TAGRouting: A Real Time Traffic Aware Green Routing for Fuel Consumption Reduction

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ABSTRACT

State of the art routing algorithms are usually based on shortest time routing or shortest distance routing. However, we identify that these approaches do not yield the routine which consumes least energy. Shortest time routing always searches for faster tracks, usually at the price of longer distance. The engine works more efficiently when road is clear, so the Miles Per Gallon (MPG) would be higher for shortest time routine. However, the increase of total distance may finally increase total fuel consumption, thus high MPG is not equivalent with low fuel consumption. Shortest distance routing seems to be able to generate minimum fuel consumption routine, but this is not always true, because shortest distance routine usually includes heavy traffic streets. The low efficiency usually offsets the benefit of shorter distance, thus short distance is not equivalent to low fuel consumption.

Current least fuel routing strategies aim at providing a routine consuming least energy, but without considering real time traffic information, so the yielded routine is not optimal.

In this work, we propose a real-time Traffic Aware Green Routing scheme (TAGRouting). This scheme uses a map data based directed graph which is labeled with real time traffic information. The corner stone of TAGRouting is the reliable estimation of fuel consumption to pass through one section of road. To this end, real world driving traces and real time traffic information are used to train the model and estimate fuel consumption. We evaluate TAGRouting with the data from urban district in Stockholm, Sweden. In this example, compared with shortest time routing, the TAGRouting can reduce fuel consumption by up to 16.9%; compared with shortest distance routing, our scheme can reduce fuel consumption by up to 18.8%.

1. INTRODUCTION

Total energy used in United States in 2013 is about 97.4 quads (a unit used by U.S. Department of Energy, 1 quad = 10^{15} BTU). This is equivalent to about 10^{17} (BTU) [1] or 17.2 Billion barrels of crude oil [2]. 27.72% of the energy is used for transportation. Thus transportation is one of the most crucial sectors that need energy reduction.

Technology advancement on engine efficiency and vehicle electrification contribute a lot in reducing energy usage of transportation sector by enhancing energy efficiency. Besides these efforts, the abundant information from the traffic system provides many opportunities to manage the energy consumption in a more efficient way. Fuel economy is an important metric for efficiency, which is valued by both customers and manufactures(see e.g. [3]). The metric to evaluate the fuel economy is usually Miles Per Gallon (MPG) or Liters/100km. There are an enormous amount of efforts in place to reduce the energy consumption of vehicle by enhancing the fuel economy. Higher fuel economy usually means higher efficiency of vehicles. However, the ultimate objective is to decrease fuel consumption, not to enhance some metrics like MPG.

In order to achieve the ultimate objective, we propose the real time Traffic Aware Green Routing (TAGRouting), which utilizes the real time traffic information and driving history, to find the least fuel consumption routine for vehicles. This scheme answers the questions: **How to Decrease the Total Fuel Consumption from Start Point to the Terminal**. TAGRouting is different from either the shortest time routing or shortest distance routing.

Shortest time routing attempts to keep vehicles driving in higher speed roads as much as possible. This method comes with better energy efficiency, but it also causes longer driving distance and increases total energy consumption. Shortest distance routing comes with shorter distance driven, but it usually causes the decrease of speed. Lower driving speed means engine operates at lower efficiency, which would leads to the increase of total fuel consumption. Real time traffic information is utilized to balance the trade-off between distance and efficiency.

The contributions of this work are listed as following:

- To characterize the relationship between fuel consumption and average driving speed, we compare the fuel economy and fuel cost rate in terms of effectiveness to estimate the total fuel consumption of passing through one section of street. Fuel cost rate is selected as the suitable proxy to estimate fuel consumption, and different regression models are compared to characterize the relationship between fuel cost rate and average speed. Finally we select Exponential Regression model due to its consistence with the nature of engine fuel consumption map.

- To provide the information of average driving speed corresponding to a section of road, real time traffic information is utilized to make the speed labeling on map data. With the fuel cost rate characteristics generated from driving history, we estimate the fuel consumption to pass one section of road.
- To evaluate the benefits of TAGRouting, an initial TAGRouting service is provided for urban district of Stockholm, Sweden. Compared with shortest time routing and shortest distance routing, the TAGRouting can reduce fuel consumption by up to 16.9% and 18.8% separately.

The system diagram of this work is depicted in Figure 1. Different blocks in the diagram would be analyzed in later parts of this work. This paper would be organized as following:

- **Section 2**: The suitability of different proxies for estimating fuel consumption of passing through sections of roads are discussed. The relationship between fuel cost rate and average road speed is characterized in different regression models, which are then evaluated to select the most suitable model for later fuel consumption estimation.
- **Section 3**: Fuel consumption estimation is heavily relying on the real time traffic information, which is discussed in this section. Also, the source of the map data, labeling of the map data and traffic data are also discussed.
- **Section 4**: In this section, results of TAGRouting is given, along with analysis related with varying traffic conditions. Comparison has been made with current routing services, such as shortest distance and shortest time routing.
- **Section 5**: We give some previous works related with energy saving routing.
- **Section 6**: Final conclusion of this work is given here.

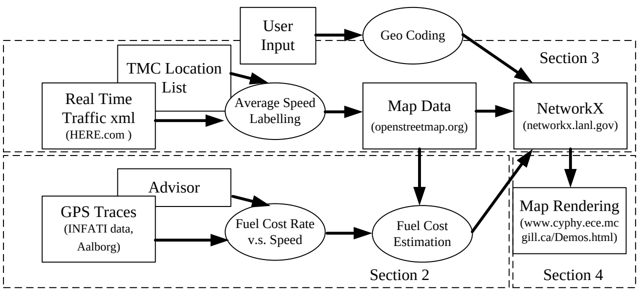


Figure 1: System Diagram

2. FUEL CONSUMPTION ESTIMATION

Fuel consumption depends on a lot of factors. They can be divided into two categories: passive or active.

Passive factors include vehicle specification and traffic condition. Vehicle specification dominates the fuel economy of a car, so different cars have different rated fuel economy. However, although the vehicle specification is stable (although affected by ageing effects), traffic condition, on the other hand, is variant, uncontrollable and usually unpredictable. With the development of traffic technologies, more and more traffic data is available, updated in real-time to prevent traffic jams, as discussed in Section 3.1.

Active factors are usually defined as driving behavior, which explains the fuel economy difference of the same car while driven by different drivers. There are many eco-driving advices widely suggested. Jakobsen et al. [4] listed and evaluated 12 advices to improve fuel economy. All these advices are trying to prevent unnecessary accelerations and maintain a steady speed. Driving behavior varies a lot among different drivers, but remains stable, which can be recognized for further control strategy optimization. There are some works for the driving pattern recognition, as in [5, 6]. This part is discussed in Section 2.4.

In the following of this section, we would investigate the relationship between fuel consumption (as the dependent variable) and these factors. Firstly in Section 2.1 and Section 2.2, we would discuss the appropriate proxy for estimating the total fuel cost of passing through one section of road. Then in Section 2.3, we would evaluate the effectiveness of different regression models, including linear, Exponential, Polynomial, and Gaussian regression models. The active factors affecting the fuel consumption characteristics would be discussed in the Section 2.4. Brief description about data source is given in Section 2.5 and method to get the fuel consumption data is given in Section 2.6.

NOTE: in later parts of this work, we use Meters Per Second (MPS) as the unit of vehicle speed. 1 MPS = 3.6 KM Per Hour (KPH) = 2.2369 Miles Per Hour (MPH).

2.1 Fuel Economy for Fuel Cost Estimation

The popular metric for fuel economy is usually Miles Per Gallon (MPG) in North America, or Liters per 100 km elsewhere. Both these two metrics are measuring the fuel cost versus distance driven. The most basic solution to evaluate the fuel consumption to drive through one section of road, is to take the average fuel economy of driving through this section of road as the fuel economy estimation. With the knowledge of the length of road, the fuel cost of passing through one section of road can be estimated.

$$fuel_{roadA} = Length_{roadA}/MPG_{roadA} \tag{1}$$

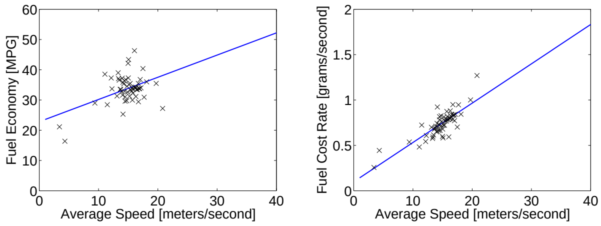
Two reasons justify the use of MPG or L/100km to gauge the fuel economy of cars:

- Distance is easier to measure, and the total distance of the commute routine is constant. People usually know how long they would drive every day.
- Fuel economy is publicly available, tested according to the driving cycle required by the governmental regulators. The MPG data is constant and irrelevant with varying traffics.

However, there are **Two Weaknesses** of using fuel economy to estimate the fuel cost to drive through one section of road as in (1):

- Fuel cost of one section of road **varies** a lot according to **different time of day**, or more accurately, to different traffic condition.

- Even at the same time of day, traffics would be different **from day to day** due to construction, accidents, or unpredictable reasons.



(a) Fuel Economy (b) Fuel Cost Rate

Figure 2: Fuel Economy v.s. Fuel Cost Rate, Road #3254

The same driver drives the same car through the same section of road, for many times, as shown in Figure 2a. Each dot represents one passing. MPG value varies from 17 to 46. So labeling each section of road with a static fuel economy value is less effective. The reason of such variation of fuel economy value, lies in the variation of traffics. As shown in the Figure 2a, MPG varies a lot at different average speed. This means the fuel cost to drive from workspace back home at 40 MPH would be different with that at 10 MPH. In order to estimate the fuel consumption to driver through one section of road, we need consider **the real time traffic condition**. More details of real time traffic information are in Section 3.1.

The reason we do not include time of a day as independent variable in Figure 2a, is that the underlying factor affecting fuel cost rate is the congestion level on roads, not the time of a day. The possible relation between time of a day and the congestion level is due to the periodic commute behaviors of people.

However, even if the traffic information is known, MPG or L/100km is not a good metric to help us to estimate the fuel cost to pass through one section of road. This is caused by the less relevance with real time traffic conditions of the metric MPG or L/100km, as seen in the Figure 2a.

In order to overcome the shortcomings of fuel economy as a proxy to estimate the fuel cost, we introduce the metric fuel cost rate in Section 2.2.

2.2 Fuel Cost Rate for Fuel Cost Estimation

Fuel Cost Rate (FCR [grams/second]) is a more accurate metric to estimate fuel required to drive though one section of road. Two reasons contribute to the effectiveness of FCR.

- The reason that engine consumes gasoline is the piston motion, not the moving of car. The fuel consumption in one second is dependent on current rotation speed and torque provided, not on the number of rotations of wheels.
- Engine would still consume fuel even at idling. According to the research conducted by Argonne National Laboratory, idling would consume 0.279cc gasoline per second, for Ford Fusion 2011 [7]. In the heavy traffic jam, this part of fuel consumption can be even more important.

With the driving data from the same driver on same car on the same road, we redraw the relation between FCR and average speed as shown in Figure 2b. The Analysis of Variables (ANOVA) of these two linear regressions are shown in Table 1.

Table 1: ANOVA for Fuel Economy and Fuel Cost Rate Regression, $\alpha = 0.05$, of Car01

Proxy	RMSE	RMSE Prediction	R^2
MPG	0.1464	0.1504	0.2944
FCR	0.0867	0.1159	0.7214

As shown in Table 1, the normalized RMSE of FCR is lower than that of fuel economy, either of the regression or the prediction. The Normalized Root Mean Square Error (NRMSE) for the fuel economy linear regression is 0.1504, while the NRMSE of FCR is only 0.1159. Further, the data in column R^2 exhibits that, at least for linear regression, fuel economy is not a suitable proxy to predict the fuel consumption of passing one section of road. In terms of linear regression, fuel cost rate is more suitable for characterizing the relationship between the fuel consumption and the current average speed. In later parts of this work, we would use the fuel cost rate to measure the fuel consumption of sections of road, as in (2).

$$fuel_{roadA} = Length_{roadA}/\bar{v}_{roadA} \times FCR_{roadA}(\bar{v}_{roadA}) \quad (2)$$

Conclusion: Fuel economy (MPG or Liters/100km) is not suitable proxy for estimating the fuel cost at different traffic conditions. **Fuel Cost Rate** would be used for estimating the fuel cost.

2.3 Regression Model

In this section, we explore the different regression models to characterize the relationship between fuel cost rate and average speed of roads. We continue to try to use the Linear Regression in Section 2.3.1, and explore the Polynomial Regression, Exponential Regression, and Gaussian Regression in Section 2.3.2. In Section 2.3.3, we discuss the potential improvement on fuel cost estimation with the access to more traffic information.

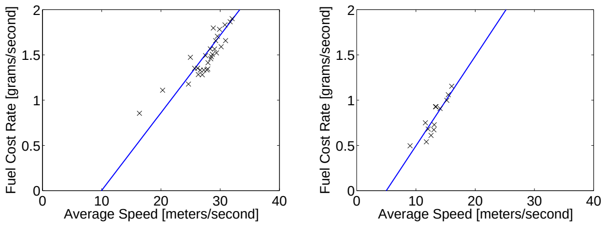
2.3.1 Linear Model

Purpose of this section is to evaluate the effectiveness of linear model, for the regression of the relationship between fuel cost rate and the traffic.

Vehicles usually exhibit higher fuel economy on highway than in the city. Even in the city, the specific conditions of sections of road would also affect the fuel cost rate characteristics. In order to evaluate the effects of different roads on fuel cost rate, we take several streets which have been passed through for many times.

In Figure 3, fuel cost rates of the same driver driving the same car exhibit similar fuel cost rate on different roads. However, when comparing them with Figure 2b, we can see that each sub figure of Figure 3 is different from Figure 2b.

In order to analyze the differences in Figure 3, we would conduct the Analysis of Variance (ANOVA) [8] of the linear regression model, as in Table 2. It should be noted that, at 95% confidence level, the linear regression result of #3254 STREET is significantly different from the the linear regression results of the other three streets. The constant value a_0 of the regression result of #3254 is out of the a_0 interval of any other street, so is the slope a_1. This means we



(a) Road #5490 (b) Road #8216

Figure 3: Passive Factors: Fuel Cost Rate on Different Roads at Similar Speed, Car01

cannot use a single linear regression model to estimate the fuel cost rate of different roads. DOF represents for degree of freedom, and R^2 is the coefficient of determination.

Despite that we cannot find a general linear model for all streets, the R^2 exhibits its suitability for specific streets, and the low p-values of all these four linear regression exhibit validity of the linear regression model.

Conclusion: the linear regression model **is not suitable** to characterize the relationship between the fuel cost rate and average speed, of different streets. However, for street specific fuel consumption estimation, linear regression is a **suitable** model.

2.3.2 *Other Regression Models*

In this section, in order to characterize the relationship between fuel cost rate and average speed, we explore three other regression models, Polynomial Model, Exponential Model, and Gaussian Model.

The Polynomial Model is defined as in (3), where the parameters a_n are to be fitted:

$$f(x) = a_n x^n + \ldots + a_1 x^1 + a_0, n \geq 1 \quad (3)$$

The Exponential Model is defined as in (4), where the parameters a_n and b_n are to be fitted:

$$f(x) = a_n e^{b_n x} + \ldots + a_1 e^{b_1 x}, n \geq 1 \quad (4)$$

The Gaussian Model is defined as in (5), where the parameters a_n, b_n, and c_n are to be fitted.

$$f(x) = a_n e^{-\frac{(x-b_n)^2}{2c_n}} + \ldots + a_1 e^{-\frac{(x-b_1)^2}{2c_1}}, n \geq 1 \quad (5)$$

It should be noted, at the same order, the Gaussian Model has the highest degree of constraints. The regression results for Polynomial Models (poly-n represents n-th order Polynomial Model), Exponential Models (exp-n represents n-th order Exponential Model), and Gaussian Model (gauss2) are exhibited in Table 3. We select all streets which have been passed through for more than 12 times, and use all the driving traces on these streets to conduct the regression. Regression results of car01 and car4 are shown as examples.

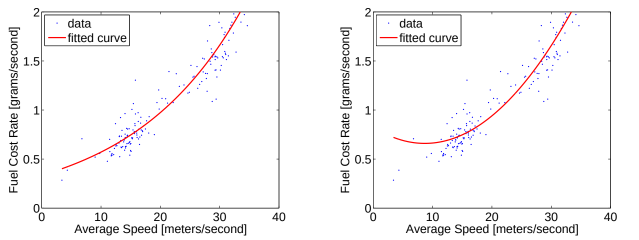
The column **RMSE** represents the Root Mean Square Error of regression, and the column **RMSE Prediction** represents the RMSE of the predictions using the regression model. Generally, the higher fitting order would result in lower RMSE of regression results, but such improvements of curve fitting are usually caused by over-fitting, which exhibits unreasonable fluctuation or lumped curvature. For example, in Figure 4b, during the low speed area, the fuel cost rate would decrease with average speed increasing, which is contradict with the actual fuel cost rate change trend. This is called Runge's Phenomenon for polynomial fitting. Driving traces corresponding to street #6265 fall in the low speed area. The RMSE of predictions using the polynomial model is 0.1116, while the RMSE of prediction using exponential model is only 0.0932. On the other hand, low order Exponential Regression always exhibit a fuel cost rate trend consistent with the actual trend, as in Figure 4a for car01.

Again in Figure 4d, during the high speed area, the fuel cost rate would also decrease with speed increasing, while there is no such over-fitting problem for Exponential model as in Figure 4c for car04.

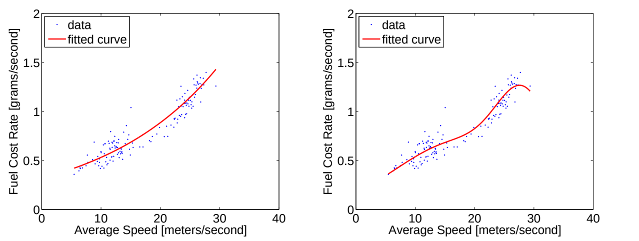
Table 3: Exponential (exp), Polynomial (poly), and Gaussian (gauss) Regression Models, $\alpha = 0.05$, of Car01 and Car04

Car	Model	RMSE [g/sec]	RMSE Prediction	R^2
	exp1	0.1755	0.2244	0.9100
	exp2	0.1753	0.2219	0.9102
car01	poly2	0.1813	0.2276	0.9040
	poly3	0.1694	0.2230	0.9161
	poly4	0.1670	0.2218	0.9185
	gauss2	0.1666	0.2214	0.9189
	exp1	0.1101	0.1177	0.7975
	exp2	0.1044	0.1151	0.8180
car04	poly2	0.1078	0.1166	0.8060
	poly3	0.1016	0.1138	0.8277
	poly4	0.0996	0.1129	0.8344
	gauss2	0.0965	0.1126	0.8444

The improvements brought by over-fitting of high order regression models disappear when using the regression models for prediction. In order to test the validity of the regression models when predicting the fuel cost of passing through one section of road, we use half of the data for regression, and the other half for prediction (generating the data in column RMSE Prediction). As seen in the table, the low order exponential regression models exhibit similar prediction ability, compared with other over-fitting models.



(a) Exponential Regression, car01, n = 1 (b) Polynomial Regression, car01, n = 3



(c) Exponential Regression, car04, n = 1 (d) Gaussian Regression, car04, n = 2

Figure 4: Different Regression Models

The reason that exponential regression model is the best

Table 2: ANOVA for Linear Model, $\alpha = 0.05$, of Car01

Road#	a_0 [g/sec]	a_0 interval	a_1 [g/m]	a_1 interval	R^2	RMSE [g/sec]	DOF	p-value
3254	0.0988	[-0.0245, 0.2220]	0.0433	[0.0351, 0.0515]	0.7214	0.0871	55	<0.00001
5490	-0.8528	[-1.3186, -0.3870]	0.0857	[0.0693, 0.1020]	0.8387	0.1569	31	<0.00001
8165	-0.7576	[-1.3592, -0.1561]	0.0803	[0.0614, 0.0991]	0.7916	0.2636	25	<0.00001
8216	-0.4935	[-0.9979, 0.0109]	0.0989	[0.0613, 0.1366]	0.7871	0.1003	11	0.00044

fitting model, lies in the fuel consumption characteristics of the engine. The fuel consumption rate of engine (grams per second) increases exponentially with the increase of engine rotation speed (Rotations Per Minute) when output torque is constant. The change of fuel consumption rate of the engine used to simulate the fuel consumption is shown in Figure 5. At different output torque, the fuel consumption rates exhibit similar exponential trend [9]. This explains the invalidity of higher order regression model or simple linear regression.

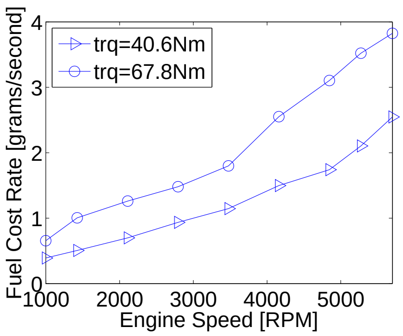


Figure 5: Fuel Consumption Map

Conclusion: Exponential Regression Model would be used to characterize the relationship between the fuel cost rate and the average speed (proxy of traffic condition), due to its consistence with the properties of fuel consumption rate of engines.

2.3.3 *Extended Traffic Information*

Real time average speed of a section of road is already publicly available, as discussed in Section 3.1. However, this is only a small subclass of the traffic information.

Except for the average speed [10], length of a street [11], more information, such as the traffic count [12], and the traffic signal timing [13] are available currently. With advent of new technology, such as Dedicated Short Range Communication (DSRC) and Vehicle to Infrastructure Communication, drivers or the cars can freely access a city's traffic information, even as some statistics of vehicle accelerations. The sharing of driving data among different cars in a real time fashion would improve the accuracy of fuel estimation of passing through one section of road.

2.4 Active Factors

In this section, we would like to answer the question "in cities, is driving behavior obviously affecting fuel cost rate?". The eco-driving tips are proven to be effective [4], where a vehicle is driven following eco-driving tips can exhibit up to 22% fuel economy improvement. This means driving behavior matters for fuel consumption profile. So a minimum fuel consumption routine for driver A may not the best choice for driver B, this means TAGRouting service should be customized for different users. **TAGRouting should be customized for users**.

In order to evaluate the differences between different drivers, we are going to compare the linear regression result derived from driving traces from different drivers. We focus on the same road #5490, so that to eliminate any affection from road specific effects. The Analysis of Variables (ANOVA) result is exhibited in Table 4.

It should be noted that, at 95% confidence level, the linear regression result of car04 is significantly different from the the linear regression results of the other three cars. The constant value a_0 of car04 is out of the a_0 interval of any other car, so is the slope a_1. The low p-values of all these four linear regression exhibits validity of the linear regression model.

Conclusion: different drivers may have different fuel cost rate curves versus average speed. This means TAGRouting should be customized for different users.

2.5 Data Source and Assumptions

Many factors affect fuel cost rate, such as driver, vehicle specification, and road condition. In order to separate effects of different factors, we would assort the driving traces by the car labels, driver labels, and street code labels, for the Regression Modeling in Section 2.3. In this way, we can customize the fuel estimation for one specific car and its corresponding driver. CAN Bus data, which measures fuel consumption accurately, would improve the accuracy of estimation. However, CAN Bus data is usually limited for distribution due to privacy or contract concerns.

We take advantage of the GPS traces provided by Aalborg University [14]. The sampling frequency is 1Hz, for GPS location and timestamp. For No.1 car in Team2, the trace is logged from 03-Feb-2001 to 26-Mar-2001. The vehicle is usually driven on the same commuting routine, which enables us to have abundant samples for the same streets. Some streets have been driven through for many times.

Figure 6 is the snipper of the GPS trace file. The SPD represents second-by-second speed, and the STRTCOD represents which road is driving on. With these two columns of data, we can simulate the fuel consumption with Advisor [9] as described in Section 2.6.

The weakness of the data is the unknown coordination system and the street codes. These information can not be released [14]. But with the STRTCOD column, we are able to distinguish entries corresponding to different sections of roads.

2.6 Fuel Consumption Simulation

The fuel consumption data used in the estimation is simulated by the vehicle model of Advisor [9], based on the driving trace data [14]. Vehicle mass is 1350 kg, max power of engine is 54KW, with peak efficiency at 0.34.

Table 4: ANOVA for Active Factors, $\alpha = 0.05$, on Road #5490

car#	a_0 [g/sec]	a_0 interval	a_1 [g/m]	a_1 interval	R^2	RMSE [g/sec]	DOF	p-value
car01	-0.8528	[-1.3186, -0.3870]	0.0857	[0.0693, 0.1020]	0.8387	0.1569	31	<0.00001
car02	-1.1777	[-1.5053, -0.8501]	0.0923	[0.0809, 0.1038]	0.8926	0.1202	44	<0.00001
car04	-0.3997	[-0.5887, -0.2106]	0.0621	[0.0543, 0.0699]	0.8140	0.0773	63	<0.00001
car06	-1.0007	[-1.4986, -0.5028]	0.0863	[0.0676, 0.1049]	0.7661	0.1711	29	<0.00001

ID	ENTRYID	CARID	DRIVER	RDATE	RTIME	XCOORD	YCOORD	MPX	MPY	SAT	HDOP	MAXS	SPD	STRTCOD
990130	1120201073657	1	0	120201	73657	556318	6321623	556314	6321623	6	1	50	44	3640
990129	1120201073656	1	0	120201	73656	556317	6321611	556314	6321611	6	1	50	37	3640
990128	1120201073655	1	0	120201	73655	556315	6321602	556313	6321602	6	1	50	30	3640

Figure 6: Snipper of GPS Trace File

3. TRAFFIC AWARE GREEN ROUTING

Current routing services online, usually provide two options, shortest distance and shortest time, which both ignore the impact of routines on fuel consumptions. We focus on another option, minimum fuel consumption. To this end, we need to build a directional weighted graph, with each arc (section of street) labeled by the fuel amount which the car consumes if the car drives through it. The fuel cost estimation as described in Section 2, is used to estimate the fuel cost of passing through on section of street at certain average driving speed.

In this section, we would firstly review the availability of traffic information in Section 3.1, and describe details of Traffic Message Channel (TMC) in Section 3.2 which is currently widely used. Brief statistics of traffic conditions are given in Section 3.3. Details of the abstraction of geographical data, traffic labeling, and routing would be discussed in Section 3.4.

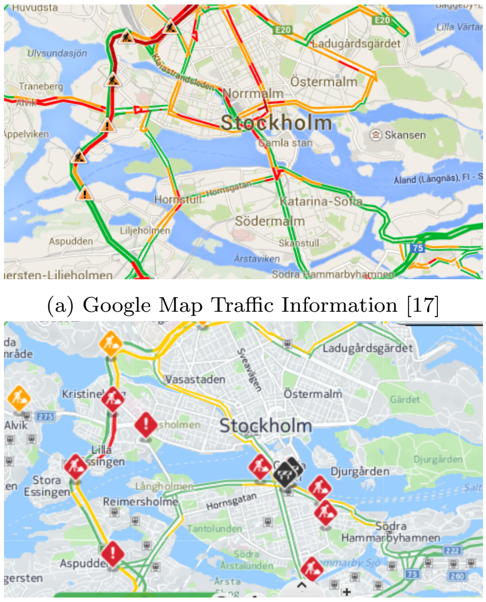
3.1 Traffic Information

The effectiveness of TAGRouting service relies on the accuracy and timeliness of traffic information. Real time traffic information sharing based on wireless technology started from 1990s with GSM era, and later use the Traffic Message Channel (TMC) based on broadcasting service since 2000s [15]. Currently, Universal Mobile Telecommunications System (UMTS) can be used to generate the real time traffic reports [16]. In the future, with the popularization of interconnected vehicles, more and more real time traffic information would be available.

As shown in the Figure 7, different colors are used to represent the current traffic on different roads, with red for slow speed, and green for high speed. Except for these average speed information, HERE map also provides the real time information for incidents, labeled by triangles.

It should be noted that, coverage of real time traffic information varies between HERE map service in Figure 7b, and Google map service in Figure 7a. The reason lies in the different techniques used by the two different companies. Real time information provided by HERE map service is based on TMC techniques, and Google Map is based on data collected from mobile services [19]. There are a lot more real time traffic service vendors, such as TOMTOM, Bing Map which also provide similar services.

The real time traffic source we finally use is provided from **HERE map service**, because it provides the access to real time traffic information in XML format with its API [18], which make the fuel consumption estimation feasible in later parts of work. Google map only provides map tiles with different colors representing the traffics, in image format. More details of TMC techniques would be introduced in Section 3.2.



(a) Google Map Traffic Information [17]

(b) HERE Map Traffic Information [18]

Figure 7: Real Time Traffic Information Source, Stockholm, 2014 Jun 24, 17:00PM

3.2 Traffic Message Channel

Traffic Message Channel (TMC), is a technology based on the broadcasting services. TMC service providers occupy certain channel, broadcasting real time traffic information just like other radio programs. The receivers installed in cars, receive and parse messages, and then display it on screen in the car [10]. The other format is XML, which is usually broadcasted via internet. The real time traffic information from NOKIA map service is in XML format.

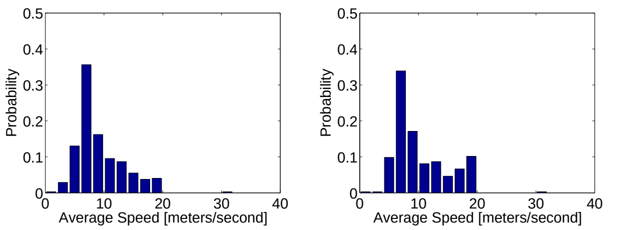
It has to be noted that, the real time traffic data provided in the XML file is in a geo-coding system different from using latitude longitude. A TMC Location List is used to translate between the real time traffic sampling points with a unique coordination on map. Unfortunately, TMC Location List is not widely publicly available. This is one reason restricting current availability of the TAGRouting services. **Without**

TMC Location List, real time traffic information cannot be labeled on the map data of cities. As a result, we select Stockholm in Sweden as the example city for the demo of our TAGRouting service.

3.3 Traffic Statistics

Traffic conditions vary from hour to hour, and day to day, as a result, the TAGRouting results also vary a lot. In this section, we provide a brief statistics of the traffic conditions at different time of day, as in Figure 8.

As can be seen in the figure, the extremely low speed streets account for a lower part in off peak hours as in Figure 8b, compared with the peak hours as in Figure 8a. In terms of average speed, during the peak hour, the average speed is 9.24 MPS (33 KPH), but in the off peak hour, the average speed is 10.69 MPS (38 KPH). The difference of the peak/off peak hour is already moderated by many streets which always have good traffic conditions. Some streets always keep good traffic, such as Valhallavagen Street where interconnected with Odengaten Street, the speed is around 60 KPH either during or off the Peak hour. On the other hand, some other streets, like E4 173, Solna, during the Peak hour of June 20th, the speed is only 31.84KPH, but during the Off Peak hour, the speed can reach 57.93 KPH.



(a) Peak Hour Traffic Statistics (b) Off-Peak Hour Traffic Statistics

Figure 8: Traffic Condition Statistics

3.4 Speed Labeling and NetworkX

As described in Figure 1, GPS driving traces and Advisor are used for characterizing the relationship between fuel cost rate and the average speed, and XML files containing TMC information are used to provide traffic information. In this section, we would discuss the source of geographical data, and the routing method.

NetworkX is an academic Python package developed and provided by Los Alamos National Laboratory [20]. It is usually used to analyze complex network. In order to utilize NetworkX for routing service, an abstracted weighted directional graph has to be provided as input, along with the start point, terminal point, and weight option. There are three weights required for the abstracted graph, time, distance, and fuel.

The street connections and street length information in this work are based on the data provided by OpenStreetMap (OSM) [11]. The steps for extracting the arcs and nodes from OSM data and calculating the weight (fuel consumption) are listed below:

1. Filter out those roads which are not for vehicles, and find the intersections which would be the nodes in the graph for routing.
2. For each node, distinguish the streets taking the node as source, and calculate the length of this section of road, which would be the **weight of distance**. Each section of road would be an arc in the graph for routing. The points with latitude longitude pair along each section of roads are also saved, for later map rendering use.
3. Use the real time traffic data provided by HERE map service to label the average speed on each edge, and then calculate the total fuel consumption of passing through this section of road at current average speed by (2), this would be labeled as the **weight of fuel**.
4. For later comparison purpose, the time required to pass through this section of road is also calculated with the known average speed, and length information. This time spent is labeled as the **weight of time**. Now the extraction of the map data to an abstract directed graph for routing has been completed.

When the minimum weight path has been found with above process, the results of the routing is rendered on OpenStreetMap, with Leaflet library [21], as shown in Section 4.

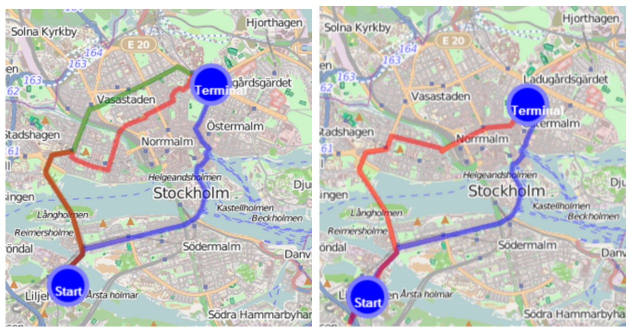
4. EVALUATION

All evaluation results in this section are available on the website [22]

In this section, TAGRouting is evaluated, compared with current available strategies, shortest time and shortest distance. In Section 4.1, example routings are given in Stockholm. The fuel saving benefits of TAGRouting are analyzed in Section 4.2, when the traffic condition changes. In Section 4.3, we investigate into the Miles Per Gallon which is usually taken to measure fuel efficiency. In Section 4.4, performance on average energy saving is analyzed.

4.1 Example Routing

The final routing result depends on real time traffic, vehicle fuel consumption characteristics, and also the road network topology. The reason we select Stockholm as the sample city for demonstrating TAGRouting is for its availability of TMC Location List and the publicly available numeric real time traffic. Details of the map can be found online.



(a) Routing Example: Different Routing Strategies (b) Routing Example: TAGRouting at Different Time of Day

Figure 9: Routing Examples

Fuel consumption, time required, and distance travelled vary a lot for TAGRouting, shortest distance Routing, and shortest time routing, sometimes they overlap with each other, sometimes, they are totally different. In Figure 9a, a screenshot of three different routines are exhibited, where the **Red** one represents the shortest time routing, the **Blue** one for shortest distance routing, and the **Green** one for TAGRouting. A small part of the three routines overlap with each other, but in general, they are quite different. The three routing strategies are compared in Table 5.

Table 5: Example Routing

Strategy	Fuel[g]	Distance [m]	Time [s]
TAGRouting	412.9	6918	739
Shortest Distance	459.9	6533	933
Shortest Time	428.6	7420	726

This start terminal pair (as in Figure 9a) is used as an example to show the routine differences of the three routing strategies. Compared with shortest time routing, fuel consumption can be reduced by up to 18.8%; compared with shortest distance routing, fuel consumption can be reduced by up to 16.9%. More examples can be found in Section 4.2.

Green routines yielded by TAGRouting are varying with traffic conditions. In Figure 9b, both routines are the results of TAGRouting, the difference is the time of day. **Red** one represents for the minimum fuel routine in the peak hours, and the **Blue** one is for off-peak hours. TAGRouting is similar with shortest time routing, varying with time, because they both depend on real time traffic. This proves that a least fuel routing strategy which are not aware of real time traffic information, cannot give the optimal routing result for fuel reduction.

4.2 Total Fuel Consumption v.s. Traffic

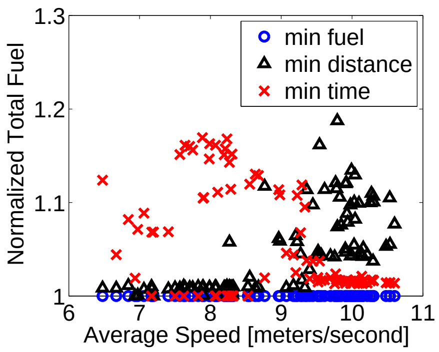


Figure 10: Total Fuel Consumption in Different Traffic

The ultimate objective of TAGRouting is to reduce the total fuel consumption, not to enhance the fuel economy like MPG. In Figure10, the total fuel consumptions of different routine strategies are shown versus the average speed of the green routine yielded by TAGRouting (proxy of traffic condition). Compared with shortest time routing, fuel consumption can be reduced by up to 18.8%; compared with shortest distance routing, fuel consumption can be reduced up to 16.9%.

In some cases, the shortest distance routine is equivalent to the green routine yielded by TAGRouting in terms of fuel consumption, and sometimes, the shortest time distance is equivalent to the green routine. Because the topology of the connected road network vary a lot, we cannot find a determinant rule to follow. However, we can still investigate into the relationship between such equivalence and the traffic conditions. In general, in the aspect of fuel consumption, in the low speed trace area, the shortest distance routine is usually equivalent to the green routine, while in the high speed area, the shortest time routine is usually equivalent to green routine. However, there is a transitional area which even such empirical rules are ineffective, and such transitional area vary from driver to driver, community to community.

4.3 High MPG $\neq$ Less Fuel

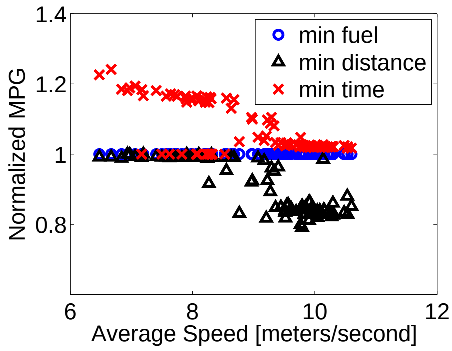


Figure 11: MPG of Different Routing Strategies

Usually higher MPG represents for higher efficiecny, however, we would see that routines with high MPG are not the ones consuming least fuel. The MPG of the 100 random routines in Off Peak hour, are compared in Figure 11. The vertical axis represents the normalized MPG, which is the MPG divided by that of green routine yielded by TAGRouting, so the dots representing the green routines are always 1. Shortest time routines always have the highest normalized MPG, this is because this routing strategy is searching for "fastest" tracks, no matter whether this results in more miles to drive. The extra distance required to take advantage of "fastest" tracks is the reason of more total fuel consumption, compared with TAGRouting. On the other hand, as seen in the figure, shortest distance routines always exhibit lowest normalized MPG, as the shortest distance routines usually suffer from heavy traffics.

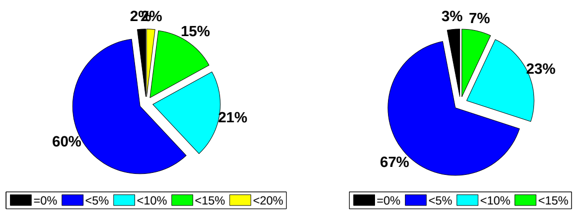
The horizontal axis is the average speed of the green routine, which is taken as the proxy of the traffic condition corresponding to different travelling need. Because for each of the start terminal pairs, we would try the three routine strategies, so there are always three dots for each x value. As can be seen in the figure, with the increase of the average green routine speed (improvement of traffic condition), the probability that a shortest time routine is equivalent to green routine is increasing.

4.4 Average Performance Analysis

Not every start terminal pair can experience the same percentage of fuel saving, as can be seen in Figure 10. Even in many cases, the shortest time routine, shortest distance routine, and the green routine have the same result. In this section, we would investigate into the average performance of TAGRouting for fuel reduction.

4.4.1 How Much Fuel Saved

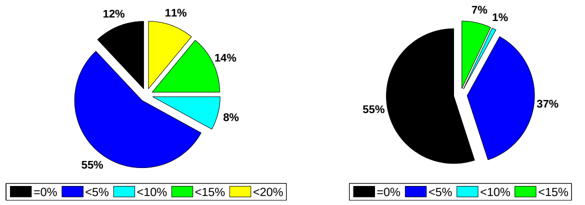
The objective of this work is to reduce the total fuel consumption. In order to make the evaluation of fuel reduction, we randomly select 100 start terminal pairs, and compare the three different routing strategies. The comparison between TAGRouting and shortest distance routing is exhibited in Figure 12, and the comparison with shortest time routing is exhibited in Figure 13.



(a) Off-Peak Hour (b) Peak Hour

Figure 12: Fuel Saved Compared with Shortest Path Routing

In Figure 12b, in only 3 out of 100 random cases, TAGRouting generates the same routine with the shortest distance routing strategy, and there are only 2 cases where TAGRouting is equivalent to shortest distance routing in Off Peak hours as in Figure 12a. 62% to 70% start terminal pairs experience a fuel saving between 0% and 5%, and 30% to 38% of start terminal pairs would have a fuel saving larger than 5%. On average, the fuel consumption saving brought by TAGRouting compared with shortest distance routing is about 4.86% in Off Peak hour and 3.02% in Peak hour. To get such fuel reduction benefits, the only thing drivers need to do is to follow the suggestions of TAGRouting.



(a) Off-Peak Hour (b) Peak Hour

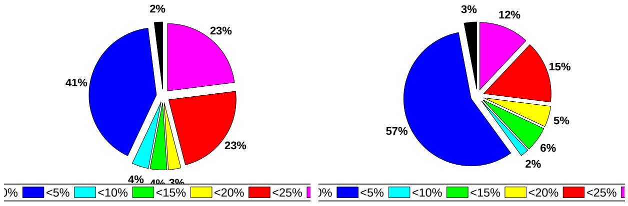
Figure 13: Fuel Saved Compared with Shortest Time Routing

We also compare the fuel consumption profile with shortest time routing strategy, in Figure 13. The average fuel saving is 4.70% in Off Peak hour, and 1.35% in Peak hour.

4.4.2 How Much Time Spent

Because the objective of TAGRouting is minimizing fuel consumption, so the time spent on fuel minimum routine might not be the least among the three routing strategies.

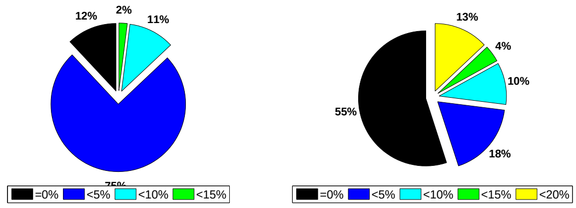
In Figure 14, we compare the time required of TAGRouting and shortest distance routing. As can be seen in the Figure 14b, during the Peak hour, 27% of start terminal pairs would have a more than 20% time saving if following TAGRouting instead of shortest distance routing, and TAGRouting can bring more fuel saving (as in Figure 12b),



(a) Off-Peak Hour (b) Peak Hour

Figure 14: Time Saved Compared with Shortest Distance Routing

while using less time. The main reason people select the shortest distance routing lies in the assumption that it would use less fuel. However, TAGRouting is a much better choice for such fuel saving concern.



(a) Off-Peak Hour (b) Peak Hour

Figure 15: Extra Time Spent Compared with Shortest Time Routing

In Figure 15, time spent of TAGRouting is compared with that of shortest time routing. As expected, the cost for less fuel consumption of TAGRouting is the extra time required. The average extra time cost in Off Peak hour is only 2.54%, and in Peak hour, it is 3.85%.

5. RELATED WORKS

Least energy consumption routing has been covered in several reported works.

In [23], the authors use two simulators: TRANSIMS [24] for driving trace simulation, and MOVES [25] for fuel cost estimation according to the driving trace simulated. With these two simulators, the fuel cost for each section of roads on map can be calculated. A green routine is generated based on this fuel cost labeled map, and TRANSIMS is used again to re-simulate the driving trace, because the traffic may vary a lot when all vehicles drive according to the newly generated routing. Such simulation-estimation-routing loop would be repeated until every vehicle has a green routine.

In [26], authors focus on routing on the scale of the whole Europe for Electrical Vehicles. To this end, in the evaluation, the battery capacity is modified from to 1000KWh (corresponding to the range of 5000Km) [26]. Benefit of routing mainly comes from the avoidance of unnecessary climbing, instead of the knowledge of real time traffics. Another contribution of this work is the fast convergence speed of the routing algorithm.

There is also a green router feature which is currently commercially available, the Garmin ecoRoute [27]. However, the fuel saving routing is utilizing the different fuel economy characteristics at highway or city, which are set by users. As discussed in Section 2.1, fuel economy is not a suitable proxy for estimating the fuel consumption, and the fuel economy usually varies a lot from street to street. However, navigation devices, such as Garmin ecoRoute, make the TAGRouting feasible at current technical level.

6. CONCLUSION

In this paper, we present the TAGRouting, a routing service generating the routine which consumes the minimum fuel. We use the real world driving trace with location information to characterize relationship between fuel cost rate and average speed, and this relationship is used for fuel consumption estimation. Real time traffic information is utilized to help estimate fuel consumption, which is used as the weight in a directed graph. The topology of streets and their lengths are calculated according to OpenStreetMap, and the minimum weight path is searched with NetworkX. In the example of TAGRouting in Stockholm, Sweden, compared with shortest time routing, the TAGRouting can reduce fuel consumption by up to 16.9%; compared with shortest distance routing, our scheme can reduce fuel consumption by up to 18.8%.

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