



VEHICLE ROUTING AND SCHEDULING OF CONTINUOUS AMBULATORY PERITONEAL DIALYSIS (CAPD) SOLUTION:

PROJECT REPORT
IENG6923 – DISTRIBUTION MANAGEMENT



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TABLE OF CONTENT:

Serial No	Content	Page No
<i>1</i>	<i>Abstract</i>	<i>2</i>
<i>2.0</i>	<i>Introduction</i>	<i>3</i>
<i>2.1</i>	<i>Problem Statement</i>	<i>3</i>
<i>2.2</i>	<i>Objective</i>	<i>3</i>
<i>2.3</i>	<i>Value Proposition</i>	<i>3</i>
<i>3</i>	<i>Literature review</i>	<i>4</i>
<i>4</i>	<i>Mathematical model</i>	<i>5</i>
<i>5</i>	<i>Solution Technique</i>	<i>7</i>
<i>5.1</i>	<i>Data Collection</i>	<i>7</i>
<i>5.2</i>	<i>Vehicle Details</i>	<i>8</i>
<i>5.3</i>	<i>Distance Calculation</i>	<i>8</i>
<i>5.4</i>	<i>Model Implementation</i>	<i>8</i>
<i>6</i>	<i>Experiment</i>	<i>9</i>
<i>7</i>	<i>Result</i>	<i>10</i>
<i>8</i>	<i>Conclusion</i>	<i>15</i>
<i>9</i>	<i>Reference</i>	<i>15</i>
<i>10</i>	<i>Appendix</i>	<i>16</i>

1. ABSTRACT:

One of the most challenging issues to resolve in a real-world setting is vehicle routing and scheduling. Numerous industries, including the food supply chain, the delivery of raw materials to companies, Uber, healthcare, the automotive industry, and others, use VRSP. The objective of this project is to set up a network of vehicles for scheduling and distributing Continuous Ambulatory Peritoneal Dialysis (CAPD) products throughout the province of Ontario. The project's main goals are to shorten patient wait times and lower operating costs. A vehicle routing and scheduling model with a time window and capacity is taken into consideration to prevent delays in the delivery of the CAPD fluids. Additionally, the vehicles' optimal path is chosen so that it meets the demands of the patients. Using Google Maps, the warehouse (single depot) and the numerous patient locations are recorded in the Ontario region. Using the Google API, the distance matrix is produced in Python. The optimisation model is then generated in Excel and solved using the Gurobi Open solver. Additionally, a series of experiments are conducted to determine how operational costs vary by altering time windows, capacity limits, and patient demand according to their severity. The models are run, and the outputs are analysed. This algorithm aids in identifying the efficient route and thereby decreases the overall transportation cost.

2.0 Introduction:

Dialysis is done when a patient's kidney fails to perform its function adequately. A type of at-home dialysis called Continuous Ambulatory Peritoneal Dialysis (CAPD) is performed to clean the blood of pollutants and so support the kidneys' healthy operation. The benefit of CAPD is that the patient does not need to frequently visit the hospital for dialysis, which lowers the risk of catching an infection. Additionally, while the patient receives dialysis, their immunity declines and they become tired. According to statistics, the Canadian populace uses home dialysis at a high rate compared to other countries. In Ontario, between 20 and 25 per cent of patients receive aided PD.

Every industry has seen a significant upgrade in the last few decades because of the development of the internet and artificial intelligence. This technological advancement has improved home healthcare and telemedicine, which is helpful for the elderly and others with limited mobility. Such healthcare scenarios make use of vehicle scheduling and routing. To transport peritoneal fluids throughout the province of Ontario, a network of 25 customers and one warehouse (depot) is built as part of this project.

The rate of alcohol consumption in Canada has increased over the past decade. Excessive consumption of alcohol leads to kidney failure which thereby leads to dialysis. Statistics state that nearly 20-25% of the dialysis population in Ontario is undergoing peritoneal dialysis. CAPD is a type of dialysis where peritoneal fluids are artificially injected into the patient's body. This procedure is done by injecting at least two quarts of the fluid into the patient's body and then draining it. For each procedure, it takes about 30 to 40 mins and mostly every CAPD patient needs to perform this around 3-5 times a day.

2.1 Problem statement:

There is a constant need for the CAPD solution. To meet the demand, a distribution network needs to be established. The products need to be delivered from the distribution centre to the patient's location. A vehicle routing and scheduling model is to be defined and designed by considering the demand and time window for the delivery (VRSPTWCap). The demand from each patient varies based on the severity of the patient's condition.

2.2 Objective:

The goal of this project is to create a distribution network in the province of Ontario that avoids patient delays and reduces overall operating costs. This can be done by optimizing the vehicle's route of travel. This is done using a homogenous vehicle (Chevrolet Express) from a single depot (warehouse).

2.3 Value Proposition:

As dialysis patients, their immunity is generally lower than that of normal human beings, making them more susceptible to serious infections and illnesses. The result of this project will help the patient to decrease the waiting time for their treatment, which will thereby further lower the danger of infection. Also, the proposed model will ensure the distribution network accounts for efficient routing and reduction in carbon footprints.

3. Literature review:

Vehicle Routing Problems have been extensively analysed to reduce transportation costs. In real-time world data, the time window is considered as the period of customer availability. This journal uses a mathematical model and an optimization algorithm to allocate shipments to vehicles. This is done to minimise the overall cost such that all customers are serviced within the given time window. The objective of the mathematical program is to minimize the routing cost of the vehicle delivery operation subject to vehicle capacity and arrival (delivery) time feasibility constraints. [1]

Logistics companies should not only consider improving service quality and reducing operating costs but also take a particular corporate social responsibility by reducing greenhouse gas emissions. Moreover, all uncertainties need to be considered while developing a VRP model. In this journal, a model is created to develop a relatively robust optimization model for a vehicle routing problem with synchronized visits and uncertain scenarios considering greenhouse gas emissions. A hybrid tabu search and simulated annealing are proposed to solve the VRP. Finally, a sensitivity analysis is performed to observe the change in fuel consumption cost and a statistical analysis is done to validate the model. Reducing carbon footprints is an important aspect that needs to be done while routing and scheduling a vehicle, due to its increasing environmental side effects, thereby putting the human race in danger. [2]

In this journal, the use of occasional drivers is discussed to reduce the overall travel cost associated with a Company. A company's main motive is to deliver all the products at a minimum cost, which in turn means decreasing the overall cost associated with the vehicle, driver, and the occasional driver. This methodology can be used in healthcare, to deliver medical supplies if the patient's location is close to the warehouse or the pharmacy. This can be used to increase the profits of the company. The problem is formulated as an IP and is solved using a commercial solver. [3]

Home healthcare services are a growing sector in the medical service business. This business is based on a delivery network, where the patients are hospitalised at their homes. However, a huge logistic complexity is involved in the home health care system. This paper discusses the advancement in the field of operation research which can be implemented in the field of the home healthcare sector. Moreover, as life expectancies increase, the need for healthcare increases remarkably. This paper suggests a framework which can be established to manage home healthcare logistics. [4]

Healthcare was the most affected during the pandemic. Several governments and countries were not prepared for the pandemic as it came to be a devastating incident in the history of mankind. This pandemic leads to an increase in the need for masks and personal protective equipment (PPE). However, manufacturing and distributing them were a big problem during the pandemic. This seemed to be a vehicle routing problem which is solved using a heuristic approach. The heuristic approach is used to find a feasible and efficient solution. Significant timesaving in planning routes, accuracy in the prediction of completing routes, and detailed maps of balanced routes are some of the advantages of the heuristic approach which are discussed in this journal. [5]

4. Mathematical model:

No of patients (n) = 25

No. of vehicles (m) = 5

The distance matrix is represented as D_{ij} . Moreover, this represents the distance from i to j.

D_{ij} = Distance from a patient I to j $i = 1,2,3...n$ $j = 1,2,3...n$	D_{ij} = Distance from patient i to warehouse $i = 1,2,3...n$ $j = n+1, n+2, n+3...n+m$
D_{ij} = Distance from warehouse to patient j $i = n+1, n+2, n+3...n+m$ $j = 1,2,3...n$	$D_{ij} = 0$ $i = n+1, n+2, n+3...n+m$ $j = n+1, n+2, n+3...n+m$

Table 1: Distance matrix description

C_{ij} = cost of travel from a patient i to j $i = 1,2,3...n$ $j = 1,2,3...n$	C_{ij} = Cost of travel from patient i to warehouse $i = 1,2,3...n$ $j = n+1, n+2, n+3...n+m$
C_{ij} = Cost to travel from warehouse to patient j $i = n+1, n+2, n+3...n+m$ $j = 1,2,3...n$	$C_{ij} = 0$ $i = n+1, n+2, n+3...n+m$ $j = n+1, n+2, n+3...n+m$

Table 2: Cost matrix description

X_{ij} is the variable matrix.

Therefore, when

$X_{ij} = 1$ {route exists from i to j}

$X_{ij} = 0$ {route does not exist from i to j}

T_{ij} = Time of travel from customer i to j

p_i = amount to be delivered at node i

r_i = amount on the truck on arrival at node i

Q = capacity of the truck/ cargo van

EST = Earliest starting time from i

LST = Latest Starting Time from i

R_{ij} = Amount of truck on arrival at node I and j

d_i = duration of task at node i

S_i = time to start the task at node i

Objective function:

$$\min \sum_{i=1}^{n+m} \sum_{j=1}^{n+m} C_{ij} * X_{ij}$$

The objective function of the model is to minimise the operation cost involved in transporting the CAPD solutions from the warehouse to the different patient locations. This is done by considering the following constraints like vehicle capacity, the time window for delivery, and customer demand. The optimal route is chosen from the model which thereby decreases the overall operating cost.

Constraints:

The first is assignment-based network formulation:

1. $\sum_{i=1}^{n+m} X_{ij} = 1 \quad \forall j = 1, \dots, n+m$
2. $\sum_{j=1}^{n+m} X_{ij} = 1 \quad \forall i = 1, \dots, n+m$
3. $X_{ij} \in \{0,1\} \quad \forall i, j = 1, \dots, n+m$

Capacity constraint:

1. $r_i + p_i - r_j \leq M_{ij} (1 - x_{ij}) \quad \forall i = 1, \dots, n; j = 1, \dots, n$
2. $0 \leq r_i \leq Q - p_i \quad \forall i = 1, \dots, n$

Time Windows:

1. $S_i + d_i + T_{ij} - S_j \leq M_{ij} (1 - x_{ij}) \quad \forall i = 1, \dots, n; j = 1, \dots, n$
2. $EST \leq S_i \leq LST$
3. $M_{ij} = LST - EST + d_i + T_{ij}$

5. SOLUTION TECHNIQUE :

5.1 DATA COLLECTION :

Data collection seems to be the most crucial step in a vehicle routing and scheduling problem. For this model, Ontario province is considered, as it is one of the most developed provinces in Canada. The use of peritoneal dialysis was highest in the province of Ontario. Moreover, the greater Toronto Area (GTA) alone contributes to about 36.1% of the total usage of PD. 25 different locations were randomly chosen from google maps and their corresponding latitude and longitudes were noted. The warehouse was considered to be the “Global distribution and warehousing” which is located in Mississauga. The patient locations are selected within a radius of 42km from the warehouse. Initially, 30 locations were chosen, and 8 vehicles were considered, but due to computational complexity, the model was reduced to 25 locations and 5 vehicles. The vehicle selected was “A Chevrolet express” cargo van.

#Patient No	Location	latitude	longitude
0	Global Distribution & Warehousing, 1195 Courtneypark Dr E, Mississauga, ON L5T 1R1	43.659249	-79.666575
1	56 Neville Crescent, Brampton, ON L6S 5L4	43.732479	-79.756526
2	Concord, Vaughan, ON	43.798329	-79.5079073
3	65 Wellesley St E, Toronto, ON M4Y 2T6	43.66546	-79.381136
4	80 Thyra Ave, Toronto, ON	43.693611	-79.293736
5	1470 Alyssum St, Pickering, ON L1W 1H9	43.824367	-79.075826
6	172 Rands Rd, Ajax, ON L1S 3Z6	43.827964	-79.028241
7	6131 Churchill Dr E, Whitchurch-Stouffville, ON L4A 7X3	44.032944	-79.265574
8	Rose-Marie French, 24 Maffey Crescent, Richmond Hill, ON L4S 0A7	43.905305	-79.455819
9	355 Woodland Acres Crescent, Maple, ON L6A 1G2	43.890334	-79.478935
10	17 Dew Drop Ct, Maple, ON L6A 1E9	43.884819	-79.478957
11	360 Athabasca Dr, Maple, ON L6A 3S2	43.88685	-79.496093
12	70 Waterloo Ave, Guelph, ON N1H 3H5	43.539391	-80.251378
13	Birdsell J William Architect, 107 Dublin St N, Guelph, ON N1H 4N2	43.544647	-80.253932
14	15 Bradwick Ct, Caledon, ON L7C 1B6	43.744958	-79.835167
15	32 Pinebrook Cir, Caledon, ON L7C 1C4	43.748329	-79.83497
16	57 Bonnie Glen Farm Blvd, Caledon, ON L7C 3X8	43.76219	-79.831627
17	11 George Gray Dr #2, Brampton, ON L6R 0B3	43.760718	-79.788261
18	32 Wood Cir, Bolton, ON L7E 1R4	43.870294	-79.721391
19	76 De Vere Gardens, North York, ON M5M 3E9	43.739907	-79.412432
20	24 Hazelwood Ave, Toronto, ON M4J 1K5	43.678541	-79.343442
21	104 Ivy Ave, Toronto, ON M4L 2H7	43.673323	-79.330711
22	95 Kalmar Ave, Scarborough, ON M1N 3G5	43.692996	-79.269407
23	102 Trinnell Blvd, Scarborough, ON M1L 1S7	43.712	-79.275351
24	140 Sandown Ave, Scarborough, ON M1N 3W7	43.715775	-79.254255
25	63 Harewood Ave, Scarborough, ON M1M 2R4	43.720703	-79.233639

Table 3: Location of the warehouse & 25 patients

5.2 Vehicle details:

Cargo van	Chevrolet Express
Price	\$ 54,397.00
Length	5,688 mm (223.95 in)
Width	2,013 mm (79.25 in)
Height	146 mm (84.50 in)
Annual repair cost	\$ 963.00

Table 4: Vehicle details

5.3 Distance calculation:

The coordinates of the warehouse and the patient's location (latitude and longitude) are obtained using Google Maps. A python code along with the google API algorithm was used to calculate the distance and travel duration from the warehouse to all locations of the patients and from one patient location to another. The computed distance matrix is then imported to excel, which is used to perform all calculations.

5.4 Model Implementation:

The MILP model is created and executed in Excel using the open solver Gurobi solver engine. The data is initially loaded, and the corresponding variables are first calculated. The constraints mentioned above are then loaded before running the open solver to achieve a feasible working solution. Several iterations were performed, and their corresponding outputs were obtained.

The screenshot shows the 'OpenSolver - Model' window. The 'What is AutoModel?' section is at the top. Below it, the 'Objective Cell' is set to '\$C\$1' with 'minimise' selected. The 'Variable Cells' are '\$H\$75:\$AK\$104,\$E\$113:\$E\$137,\$E\$151:\$E\$175'. The 'Constraints' section lists the following constraints:

- <Add new constraint>
- \$H\$107:\$AK\$107 = 1
- \$AM\$75:\$AM\$104 = 1
- \$H\$75:\$AK\$104 bin
- \$H\$113:\$AF\$137 <= 0
- \$E\$113:\$E\$137 <= \$D\$113:\$D\$137
- \$E\$113:\$E\$137 >= \$C\$113:\$C\$137
- \$E\$151:\$E\$175 >= \$C\$151:\$C\$175
- \$E\$151:\$E\$175 <= \$D\$151:\$D\$175
- \$H\$151:\$AF\$175 <= 0
- \$AP\$76 = \$AP\$77
- \$AP\$76 >= \$AN\$38

The 'Sensitivity Analysis' section has checkboxes for 'List sensitivity analysis on the same sheet with top left cell' and 'Output sensitivity analysis:'. The 'Solver Engine' is set to 'Gurobi'. At the bottom, there are buttons for 'Clear Model', 'Options...', 'Save Model', and 'Cancel'.

Figure 1: Constraints entered in open solver

6. EXPERIMENT:

The data matrix is used as the source to start performing various calculations. Initially, the vehicle routing model is set up to figure out how many vehicles are used in the optimal route and to identify the overall operating cost. The VRP model was set up with the total demand summing up to 232. The demand of every patient was randomised (assuming they have different severity). The capacity of the individual vehicle is considered to be 60. Therefore, for 5 vehicles the total available capacity is 300. After computing the required constraints and performing the cuts, the operational cost of the VRP model is calculated to be \$1182. In this model, all 5 vehicles were put into use.

Model	Number of vehicles used	Operating cost in (\$)
VRP model	5	1182

Table 5: output of VRP model

In the next model, I added the time window constraint. The earliest start time was randomly generated between 480 to 960 minutes and the average time window width between the EST and LST was averaged to be 10 minutes. By adding these time window constraints to the existing model, the output is verified. The operating cost associated with this model is reduced to about \$714. Moreover, it was noted that when the time window slack was increased to 120 minutes, the corresponding operation cost decreased to \$572. The number of vehicles used decreases to 3. The operating cost further decreased when the time window slack was increased. Therefore, it is understood that when the time window gap increases, the operation cost decreases, as the number of vehicles that are used decreases simultaneously.

Model	Number of vehicles used	Operating cost in (\$)
VRPTW (average 10 minutes)	5	714
VRPTW (time window=120)	3	572

Table 6: Output of VRPTW models

Furthermore, capacity constraints were newly added to the model. I had considered all the vehicles to be homogenous, the vehicle capacity is assumed to be 60. The capacity matrix (R_{ij}) is created, and the corresponding operation cost value is noted. In the first scenario, the demand between the patients was randomly assigned based on their severity. The sum of the demands of the 25 patients was calculated to be 232 and the overall capacity of the vehicle was calculated to be 300. By computing the model with these data, the operating cost was calculated to be \$717.

In the next case, the demand of every patient was assumed to be equal to 12. When the demand of every patient was made constant at 12, the total demand of the model was calculated to be 300 and the total capacity of the vehicle was maintained to be 300. Therefore, the operational cost has increased to \$775. Now considering the ideal case. The total demand from patients is constant and the time window gap between every patient is also maintained at 10. The operating cost is calculated to be \$693. The table below depicts the output of the experiments made to the VRSPTWCap model.

CASE	Model	Number of vehicles used	Demand	The capacity of the truck	Operating cost in (\$)
1	VRSPWCap	5	Varying between (5 to 15)	60	717
2	VRSPWCap	5	Fixed demand of 12	60	775
3	VRSPWCap (Fixed TW)	5	Fixed demand of 12	60	693

Table 7: Output of VRSPWCap models

7. RESULT:

On solving the model using an open solver, several operations' costs were estimated for 25 customers and 5 vehicles. Amongst those, the model with varying demand averaging 10 boxes and with an average time window slack of 10 minutes is the best solution practically (CASE 1). This is because the demand varies from patient to patient based on their criticality. As discussed earlier the distances are computed using python, and the model is implemented in excel. To decrease the computational complexity the model is solved using the Gurobi optimizer. The model had an optimal gap of 0.46%, meaning that the model had complexities in the data.

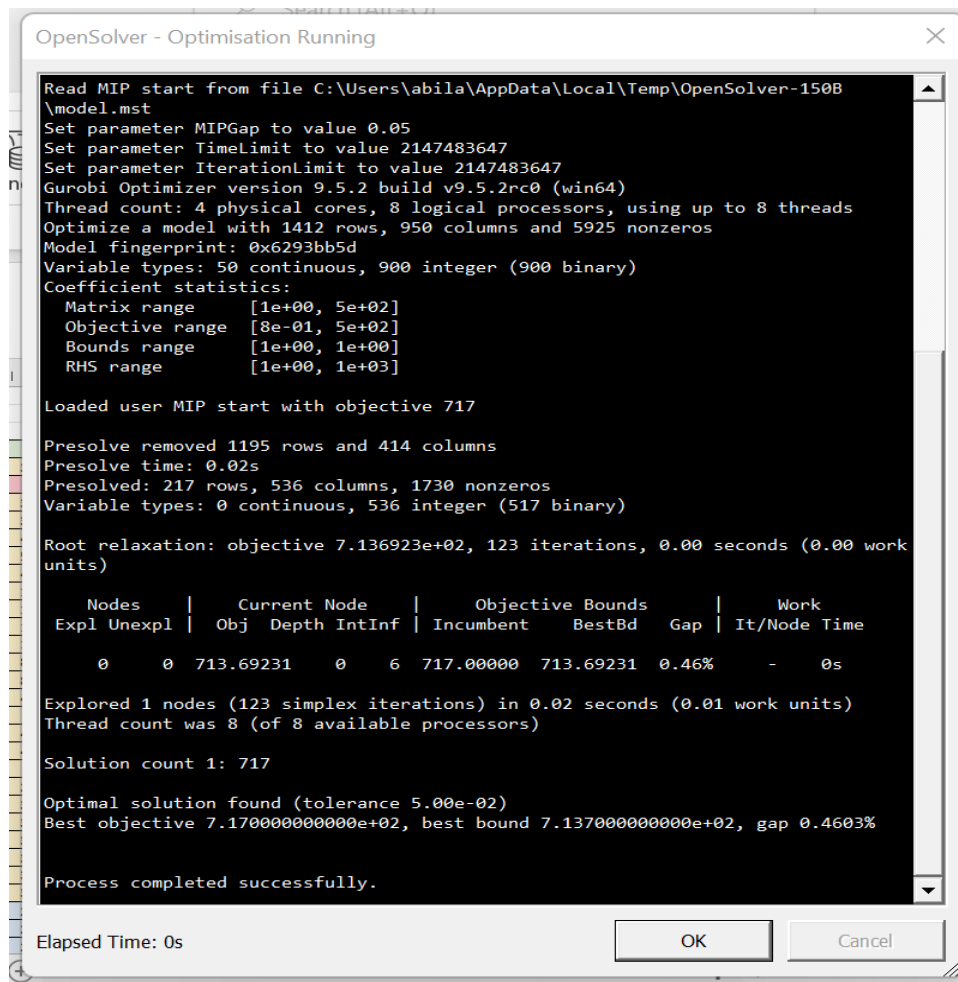


Figure 2: Optimisation progress dialogue box

By considering all the demand and time window constraints the minimum cost required to operate 5 vehicles to deliver CAPD solution to 25 patients per day is \$717.

CASE 1: WHEN THE DEMAND & TIME WINDOW VARIES BETWEEN PATIENTS:

After considering vehicle capacity and time window constraints, the network below shows the five vehicles travelling along the best possible route.

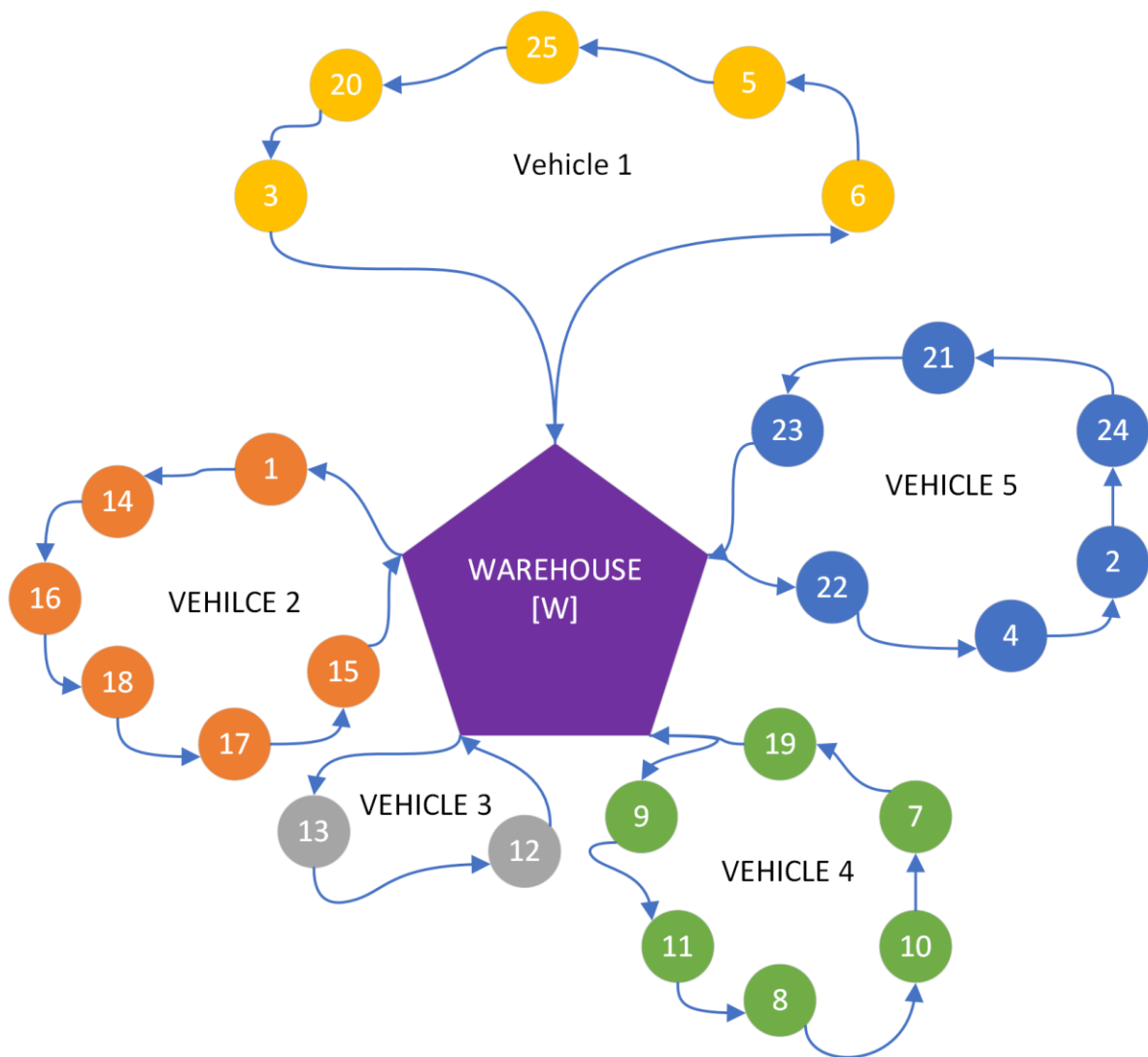


Figure 3: Vehicle Network for varying demand & Time Window

The table below shows the route in which all five vehicles commute.

#patient No	Location name	Vehicle	Route	Load	Capacity	Utilization factor
6	172 Rands Rd, Ajax, ON L1S 3Z6	V1	W-6-5-25-20-3-W	55	60	92%
5	1470 Alyssum St, Pickering, ON L1W 1H9					
25	63 Harewood Ave, Scarborough, ON M1M 2R4					
20	24 Hazelwood Ave, Toronto, ON M4J 1K5					
3	65 Wellesley St E, Toronto, ON M4Y 2T6					
1	56 Neville Crescent, Brampton, ON L6S 5L4	V2	W-1-14-16-18-17-15-W	44	60	73%
14	15 Bradwick Ct, Caledon, ON L7C 1B6					
16	57 Bonnieglan Farm Blvd, Caledon, ON L7C 3X8					
18	32 Wood Cir, Bolton, ON L7E 1R4					
17	11 George Gray Dr #2, Brampton, ON L6R 0B3					
15	32 Pinebrook Cir, Caledon, ON L7C 1C4	V3	W- 13 - 12 - W	28	60	47%
13	Birdsell J William Architect, 107 Dublin St N, Guelph, ON N1H 4N2					
12	70 Waterloo Ave, Guelph, ON N1H 3H5					
9	355 Woodland Acres Crescent, Maple, ON L6A 1G2	V4	W - 9 - 11 - 8 - 10 - 7 - 19 - W	56	60	93%
11	360 Athabasca Dr, Maple, ON L6A 3S2					
8	Rose-Marie French, 24 Maffey Crescent, Richmond Hill, ON L4S 0A7					
10	17 Dew Drop Ct, Maple, ON L6A 1E9					
7	6131 Churchill Dr E, Whitchurch-Stouffville, ON L4A 7X3					
19	76 De Vere Gardens, North York, ON M5M 3E9	V5	W - 22 - 4 - 2 - 24 - 21 - 23 - W	51	60	85%
22	95 Kalmar Ave, Scarborough, ON M1N 3G5					
4	80 Thyra Ave, Toronto, ON					
2	Concord, Vaughan, ON					
24	140 Sandown Ave, Scarborough, ON M1N 3W7					
21	104 Ivy Ave, Toronto, ON M4L 2H7					
23	102 Trinnell Blvd, Scarborough, ON M1L 1S7					

Table 8: Output of varying demand & time window

The table above shows the result of the model for the given demand from the patients. The individual vehicle utilization factor is also depicted in the table which is found using the load carried by truck/vehicle by the capacity of the individual vehicle. The total utilisation factor of the 5 vehicles was calculated to be 78%.

Vehicle	Route	Speed of Truck (km/hour)	Total Distance Travelled in (km)
V1	W-6-5-25-20-3-W	60	131
V2	W-1-14-16-18-17-15-W	60	89.2
V3	W-13-12-W	60	133.2
V4	W-9-11-8-10-7-19-W	60	164.4
V5	W-22-4-2-24-21-23-W	60	188.1

Table 9: Total distance travelled by each vehicle in Case 1

CASE 2: When the demand is 12 from all patients. The vehicle network below shows the change in the network diagram.

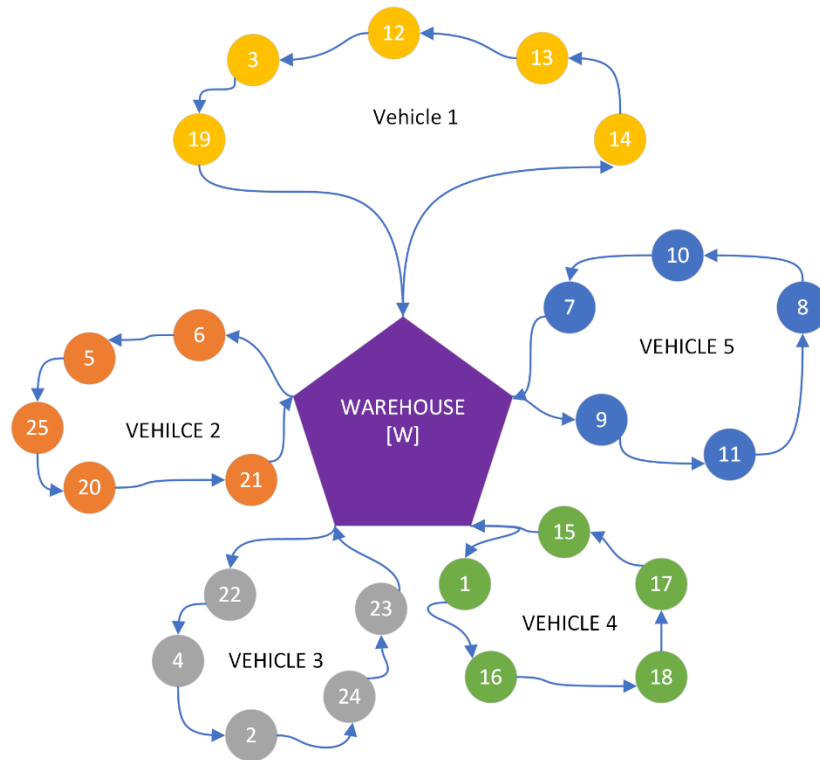


Figure 4: Vehicle Network for fixed demand & varying Time Window

Vehicle Number	Route	Vehicle Capacity	Load carried	Utilisation Factor	Distance travelled (Km)
Vehicle 1	W-14-13-12-3-19-W	60	60	100%	213.3
Vehicle 2	W-6-5-25-20-21-W	60	60	100%	144.1
Vehicle 3	W-22-4-2-24-23-W	60	60	100%	172.2
Vehicle 4	W-1-16-18-17-15-W	60	60	100%	85
Vehicle 5	W-9-11-8-10-7-W	60	60	100%	159.5

Table 10: Total distance travelled by each vehicle in Case 2

In such cases, the vehicle is loaded to the maximum available capacity. Every truck is loaded with 60kg of CAPD solution. However, in this case, the total demand has increased compared to case 1 and therefore the overall operating cost has also risen to \$775.

Case 3: Both Time Window and Demand is Fixed:

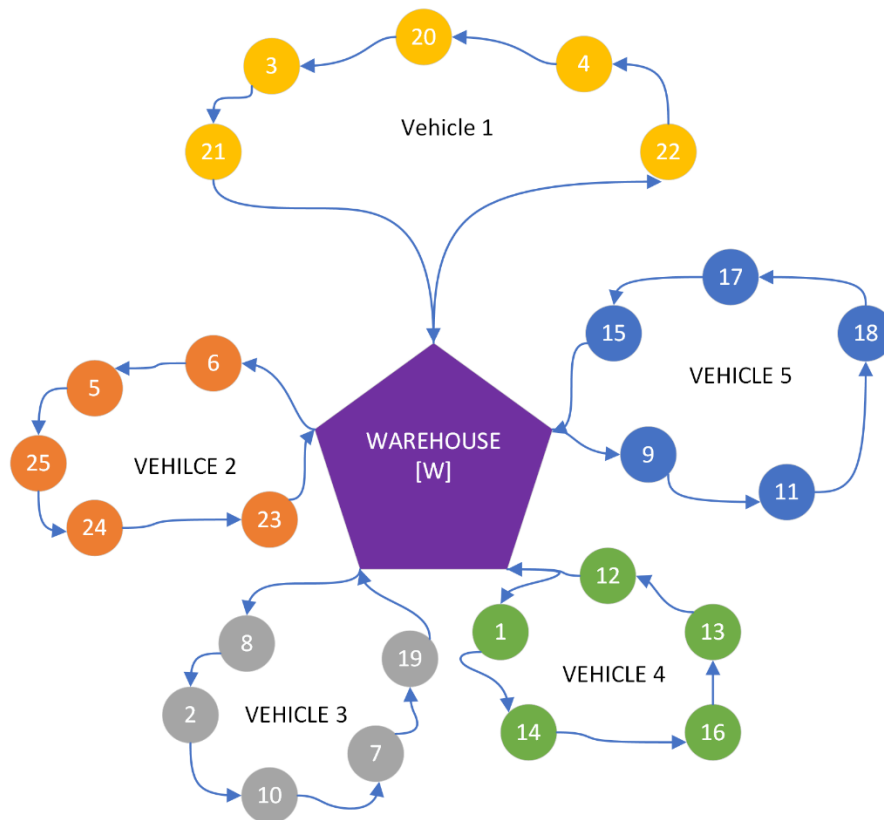


Figure 5: Vehicle network model for fixed TW & demand

Vehicle Number	Route	Vehicle Capacity	Load carried	Utilisation Factor	Distance travelled (Km)
Vehicle 1	W-22 – 4- 20- 3-21-W	60	60	100%	102.8
Vehicle 2	W-6-5-25-24- 23-W	60	60	100%	141.9
Vehicle 3	W-8-2-10-7-19- W	60	60	100%	182.1
Vehicle 4	W-1-14-16-13- 12-W	60	60	100%	151.8
Vehicle 5	W-9-11-18-17- 15-W	60	60	100%	114.6

Table 11: Distance travelled by each vehicle when time window and demand are fixed

The network diagram above depicts the change in the route of the 5 vehicles. In this case, both the demand and Time window is fixed (ideal case). Considering this to be an IDEAL scenario, the operating cost is calculated to be \$693.

8. CONCLUSION:

The solution for several models is discussed in the above section and it is clear that in real-world scenarios, the VRSPWCap model (case 1) seems to be more reliable. The model generated gives the most optimal route in which the vehicles can travel such that the operational cost is minimum. This formulation could be used for any capacity and demand and any number of patients and vehicles. But the computational complexity needs to be kept in mind to find the optimal route.

The result obtained from the model is satisfactory in a reasonable computational time. However, as the problem size increases, the computational complexity increases which thereby makes it difficult to compute. Heuristics algorithms can be used to solve problems with a larger dataset.

In future, constraints like traffic constraints and vehicle ranges can be considered to enhance the complexity of the problem. Moreover, the vehicle I chose was a Chevrolet express. However, considering the CO₂ emissions, EVs can be used to reduce carbon footprints. Additionally, the recharging time also needs to be computed in the time window. These are some of the future scopes of the project.

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10. Appendix:

Python code for distance matrix:

```
import csv
import json

import pandas as pd
import googlemaps
from itertools import tee

import requests

def pairwise(iterable):
    a, b = tee(iterable)
    next(b, None)
    return zip(a, b)

def test1():
    df = pd.read_csv('test.csv')
    c=0
    dict_wor={}
    dict_list=[]
    df_marks = pd.DataFrame(dict_list)
    for (i1,row1), (i2, row2) in pairwise(df.iterrows()):

        loc = row1['Location']

        for (i1, row1), (i2, row2) in pairwise(df.iterrows()):
            list1=[]
            loc2 = row1['Location']
            index2 = row1['#patient No']
            c=c+1
            import urllib.parse
            origin = urllib.parse.quote(loc)
            dest = urllib.parse.quote(loc2)
            url =
"https://maps.googleapis.com/maps/api/distancematrix/json?origins="+origin+
"&destinations="+dest+"&key=AIzaSyAmhicKS1aPOYS21E8tTMx3ovkJtyPpI_s"

            payload = {}
            headers = {}

            response = requests.request("GET", url, headers=headers,
data=payload)

            resp = json.loads(response.text)

dict_wor[index2]=resp['rows'][0]['elements'][0]['distance']['text']

list1.append(resp['rows'][0]['elements'][0]['distance']['text'])
        file = open('test1.txt', 'a')
        for items in list1:
            file.writelines(items + '\n')
        file.close()

if __name__ == '__main__':
    test1()
```