0.785866
Timestep 9: Hub 40 to Hub 16
            truck capacity: 13.0
            distance travelled: 0.938651
Timestep 10: Hub 16 to Hub 1
            truck capacity: 0.0
            distance travelled: 3.0
```



Appendix H: Optimized Tour Results with no Truck Capacity Constraint

```
Status: Optimal
Total distance: 12.198279
Timestep 1: Hub 1 to Hub 15
            truck capacity: 0.0
            distance travelled: 1.832
Timestep 2: Hub 15 to Hub 17
            truck capacity: 15.0
            distance travelled: 1.03
Timestep 3: Hub 17 to Hub 5
            truck capacity: 10.0
            distance travelled: 1.11201
Timestep 4: Hub 5 to Hub 33
            truck capacity: 19.0
            distance travelled: 0.158003
Timestep 5: Hub 33 to Hub 14
            truck capacity: 34.0
            distance travelled: 0.522
Timestep 6: Hub 14 to Hub 6
            truck capacity: 26.0
            distance travelled: 0.974
Timestep 7: Hub 6 to Hub 30
            truck capacity: 17.0
            distance travelled: 0.212002
Timestep 8: Hub 30 to Hub 34
            truck capacity: 10.0
            distance travelled: 0.321006
Timestep 9: Hub 34 to Hub 3
            truck capacity: 5.0
            distance travelled: 0.246008
Timestep 10: Hub 3 to Hub 36
            truck capacity: 13.0
            distance travelled: 2.68509
Timestep 11: Hub 36 to Hub 1
            truck capacity: 3.0
            distance travelled: 3.10616
```

```
Status: Optimal
Total distance: 19.286178999999997
Timestep 1: Hub 1 to Hub 8
            truck capacity: 0.0
            distance travelled: 2.01384
Timestep 2: Hub 8 to Hub 21
            truck capacity: 9.0
            distance travelled: 1.61819
Timestep 3: Hub 21 to Hub 23
            truck capacity: 19.0
            distance travelled: 0.758601
Timestep 4: Hub 23 to Hub 25
            truck capacity: 34.0
            distance travelled: 0.105043
Timestep 5: Hub 25 to Hub 35
            truck capacity: 44.0
            distance travelled: 3.31832
Timestep 6: Hub 35 to Hub 27
            truck capacity: 39.0
            distance travelled: 0.239201
Timestep 7: Hub 27 to Hub 20
            truck capacity: 54.0
            distance travelled: 1.02819
Timestep 8: Hub 20 to Hub 22
            truck capacity: 41.0
            distance travelled: 1.70932
Timestep 9: Hub 22 to Hub 41
            truck capacity: 36.0
            distance travelled: 1.53492
Timestep 10: Hub 41 to Hub 11
            truck capacity: 28.0
            distance travelled: 2.06626
Timestep 11: Hub 11 to Hub 13
            truck capacity: 18.0
            distance travelled: 0.952064
Timestep 12: Hub 13 to Hub 1
            truck capacity: 8.0
            distance travelled: 3.94223
```

```
Status: Optimal
Total distance: 16.586247000000004
Timestep 1: Hub 1 to Hub 29
            truck capacity: 0.0
            distance travelled: 1.906
Timestep 2: Hub 29 to Hub 7
            truck capacity: 12.0
            distance travelled: 0.556094
Timestep 3: Hub 7 to Hub 38
            truck capacity: 21.0
            distance travelled: 1.26996
Timestep 4: Hub 38 to Hub 37
            truck capacity: 36.0
            distance travelled: 0.417809
Timestep 5: Hub 37 to Hub 9
            truck capacity: 26.0
            distance travelled: 0.379301
Timestep 6: Hub 9 to Hub 24
            truck capacity: 16.0
            distance travelled: 3.29762
Timestep 7: Hub 24 to Hub 39
            truck capacity: 7.0
            distance travelled: 1.20097
Timestep 8: Hub 39 to Hub 12
            truck capacity: 0.0
            distance travelled: 3.42567
Timestep 9: Hub 12 to Hub 26
            truck capacity: 6.0
            distance travelled: 0.727633
Timestep 10: Hub 26 to Hub 10
            truck capacity: 13.0
            distance travelled: 1.77668
Timestep 11: Hub 10 to Hub 1
            truck capacity: 5.0
            distance travelled: 1.62851
```

```
Status: Optimal
Total distance: 8.3855554
Timestep 1: Hub 1 to Hub 31
            truck capacity: 0.0
            distance travelled: 1.903
Timestep 2: Hub 31 to Hub 4
            truck capacity: 5.0
            distance travelled: 0.303015
Timestep 3: Hub 4 to Hub 19
            truck capacity: 10.0
            distance travelled: 0.108005
Timestep 4: Hub 19 to Hub 40
            truck capacity: 22.0
            distance travelled: 1.45865
Timestep 5: Hub 40 to Hub 18
            truck capacity: 35.0
            distance travelled: 0.785866
Timestep 6: Hub 18 to Hub 28
            truck capacity: 23.0
            distance travelled: 0.366005
Timestep 7: Hub 28 to Hub 2
            truck capacity: 32.0
            distance travelled: 0.238
Timestep 8: Hub 2 to Hub 32
            truck capacity: 25.0
            distance travelled: 0.0440114
Timestep 9: Hub 32 to Hub 16
            truck capacity: 13.0
            distance travelled: 0.179003
Timestep 10: Hub 16 to Hub 1
            truck capacity: 0.0
            distance travelled: 3.0
```