Improving Eco-Friendly Routing Considering Detailed Mobility Profiles, Driving Behavior and Vehicle Type

Ahmed Fahmin[1], Shenyi Zhang[1], Muhammad Aamir Cheema[1], Adel N. Toosi[1], and Hesham A. Rakha[2]

[1] Faculty of Information Technology, Monash University, Melbourne, Australia
[2] Charles E. Via, Jr. Department of Civil and Environmental Engineering, Virginia Tech, USA

ahmed.fahmin@monash.edu, szha0177@student.monash.edu, {aamir.cheema,adel.n.toosi}@monash.edu, hrakha@vt.edu

Abstract. Traditional vehicle routing algorithms aim to find the fastest or shortest route, whereas eco-friendly routing algorithms aim to find the route that minimizes vehicle fuel consumption or greenhouse gas (GHG) emissions. To accurately estimate fuel consumption and emissions along a route, a detailed mobility profile of the vehicle traveling on the route is needed including acceleration/deceleration and idling time. However, the existing techniques that aim to find eco-friendly routes make a simplistic assumption by assigning each road segment of the road network an average speed or average fuel consumption along the road, ignoring detailed mobility profiles and driving behavior (e.g., aggressive or moderate) altogether. This simplistic treatment leads to sub-optimal route choices because such representation fails to capture driving behaviors and detailed mobility profiles of the candidate routes resulting in poor quality estimates. Furthermore, many of the existing techniques employ a one-size-fits-all approach ignoring that different vehicles (e.g., truck vs car) and drivers exhibit different behaviors, thus, the most eco-friendly route may be significantly different for different types of vehicles and/or drivers. This paper addresses these limitations and presents an eco-routing algorithm that computes the most fuel economical route considering the detailed mobility profiles, driving behavior, and vehicle type. We conduct an extensive experimental study on a real road network considering different vehicles and driving behaviors and show that our algorithm generates routes that reduce fuel consumption by up to 35%.

Keywords: Eco-routing · Navigation systems · Mobility profile · Microscopic simulation · Intelligent transportation systems

1 Introduction

Road transport is a major contributor to greenhouse gas (GHG) emissions. In 2013–2014, domestic transport accounted for around 17% of Australia's GHG emissions, with approximately 60% of this attributable to light vehicles. From 2013–2014 to 2029–2030, transport emissions are projected to increase by 25% [1]. Reports from various other countries also show that the road transport accounts for 16% to 20% of the total global GHG emissions [2]. Various studies show that eco-friendly navigation strategies can significantly reduce fuel consumption and GHG emissions. For example, it was shown that approximately 12%–33% of fuel can be saved by using the most fuel economical route instead of selecting the fastest or shortest route [11]. Similarly, our previous work [5] also showed that 18%-23% of fuel could be saved by choosing a longer route that has better traffic conditions for the same origin-destination pair. Another study [11] validated the actual effects of different routes on fuel consumption, showing that the fuel consumption could be reduced by up to 33% at the expense of a 3% increase in trip-time. Inspired by this, many existing studies have focused on designing eco-friendly routing algorithms with a focus on minimizing fuel consumption and GHG emissions. Note that fuel consumption is directly proportional to GHG emissions and the techniques designed to minimize fuel consumption can be easily extended to minimize GHG emissions, and vice versa [20]. In the rest of the paper, we focus on minimising the fuel consumption (and our techniques can be immediately applied to minimise emissions by using the emission models instead of fuel consumption models).

Accurately estimating a route's fuel consumption is the key to developing an effective eco-routing algorithm. A large body of work has focused on developing models to estimate fuel consumption and emissions for different types of vehicles (see [30] for a comprehensive survey). Microscopic models such as VT-CPFM [23] are the most accurate fuel consumption models. However, these models require detailed mobility profiles (e.g., instantaneous speed, acceleration/deceleration, idling time) as well as parameters specific to vehicles (e.g., vehicle mass, engine details) and driving behaviors (e.g., hard brake vs soft brake). However, almost all existing eco-routing algorithms make simplistic assumptions. For example, they assume that the vehicles travel along an edge with a constant speed (e.g., at average link speed) [8, 11] ignoring the detailed mobility profile such as acceleration, deceleration, etc. Some works [13,22] create a weighted graph where each road segment (i.e., edge) is assigned a fuel consumption cost which is estimated based on the fuel consumption cost of other vehicles that traveled along this road (e.g., using historical or real-time data). This simplistic treatment compromises accuracy as the average values also fail to capture the detailed mobility profiles and do not take into account different vehicle types (cars vs trucks) and driving behaviors (aggressive vs moderate driving). Consequently, such simplistic treatment leads to sub-optimal route choices resulting in poor quality estimates (up to 40% inaccurate [30]). Furthermore, most of these techniques employ a one-size-fits-all approach ignoring that different vehicles (e.g., truck vs car) and drivers exhibit different behaviors; thus, the most eco-friendly route may be significantly different for different types of vehicles and/or drivers [20].

One of our earlier works [26] addressed the limitations mentioned above. However, the solution proposed in [26] assumes a connected vehicles environment where the server receives up-to-date travel information from the vehicles in real-time (e.g., each vehicle traveling on an edge sends its instantaneous speed, acceleration, deceleration etc. to the server which uses this information for accurate fuel consumption estimation in the navigation algorithm). While this strategy provides more accurate fuel consumption estimates, the assumption that the vehicles can send their detailed travel information for each edge to the server may not always hold, e.g., there may not be any (or enough) connected vehicle(s) on the road, the vehicles may not want to share their travel information due to privacy reasons, etc. In this paper, we remove this assumption and provide an eco-routing algorithm that does not rely on vehicles sharing their travel information with the server. Instead, we rely on the input road network graph where edge weights correspond to the speed on the edge (which can be obtained based on the current or historical traffic data). We create the mobility profile of a vehicle on-the-fly considering the maximum possible edge speed, traffic lights, vehicle type, and driving behavior.

We make the following contributions in this paper: (i) to the best of our knowledge, we are the first to propose an eco-friendly routing algorithm that uses highly accurate microscopic fuel consumption models and does not rely on vehicles sharing their travel information; (ii) we conduct an exhaustive evaluation of the proposed algorithm using a real-world road network considering three different types of vehicles and different driving behaviors; and (iii) we compare our proposed eco-routing algorithm with other routing strategies, including the shortest path algorithm, fastest path algorithm, and a recent work that estimates fuel consumption considering average speed. The results demonstrate that our approach generates routes that save up to 35% fuel at the expense of around 10% longer travel time or distance.

The rest of the paper is organized as follows. In Section 2, we formally define the problem and discuss related works. In Section 3, we present our proposed eco-friendly routing algorithm. In Section 4, we present our experimental study. Finally, Section 5 concludes the paper and presents directions for future work.

2 Preliminaries

2.1 Problem Formulation

A road traffic network is represented as a directed graph $G = (V, E)$ that consists of a set of nodes/vertices V and a set of edges/links E. Each edge $e = (u, v) \in E$ is a directed edge from vertex $u \in V$ to vertex $v \in V$ and is associated with its length e^l (i.e., the length of the road segment connecting vertex u to vertex v) and the maximum speed on this edge e^s (e.g., the speed limit of the edge or the maximum possible speed based on the current traffic). A path from a source $s \in V$ to a target $t \in V$ is a path on the graph G defined as a sequential list of edges: $(s, u), \ldots, (v, t)$. The input to the routing algorithm is the graph G, source s, target t, the vehicle type the user is driving (e.g., Honda Accord 2022), and the driving behavior (typical acceleration, deceleration values for the driver). Fuel consumption of a path is the total fuel consumed by the user traveling on the path on the specified vehicle following the given driving behavior. The problem is to return the path from s to t that has the minimum fuel consumption among all paths from s to t in G.

2.2 Related Work

There are two key components of an eco-friendly navigation system. First, it requires models to accurately estimate fuel consumption or emissions. Second, it requires a routing algorithm that can compute the most eco-friendly route. A large body of work has focused on developing models to estimate fuel consumption and emissions for different types of vehicles (see [30] for a comprehensive survey). Microscopic models such as VT-CPFM [23] are the most accurate fuel consumption models. We employ the VT-CPFM model in this paper (see details in Section 3.2). These models require detailed mobility profiles (e.g., instantaneous speed, acceleration/deceleration, idling time) as well as parameters specific to vehicles (e.g., vehicle mass, engine details) and driving behaviors (e.g., hard brake vs soft brake). Next, we discuss the existing work on routing algorithms.

Routing algorithms have received significant research attention in the past couple of decades [6,14,17,18,21,28]. Dijkstra's algorithm [12] and A*-search are among the most fundamental algorithms that do not rely on any specific preprocessing on the graph. A large body of work has focused on developing routing algorithms that build indexes on the graph in a pre-processing phase and significantly improve the query performance, e.g., see contraction hierarchies [14,24], hub-labeling [4,6,19] etc. However, these more efficient algorithms are not typically suitable for eco-friendly routing because the fuel-consumption is typically computed on-the-fly and, therefore, pre-processing may not be possible. For this reason, most existing algorithms [7,11,25,26] including this work use Dijkstra's or A*-search. Guo et al. [15] presented a Mesoscopic model for eco-routing and further integrated it with Dijkstra's algorithm to select eco-friendly routes. Boriboonsomsin et al. [9] use the Dijkstra algorithm with the binary heap priority queue to calculate routes for their eco-routing navigation system. Users' route preferences, such as favoring freeways or avoiding toll roads, are taken into account in their path building approach. When it comes to electric vehicles, De Nunzi et al. [10] propose a novel macroscopic energy consumption model and a novel eco-routing strategy based on Bellman-Ford's algorithm. All existing routing algorithms suffer from the limitations discussed in Section 1 which are addressed by our work.

3 Methodology

3.1 Overview

We adapt Dijkstra's algorithm [12] for computing the route with the minimum fuel consumption cost (see Algorithm 1). The key difference compared to Dijkstra's algorithm is that the fuel consumption costs are calculated by generating mobility profiles on-the-fly. Specifically, when the algorithm extracts a vertex v, its adjacent edges are expanded as follows. Based on the road network G, vehicle parameters vp, and the driving behavior db, our algorithm generates a detailed mobility profile on-the-fly for each edge adjacent to v (line 10). A detailed description of how this mobility profile is generated on-the-fly is presented in Section 3.3. The algorithm then employs the VT-CPFM fuel consumption model to compute the fuel consumption cost for traveling on this edge while taking the mobility profile generated for the edge and the vehicle type into account (line 11). Then, similar to traditional Dijkstra's algorithm, each adjacent vertex u of v is inserted in the priority queue with minimum estimated fuel consumption cost to travel from s to u. The algorithm stops when the target t is expanded.

Algorithm 1: Proposed Eco-Friendly Routing Algorithm

Input: $G = (V, E)$: road network; vp: vehicle parameters (Table 1) ; db: driver behavior (i.e., acceleration/deceleration values); s: source ; t: target

Output: The most fuel economical route from s to t

1 **foreach** $v \in V$ **do**
2     $fc[v] \leftarrow \infty$; // $fc[v]$ is fuel consumption to reach v
3     $pred[v] \leftarrow null$; // $pred[v]$ stores predecessor of v on optimal path
4 insert s in a priority queue Q with $fc[s] = 0$;
5 **while** Q *is not empty* **do**
6     $v \leftarrow$ vertex in Q with the minimum cost ;
7   **if** v *is the target node* t **then**
8   extract path from s to t using $pred[]$ and **return** the path;
9   **foreach** *neighbor* u *of* v **do**
10         $MP(v, u) \leftarrow getMobilityProfile(v, u, G, vp, db)$; // Section 3.3
11         $edgeCost \leftarrow$ VT-CPFM$(G, vp, MP(u, v))$; // Section 3.2
12   **if** $fc[v] + edgeCost < fc[u]$ **then**
13             $fc[u] \leftarrow fc[v] + edgeCost$;
14             $pred[u] \leftarrow v$;

3.2 VT-CPFM Fuel Consumption Model

In this research, we use VT-CPFM fuel consumption model [23] which is among the most accurate fuel consumption models. We remark that our proposed framework can easily employ other microscopic fuel consumption models if required. In VT-CPFM, fuel consumption at time t denoted as $FC(t)$ is computed as

$$FC(t) = \begin{cases} \alpha_0 + \alpha_1 P(t) + \alpha_2 P(t)^2, & \forall P(t) \geq 0 \\ \alpha_0, & \forall P(t) < 0 \end{cases} \quad (1)$$

where $P(t)$ denotes instantaneous vehicle power at the wheels (kW) at time t, and α_1, α_2 and α_0 denote vehicle-specific model coefficients. The instantaneous power of the vehicle $P(t)$ is computed as

$$P(t) = \left(ma(t) + mg\frac{C_r}{1000}(c_1 v(t) + c_2) + 0.5\rho_a A_f C_D v^2(t) + mg \cdot \tan(\theta) \right) \times \frac{v(t)}{1000\eta_d} \quad (2)$$

where m is the vehicle mass in kg, $a(t)$ is the value of acceleration in m/s^2 at t, g is the gravitational acceleration ($9.8066m/s^2$), θ is the road inclination angle (assumed to be zero if unavailable), C_r, c_1, c_2 are the rolling coefficients (unit-less), $v(t)$ is the instantaneous vehicle speed in m/s at t, ρ_a is the air density at sea level ($1.2256kg/m^3$), A_f is the frontal area (m^2) of the vehicle, C_D is the drag coefficient (unit-less), η_d is the driveline efficiency. For details of the VT-CPFM model and how the coefficients are calculated, please see [23, 27].

3.3 Generating Detailed Mobility Profile

Recall that accurately estimating fuel consumption using VT-CPFM model requires instantaneous speed $v(t)$ and acceleration $a(t)$ at each t. To this end, we generate a mob|ility profile on-the-fly which contains instantaneous speed and acceleration information needed by the VT-CPFM model.

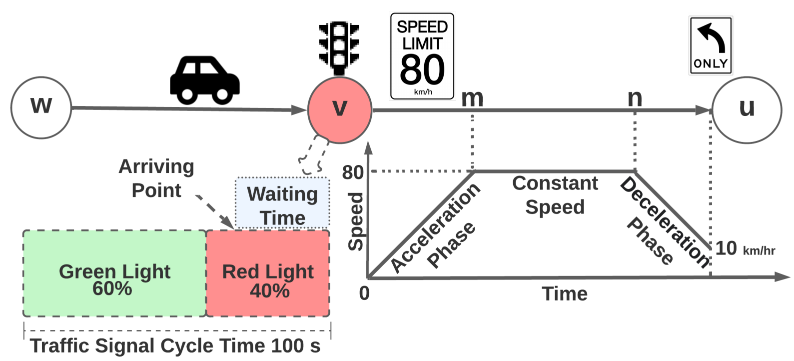


Fig. 1: Generating Mobility Profile

Assume that a vehicle is at vertex v and will travel on the adjacent edge $e = (v, u)$ (see Fig. 1 as an example). Let s^v be the initial speed of the vehicle at vertex v (e.g., if the vehicle had stopped at v due to a traffic light, then s^v is 0). Let s^e be the maximum possible speed for the edge (e.g., say 80 km/h is the speed limit for the road) and s^u be the speed at which the vehicle will arrive at u, e.g., if the vehicle needs to slow down to 10 km/h at u (say for a left turn), s^u will be 10 km/h. The mobility profile is generated in up to three phases: 1) in the acceleration phase, the vehicle accelerates until the speed reaches from s^v to s^e (or until the vehicle reaches at the end of the edge); 2) if the vehicle reaches the maximum possible speed of the edge s^e, it continues traveling at s^e

until it is about to reach the end vertex u; and 3) when the vehicle is arriving at u, the vehicle decelerates such that the speed reduces to s^u when it reaches u. The acceleration and deceleration of the vehicles are set based on the driving behavior of the user and the vehicle type (which are inputs to the algorithm). Consider the example in Fig. 1. The mobility profile for the vehicle traveling from v to u is generated by accelerating the vehicle starting from v until the speed reaches from 0km/h to 80km/h at point m on the edge. The vehicle continues traveling at this speed on the edge until point n and then decelerates towards the end of the edge such that its speed reduces to 10km/h when it arrives at u.

For a more accurate fuel consumption estimation, we also consider the idling time at traffic intersections. Fig. 1 shows an example where a vehicle travels from vertex w to vertex v which has a traffic light. If the real-time traffic signal information is available (e.g., using vehicle-to-infrastructure communication), it can directly be used by our algorithm to compute idling time at the red light if any. Otherwise, we handle this as follows. Assume that the traffic light has a 100 seconds cycle (60 seconds green and 40 seconds red). Our algorithm computes the arriving time considering the mobility profile and then calculates the probability of meeting a red light when the vehicle arrives at vertex v. Specifically, the system generates a random number n between 1 to 100 and assumes that the vehicle reaches at v at time n in its cycle, e.g., if n is at most 60, the vehicle arrives at the light when it is green and if n is greater than 60 it arrives at the signal when it is red and needs to wait for $(100 - n)$ seconds.

4 Experiments

In this section, we present our experimental study. First, we show how the fuel consumption estimates are affected when the average speed is used instead of the instantaneous speed. Then, we compare the route generated by our approach with some competitors in terms of total fuel consumption, travel distance, and travel time. We also show the effect of driving behavior and vehicle types.

4.1 Experimental Setup

We downloaded the road network of Melbourne from OpenStreetMap [16] which includes length and speed for each edge as well as traffic signal information. The road network contains $784,622$ nodes and $862,711$ edges. We assume that each traffic signal cycle consists of 60% green time duration and 40% red time duration. We randomly generated 1 million source-target pairs in the road network. We computed the shortest distances between each pair and divided the queries based on these distances into 75 buckets (1km - 75km). We ran each experiment on all the query buckets and took the average unless mentioned otherwise.

We use three different vehicles: *Honda Accord*, *Ford Expedition* and a *truck*. The vehicle-specific parameters are acquired from the U.S. Environmental Protection Agency (EPA) website [3]. Table 1 shows these parameters. The Honda

		Vehicle Model		
		Honda Accord	Ford Expedition	Truck (International/9800 SBA)
Mass m (kg)		1469	2626	7239
Drag coefficient C_D		0.325	0.41	0.78
Frontal Area A_f (m^2)		2.3	3.88	8.9
Rolling Coefficients (unit-less)	C_r	1.75	1.75	1.75
	c_1	0.0328	0.0328	0.0328
	c_2	4.575	4.575	4.575
Acceleration a (m/s^2)		3.725	4.326	1.788

Table 1: Vehicle Specific Parameters

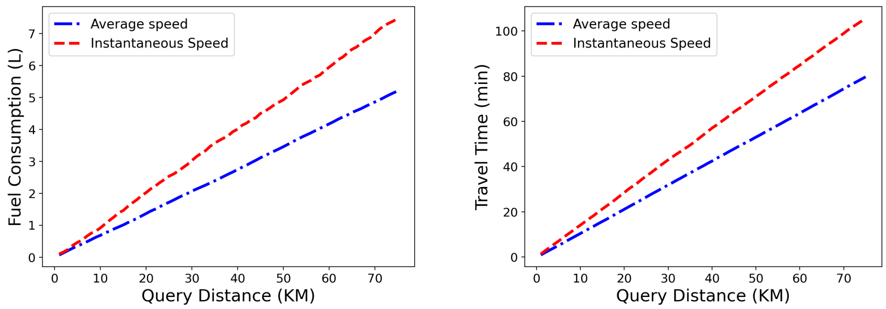
Accord is representative of sedan passenger cars, and Ford Expedition is a full-size sport utility vehicle (SUV). We tested one of the truck models (International/9800 SBA) to characterize typical truck fuel consumption behavior. Many other studies [20, 26, 29] have also utilised these vehicles. The acceleration values for these vehicles were obtained from the manufacturer's website (for example, the Honda Accord takes 7.2 seconds to go from start to 60 mph). To explore the impact of driver behavior, we assume three types of driver profiles, e.g., aggressive, calm, and conservative. Drivers with a calm profile always accelerate as per the manufacturer's website. We assume that the aggressive drivers tend to accelerate 10% more than the calm drivers, and conservative drivers undercut by 15%. The default driving behavior is calm unless mentioned otherwise.

4.2 Competitors

We compare our algorithm (shown as "Mobility Profile" in experimental results) with three other competitors: 1) shortest path algorithm (shown as "Shortest") which returns the shortest path in terms of total distance; 2) fastest path algorithm (shown as "Fastest") which returns the shortest path in terms of travel time; 3) a recent vehicle path planning (VPP) method [15] (shown as "VPP") which computes the most eco-friendly route but considers average speed for each edge for fuel estimation instead of considering the detailed mobility profile. VT-CPFM fuel consumption model is among the most well-known and accurate models for estimating fuel consumption. Therefore, we use the VT-CPFM fuel consumption model to compute the actual fuel consumption for the route generated by each of the approaches.

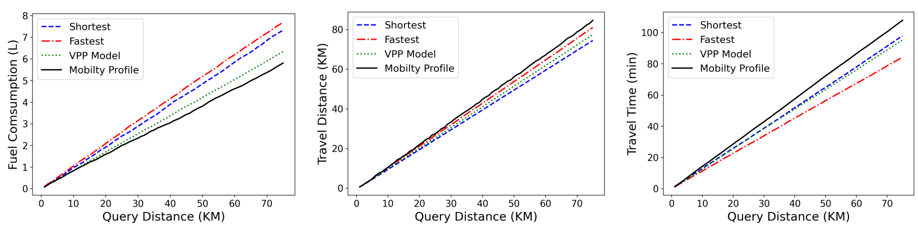
4.3 Results

Effect of using average speed instead of instantaneous speed. Similar to the existing works that show that using average speed to estimate fuel consumption results in poor estimation, we also conduct experiments on how the fuel consumption estimates are affected when instantaneous speed (e.g., the speed



(a) Fuel Consumption Comparison (b) Travel Time Comparison

Fig. 2: Effect of considering Average Speed and Instantaneous Speed on estimation of fuel consumption and travel time (Honda Accord)



(a) Fuel Consumption (b) Travel Distance (c) Travel Time

Fig. 3: Performance Comparison (Honda Accord)

at each time t) is used instead of average speed on the edge. We computed the shortest path (in terms of distance) for each query and then estimated the fuel consumption of this path using the VT-CPFM model and show the results in Figure 2a. The results show that, as expected, using the average speed significantly underestimates the fuel consumption (up to 42%) as it ignores acceleration, deceleration, and idling time which are major contributors to fuel consumption. Figure 2b shows the effect on total travel time when the travel time is estimated, assuming that the vehicle moves on the edge with constant (average) speed compared with when instantaneous speed is taken into account. The results show that using the average speed significantly underestimates the travel time (by up to 34%) because it ignores idling time, acceleration, deceleration, etc.

Comparisons of routes generated by different algorithms In this experiment, we run each algorithm to generate routes for each query and compare these routes on their total fuel consumption, total distance and total travel time. Figure 3 shows the results. Figure.3a shows that considering the detailed mobility profile significantly reduces the fuel consumption especially when the distance between source and target is bigger. However, Figure. 3b and Figure. 3c, that this saving in fuel consumption comes at the expense of routes that are slightly longer and take more travel time. Table. 2 shows the average percentage increase or decrease of the competitors compared to our approach, e.g., assuming conservative driving, the shortest path consumes 33.4% more fuel compared to our approach, whereas its distance is 11.4% smaller. The results show that our approach significantly reduces fuel consumption at the expense of a somewhat longer route or more travel time.

Driver Behavior	**Shortest Path**			**Fastest Path**			**VPP [15]**		
	Fuel	**Dist.**	**Time**	**Fuel**	**Dist.**	**Time**	**Fuel**	**Dist.**	**Time**
Honda Accord									
Aggressive	19.2% ↑	12.3% ↓	3.7% ↓	25.3 ↑	3.1% ↓	9.2% ↓	8.9% ↑	7.2% ↓	5.5% ↓
Calm	26.9% ↑	11.2% ↓	4.6% ↓	31.2% ↑	3.4% ↓	10.6% ↓	12.7% ↑	7.8% ↓	6.7% ↓
Conservative	33.4% ↑	11.4% ↓	5.9% ↓	35.3% ↑	3.9% ↓	13.4% ↓	16.1% ↑	7.1% ↓	8.2% ↓
Ford Expedition									
Aggressive	17.3% ↑	10.1% ↓	4.1% ↓	19.5 ↑	3.5% ↓	9.6% ↓	7.8% ↑	6.9% ↓	6.3% ↓
Calm	23.7% ↑	10.4% ↓	5.2% ↓	27.5% ↑	2.7% ↓	11.5% ↓	10.9% ↑	7% ↓	7.8% ↓
Conservative	28.1% ↑	10.3% ↓	6.3% ↓	32.9% ↑	3.3% ↓	12.9% ↓	13.1% ↑	7.2% ↓	8.5% ↓
Truck (International/9800 SBA)									
Aggressive	10.4% ↑	10.2% ↓	3.4% ↓	17.1 ↑	2.2% ↓	12.2% ↓	5.2% ↑	6.9% ↓	6.8% ↓
Calm	15.5% ↑	9.8% ↓	4.2% ↓	22.4% ↑	2.9% ↓	14.3% ↓	7.9% ↑	6.3% ↓	7.9% ↓
Conservative	18.6% ↑	10.4% ↓	4.8% ↓	25.6% ↑	2.7% ↓	16.5% ↓	12.1% ↑	7.2% ↓	9.2% ↓

Table 2: Percentage increase (↑) or decrease (↓) of competitors compared to our algorithm in terms of fuel consumotion, distance and travel time

5 Conclusions and Future Work

Almost all existing eco-friendly routing algorithms make a simplistic assumption that the vehicles move with a constant speed on an edge ignoring the acceleration, deceleration, idling time etc. Consequently, this results in a poor estimate of the fuel consumption model which leads to poor quality eco-friendly routes. We addressed this limitation and considered detailed mobility profiles of the vehicles. We also considered the impact of traffic signals to include the idling time of the vehicles at red lights. Furthermore, we considered account vehicle type and driving behavior for more accurate fuel consumption estimates. Our experimental study on a real-world road network and three different vehicles showed that our proposed eco-routing algorithm returns routes with significantly lower fuel consumption.

Almost all existing works, including this work, rely on basic shortest path algorithms such as A*-search or Dijkstra's algorithm to compute the path with the lowest fuel consumption or emissions. However, these algorithms are not suitable for large graphs such as road networks as it may take several seconds for these algorithms to answer a single shortest path query. Hence, such approaches are unsuitable for large-scale deployment in real-world navigation systems that need to compute tens of thousands of routes per second. An interesting direction for future work is to design new data modeling, indexing, and query processing techniques to efficiently compute eco-friendly routes while considering detailed mobility profiles, driving behavior, and vehicle types. Another interesting direction for future work is to study more advanced eco-friendly routing queries such as travel time/distance constrained eco-friendly routes (e.g., find the most eco-friendly route such that the length of the route is no longer than 1.2 times of the shortest route), diverse eco-friendly routes or finding kNNs in terms of fuel consumption instead of distances. Also, in this work, we assumed 100-seconds traffic light cycle (green light 60% and red light 40%). In future work, we will also use a phase split and compute the green light times depending on which phase controls the link. Furthermore, micro-simulation of a network should also be used to compare our estimated fuel consumption to the actual fuel consumption.

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