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MINIMIZING THE CARBON EMISSIONS ON ROAD NETWORKS

Umman Mahir Yıldırım[1], Bülent Çatay[2]

The models and algorithms developed for transportation planning, vehicle routing, path finding and the software that utilize them are usually based on distance and constant travel times between the relevant locations and aim at minimizing total distance or travel time . However, constant travel time assumption is not realistic on road networks as the traffic conditions may vary from morning/evening rush hours to off-peak noon/night hours, from the weekends to business days, even from one season to another. Thus, distance/time based optimization does not exactly reflect the real fuel consumptions, hence the actual costs; neither can they be used to accurately account for the greenhouse gas (GHG) emissions. A distance/constant time based optimization model may even yield an infeasible solution when time-windows exist or the route length is time limited. In this study, we first analyze the peculiar characteristics of the Greenest Path Problem (GPP) where the objective is to find the least GHG generating path from an origin to a destination on the road network. We then propose a fast heuristic method for determining the greenest path, by incorporating fuel consumption and GHG emission objectives. Finally, we integrate the proposed algorithm into the Green Vehicle Routing Problem that minimizes the GHG emissions rather than the total distance or travel time. The developed heuristic is benchmarked against the existing algorithms by using synthetic traffic data on a real road network to illustrate potential savings and sustainability benefits.

Keywords: Shortest path problem, time-dependent networks, heuristics, greenest path problem

1 INTRODUCTION

Transportation has hazardous and threatening impacts on the environment. Among these, Greenhouse Gas (GHG), especially CO_2 emissions are the most concerning since they have direct and indirect consequences on human health. New planning techniques and approaches are needed in road transport by explicitly accounting for these negative impacts because of the growing concerns about the environmental sustainability. Research in this direction has recently gained momentum in the developed countries and modern societies.

In this paper, we focus on the Greenest Path Problem (GPP), an extension of the Time-Dependent Shortest Path Problem (TDSPP). The objective in TDSPP is to find the minimum cost path (fastest path) on a network with time-dependent travel costs, that is, the cost of the travel depends on the time of the departure. On the other hand, the objective in GPP is to find the minimum fuel consuming/GHG emitting path.

Both the shortest and fastest paths between two nodes can be easily found using the Dijkstra's Algorithm (DA) ([7]). The fastest path found in the morning rush hours will differ from the fastest path found at noon when the traffic density is relatively low. So, the fuel consumption and GHG emissions will also be different in these two time intervals. Many concepts in the fastest path problem are also applicable to GPP. However, it is not possible to find the least fuel consumption or GHG emission yielding path, namely the *greenest path*, using DA or any shortest/fastest path algorithm due to the distinctive properties of the problem. Thus, a dynamic network structure and an efficient method are needed to determine the greenest route between the nodes in typical road networks.

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Among the studies on the TDSPP, [14] and [15] introduced the waiting concept in the time-dependent context. [1] analyzed different waiting conditions whereas [18] proposed an approach for the non-waiting case. [16] and [4] proposed Dijkstra-like algorithm. On the other hand [12], [6] and [13] gave an extension of the A* algorithm ([10]), an extension of DA that uses a heuristic function to estimate the distance and direct the search towards the sink node. [5] and [3] proposed methods that are built on uni-directional and bi-directional searches respectively.

[2] is the first study which is capable of minimizing a generic cost function rather than the travel time on a time-dependent network. The study proposes an exact method under a certain discretization scheme. The time intervals are discretized into time points and a static network is obtained by using a time-space expansion. To find the minimum cost all-to-1 paths for all departure times, a backward labeling algorithm is implemented. The algorithm visits the entire time-space network. Having all-to-1 paths for all departure times at the end of the algorithm may seem advantageous. Nevertheless, when only the minimum cost path starting from a single node is sought, this information becomes redundant. In addition, on a real network where the number of nodes may reach up to millions these calculations become computationally intractable.

To the best of our knowledge, [17] is the only heuristic approach to find the minimum cost path on a time-dependent network. The proposed Heuristic 2 extends DA by dividing the time horizon into time intervals and keeping the minimum cost label within each interval. Then, all of the labels corresponding to each time interval are carried to the adjacent nodes increasing the total number of labels dramatically. [17] also showed that for large datasets, [2] is less accurate and less effective compared to their proposed heuristics. Besides, they observed that with the increasing size of the network and using a sufficiently small time unit for discretization, memory problems are inevitable when applying [2].

With this motivation from the gap in the literature, we propose a fast heuristic for finding the greenest path on a time-dependent road network with time varying speeds for which the traditional path finding algorithms do not work. The rest of the paper is organized as follows; the next section provides a description of the GPP. The details of the proposed heuristics are provided in Section 3. The computational results are presented in Section 4. In Section 5, we finally give the concluding remarks and the future research directions.

2 PROBLEM DESCRIPTION

The GPP problem is defined on a time-dependent directed network and seeks for the greenest from a predefined source node S to a particular node n, assuming that we begin the trip at $t \in [0, T]$, where T is an upper bound on the length of the planning horizon.

The European Environment Agency developed models to estimate the speed dependent fuel consumption ([9]). These models were used to obtain the fuel consumption curve for diesel-powered light commercial vehicles as depicted in Figure 1. Due to the structure of the cost function, the principle of optimality is not valid in GPP and the optimal paths are not necessarily concatenated. In other words, the optimal paths do not form a tree.

Table 1. GHG emissions at different speeds

Speed	20	30	40	50	60	70	80
GHG emission (g/km)	1.4	1.2	0.9	0.8	0.5	1.7	1.8

An important characteristic of the GPP that makes it hard to solve is that there is no direct correlation between the cumulative travel time and the GHG emission. In other words, no pattern exists for the GPP and no dominance can be obtained between time-cost pairs. In the following, we will depict different scenarios to further analyze these characteristics of the problem. In each figure, the numbers

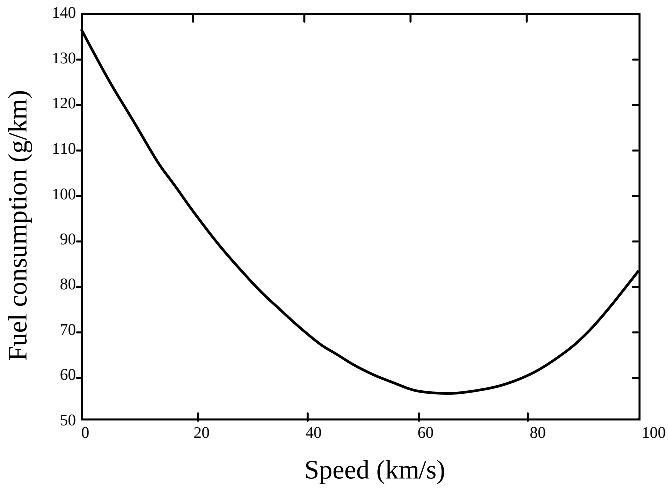


Figure 1. The relationship between speed and fuel consumption for a light duty diesel vehicle ([8])

in parentheses show the arc lengths whereas the numbers in brackets refer to the speed on an arc in the corresponding time interval. We assume that the GHG emission quantities at different speeds are as given in Table 1.

The planning horizon is divided into two equal intervals of length 1 time unit, namely $Z_1 = [0,1]$, $Z_2 = (1,2]$. One can assume that $Z_3 = (2, \infty)$ and the GHG emission corresponding to that time interval is equal to infinity.

Table 2. Calculations for scenario 1

Path	Detail	GHG emission	Time
1.1	0-1-2	28.0	0.70
1.2	0-2	32.0	0.50
1.1.a	0-1-2-3	69.6	1.80
1.2.a	0-2-3	64.0	1.00
1.1.b	0-1-2-4	38.4	1.07
1.2.b	0-2-4	46.0	1.00

Figure 2 and Table 2 give the details of scenario 1. Two alternative paths lead to internal node 2: path 1.1 visits node 1 whereas path 1.2 arrives at node 2 earlier but with a higher cost (GHG emission). However, as path 1.1 arrives later, the travel from intermediate node 2 to destination node 3 falls into the second time interval where the travel speed is less efficient. Thus, the path with higher cost and earlier time to node 2 results in less cost and earlier time when the arrival to node 3 is concerned.

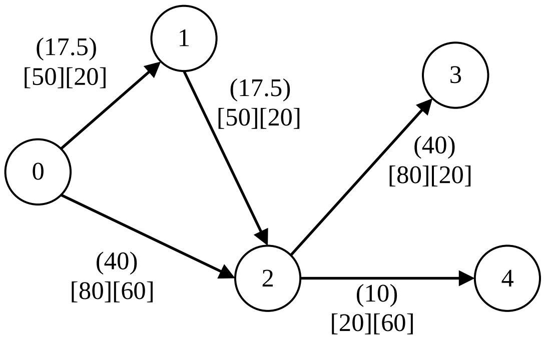


Figure 2. Sample network for scenario 1.

On the contrary, the travel speed in the second time interval on arc (2-4) is more efficient compared to that in the first interval. This makes the arrival within the second time interval more attractive. Accordingly, the final cost at the destination node 4 is lower on path 1.1.b. The path with lower cost yet later time in the previous stage yields lower cost and later arrival time at the destination.

Table 3. Calculations for scenario 2

Path	Detail	GHG emission	Time
2.1	0-1-2	40.0	1.00
2.2	0-2	32.0	0.50
2.1.a	0-1-2-3	60.0	1.67
2.2.a	0-2-3	64.0	1.00
2.1.b	0-1-2-4	88.0	1.75
2.2.b	0-2-4	64.0	1.00

Scenario 2 is depicted in Figure 3 with calculations in Table 3. This scenario is similar to scenario 1 from the cost point of view. But in this case, path 2.1 arrives at the intermediate node 2 later than path 2.2 due to its visit to node 1. As the speed in the second time interval is more efficient on arc (2,3), the cost at the destination node via path 2.1.a is less than the one via path 2.2.a. In summary, the path with higher cost and later time in the previous stage results in lower cost and later time at the destination.

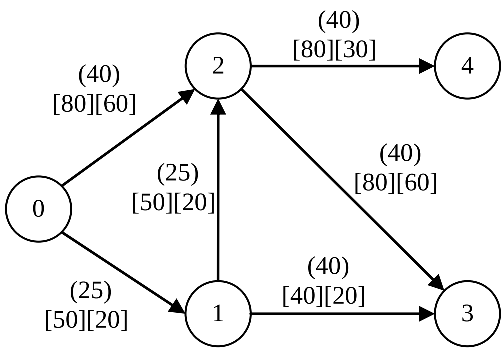


Figure 3. Sample network for scenario 2.

Moreover, lower cost path at any intermediate node may still have lower cost at the destination. The destination node 4 has speed values of 80 and 30 in time intervals 1 and 2, respectively. This helps the early arriving path to preserve its lower cost relative to the other. In this case, the path with lower cost and earlier time in the previous stage gives lower cost and earlier time at the destination.

Table 4. Calculations for scenario 3

Path	Detail	GHG emission	Time
3.1	0-1	16.0	0.25
3.2	0-1-2	18.0	0.50
3.1	0-1-2	36.0	0.75
3.2	0-1-2-3	38.0	1.00
3.1	0-1-2-4	59.0	1.16
3.2	0-1-2-3-4	53.0	1.50

Scenario 3 in Figure 4 further extends the previous scenarios to illustrate that the gain may not be immediately observed on the following arc. Path 3.2 visits intermediate node 1 before visiting node 2. Then, both paths visit node 3 before reaching the destination node 4. The speed efficiency is the same in both intervals on the arc (2,3). The less efficient speed on the first interval of arc (3,4) causes path

3.1 to have higher cost, as given in Table 4. So, the path with higher cost and later time at two consecutive intermediate nodes results in lower cost and later time at the destination.

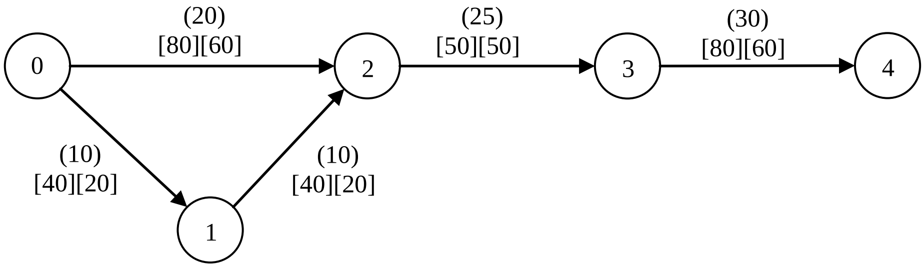


Figure 4. Sample network for scenario 3.

Table 5. Calculations for scenario 4

Path	Detail	GHG emission	Time
4.1	0-3	32.0	0.50
4.2	0-2-3	30.0	1.00
4.3	0-1-3	28.0	0.70
4.1	0-3-4	46.0	1.00
4.2	0-2-3-4	35.0	1.16
4.3	0-1-3-4	38.4	1.07

Finally, scenario 4 in Figure 5 and Table 5 shows that no pattern is valid in GPP and no dominance can be obtained between time-cost pairs. Among the three paths, the one whose cost is the second highest at intermediate node 3 gives the least cost path to destination node 4.

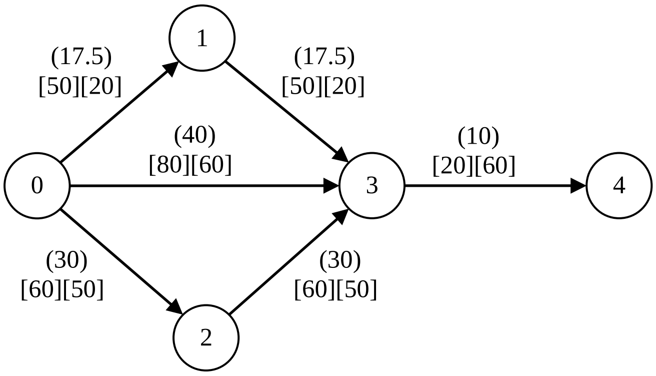


Figure 5. Sample network for scenario 4.

These scenarios also emphasize the fact that the optimal paths are not necessarily concatenated. In other words, the optimal paths do not form a tree. For example, consider scenario 1.a where the optimal path to node 2 is (0-1-2) while the optimal path to node 4 is (0-2-4), not (0-1-2-4).

The scenarios are generated to exhibit the cost behavior of different cost-time combinations. For illustrative purpose, we utilized some extreme cases such as the speed jumping from 30 to 80 or vice versa from one time interval to another. Although such jumps can be observed in real life when the time intervals are long, smoother increments or decrements are more common. For a more realistic model, one may shorten the duration of the time intervals while using a discrete-time approach.

3 GREENEST PATH ALGORITHM (GPA)

The Greenest Path Algorithm (GPA) is an extension of DA to the time-dependent case where the objective is to minimize a generic cost function. The algorithm maintains a cost label, an upper bound on the minimum cost path length to node i arriving in time interval t, with each node i for every time interval in [0, T] where node i can be visited. Keeping the minimum cost label within each interval is analogous to keeping the shortest distance label at each node in DA. When a node is selected from the queue, all the labels on all intervals are compared with the current labels on an adjacent node in the corresponding time interval. If the total cost of the current label carried to the adjacent node is less than the label at the adjacent node in the same time interval, the label on the adjacent is replaced. We refer this process as the evaluation of the labels. A limit on the total number of labels at each node is implemented to circumvent the computational burden of the increasing number of labels. Note that, when the limits on the total number of labels are relaxed, that is, set to infinity, GPA becomes an optimal algorithm for the GPP.

The main novelty with the algorithm comes from the usage of upper bounds to direct the search towards the sink node. We decrease the search space using upper bounds for the intermediate solutions. We implemented two kinds of bounds; one on the actual cost (AC) and one on the potential cost (PC). We compare the actual and the potential costs (summation of the actual cost with the possible minimum cost from to reach to the sink node) with the current upper bound which can be found using a simple heuristic. As no pattern exists for the greenest path problem, keeping only the minimum cost label may yield a suboptimal path whereas increasing the number of labels kept in a single time interval may improve the solution quality.

Also it is important to distinguish the terms “time bin” and “time interval”. Time bin is pertained to a time-dependent instance. It refers to a certain length of time which differs from others by a different speed value. On the other hand, being a parameter of the GPA, time interval is used to limit the number of labels that are kept in a certain length of time. Note that all the time bins and all the time intervals can be either equally distributed in length or otherwise among themselves.

4 COMPUTATIONAL STUDY

In this section, we first give details of the cost function and the networks used in this study. Then, we briefly comment on the effect of the proposed upper bounds. Finally, we compare the performance of the proposed method with [17]. We prohibit waiting at all nodes. Yet, due to the theoretical gain by cycling and the computational burden to check for the cycles, we do not implement a cycle check in our algorithm. The algorithms are coded in C# programming language and executed on an Intel Xeon 3.30 GHz computer with 32.0 GB RAM and 64-bit operating system.

The cost (emission rate in this study) is directly related with the speed. However, the method is not affected by the type of the cost function. In order to obtain the rate of emission (ε) per kilometer with different speeds, we use the fuel consumption function of [11];

$$\varepsilon = 0.0617v^2 - 7.8227v + 429.51$$

where ε is the rate of emissions (g/km) for an unloaded goods vehicle on a road with a zero gradient and v is the average speed of the vehicle (km/h).

For our computational experiments, we create congestion on the undirected Washington DC road network of Topologically Integrated Geographic Encoding and Referencing (TIGER) which includes 9,559 nodes and 14,909 arcs.

In our preliminary experiments, we observed that using AC reduces the computational time by 60.4% and the number of labels by 70.7% while keeping the cost at the same level. On the other hand, using

PC dramatically decreases the number of labels, hence the computational time, by 96.3% and 93.3% respectively. So, we decided to utilize both PC and AC bounds.

For the number of labels, we use 1, 10, 100 and 1,000. The lengths of the time intervals are set to 30, 60 and 600 seconds. Although using multiple labels in a single time interval can yield better solutions in theory, we did not observe such a pattern in our preliminary tests. Thus, we keep a single label in each time interval.

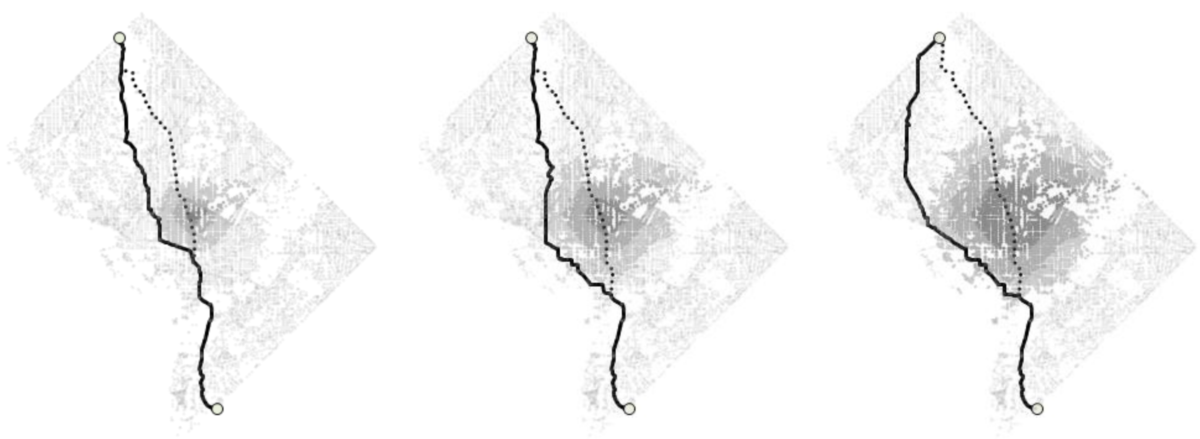
Table 6. Comparison for Washington DC data.

Time Interval Length		Label limit 1		10		100		1000	
		WÇE	GPA	WÇE	GPA	WÇE	GPA	WÇE	GPA
30	OF	6.277	6.259	6.243	6.251	6.232	6.232	6.232	6.232
	CT	0.8	0.8	1.3	1.2	6.7	3.1	37.1	2.8
60	OF	6.277	6.259	6.251	6.232	6.232	6.232	6.232	6.232
	CT	0.4	0.3	1.2	0.6	4.9	1.2	14.5	1.4
600	OF	6.277	6.259	6.232	6.232	6.232	6.232	6.232	6.232
	CT	0.1	0.1	0.5	0.1	1.2	0.1	1.2	0.1

Table 6 compares the objective function (OF) in kg and computational time (CT) in seconds of [17] (WÇE) and GPA. The computational time decreases with the increasing time interval length and decreasing label limit. When the label limit is set to 1, both algorithms become insensitive to the changing values of time interval length.

GPA performs better or matches the performance of WÇE in all settings taking the objective function into account except when label limit is equal to 1 and the time interval length is equal to 30. From the computational effort point of view, GPA performs better with the increasing label limit. When the label limit is increased to 1,000 from 100, WÇE uses nearly all the label capacity (10 millions) whereas the total number of labels found by GPA increase only by 18%, hence the lower computational times.

We observe that the greenest paths obtained on the Washington DC data travels around the congested area whereas the shortest path goes through the congested center. Figure 6 visualizes the expansion of the congestion and the corresponding shortest and the greenest paths. Higher level of congestion in Figure 6 (b) and Figure 6 (c) causes the greenest path to change towards to the western side of the city.



(a) (b) (c)

Figure 6. GPA path and the shortest path comparison on real data for three different congestion levels

5 CASE STUDY

To integrate the proposed algorithm into the Green Vehicle Routing Problem (GVRP), we create an instance with a single depot and 25 customers in Washington, DC area. The distribution of the customers is shown in Figure 7. The depot is shown with a yellow square and the customers are shown with blue circles. The demand values are distributed between 5 and 30 units. The capacity of a single vehicle is 80 units.

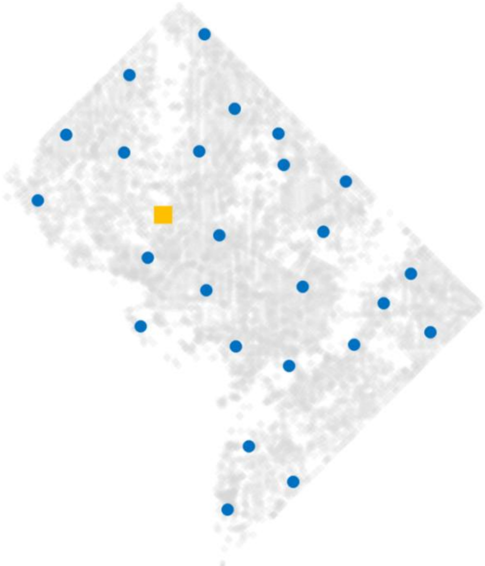


Figure 7. VRP instance based on Washington DC data

Table 7. Comparison of time independent and time-dependent VRP solutions

	Distance (km)		GHG emission (g)	
	Time-Independent VRP	Green VRP	Time-Independent VRP	Green VRP
Route 1	17.25	17.59	3,591.76	3,213.33
Route 2	20.31	22.56	4,284.10	4,157.88
Route 3	21.00	22.09	4,242.79	4,094.42
Route 4	20.34	20.34	3,717.50	3,717.50
Route 5	29.99	30.20	6,524.00	5,686.15
Route 6	31.06	31.06	5,708.90	5,708.90
TOTAL	139.95	143.85	28,069.04	26,578.17

We have two different solutions where the time-dependent, GHG minimizing Green VRP is compared with the time-independent version. Both methods yield six routes, two of them, namely route 4 and 6, being exactly the same. The results are summarized in Table 7. The second and the third columns give the distance values of each solution in detail. The fourth and the fifth columns give the corresponding GHG emission values in grams. The total distance of the Green VRP is 2.78% higher whereas it generates 5.31% less GHG emission. We observe that, building the routes by taking the congestion and the time-dependent travel times into account yields a decrease in the emission values as expected. This gain not only comes from using different links and routes but also from visiting the same customers in a different order. The routes generated are shown in Figure 8.

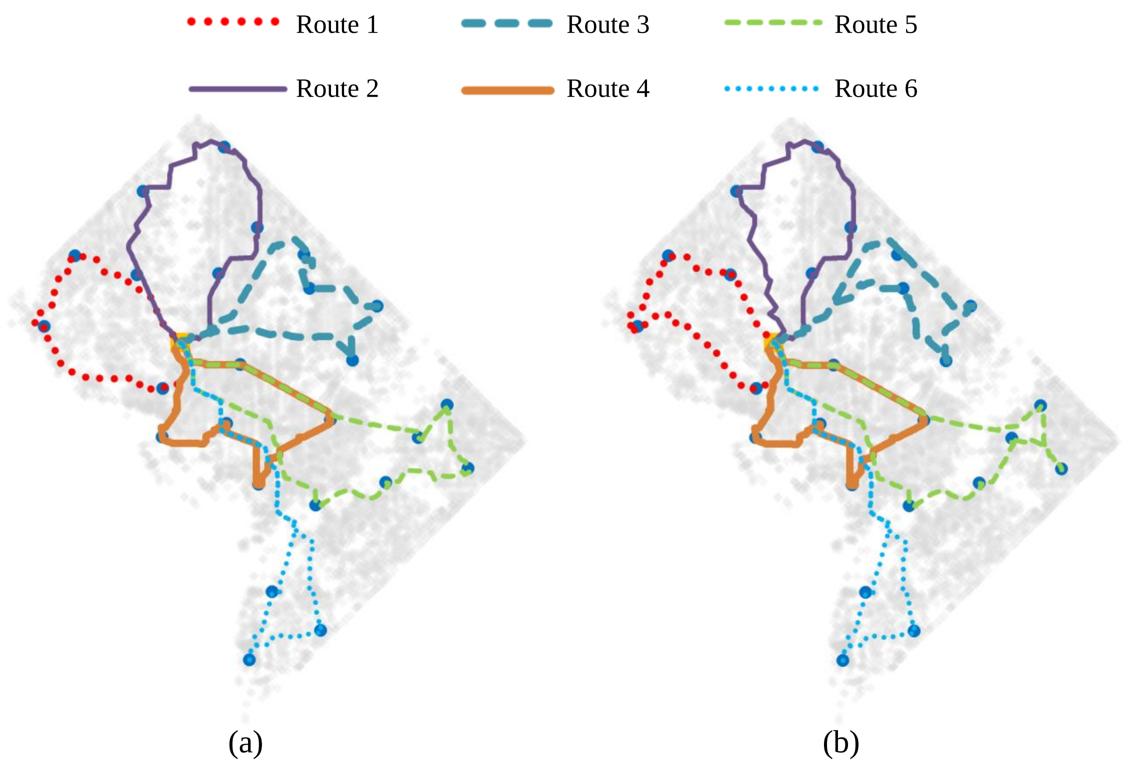


Figure 8. Solving VRP using (a) time-independent and (b) time-dependent information.

6 CONCLUSION AND FUTURE RESEARCH

With the growing concerns about the hazardous effects of transportation, sustainable logistics operations require new ways of doing business and planning approaches to decrease the negative impacts on the environment. Yet, finding the greenest path differs from the traditional path finding algorithms in having no pattern towards the optimal solution of the problem, which makes GPP a complicated optimization problem.

In this paper, we proposed GPA, a fast algorithm that determines greenest paths using bounds on the solution. Our tests using synthetic traffic data on a real road network showed that GPA provides promising results. It achieved better average results in faster time compared to the only currently available heuristic method of [17]. Testing the sensitivity of the algorithm to the changing values of time interval length and label limit, we reported the trade-off between the solution quality and the computational effort. We also integrated the proposed algorithm into the GVRP and reported the decrease in the emissions by taking the time-dependent travel times into consideration.

In this study, we did not allow waiting at any node. Further research will address incorporating different waiting policies into the GPA. In spite of their theoretical gain, we did not observe any advantage of using cycles or rarely observed where a label with larger time yielded a better solution in our tests on the real network. However, to better test the effect of the cycling concept on the GHG emissions in real life, we will test GPA on other real networks.

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