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Fuel consumption at signalized intersections: Investigating the impact of different signal indication settings

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ABSTRACT

The fuel consumption of vehicles depends on various factors including vehicle design, driving style, traffic management, and road design. Many manufacturers have been developing efficient and smart vehicles, which contributes to minimizing vehicle fuel consumption. However, traffic management and control could restrict the efficiency of having a sustainable mobility system. Intersections are considered as critical locations, in terms of fuel consumption, due to the significant impact of traffic control at these locations on the vehicle maneuver either by stopping or acceleration to clear these bottleneck points. Analyzing the effect of different intersection signal settings is, therefore, important to optimize vehicle fuel consumption. In this study, we used simulator data of sixty-six drivers going through signalized intersections equipped with two different signal indication settings, namely, control and flashing green conditions. We calculated total fuel consumption using the VT-CPFM and COPERT models and then applied GLME with two different model distributions: normal and log-normal to study the correlation between the two treatments and fuel consumption. Results showed that by displaying the remaining green time, flashing green treatment (i.e., signals with traffic light sequence: green, flashing green, yellow and red-green) produced a lower fuel consumption in comparison to control condition (green, yellow and red sequence), yielding to a similar performance of eco-driving. It was found that as drivers become aware ahead of time when the traffic light will be turning red due to the flashing green signal indication, eventually they either speed up a little to cross the intersection in time, or they early start decelerating, which creates a more optimal deceleration pattern. Results also showed that the VT-CPFM model resulted in more realistic results than COPERT due to its ability to capture the transient changes in speed and acceleration.

1. Introduction

Vehicle fuel efficiency is one of the most important factors in transportation energy use. For example, about 28% of total U.S. energy consumption usually because of transporting people and goods from one place to another (Raza et al., 2019). Marginal fuel consumption reduces when fuel efficiency (in miles per gallon) increases. Although switching towards a more fuel-efficient vehicles, such as hybrid vehicles, enhances fuel savings, the gains might be marginal for an individual consumer but substantially more important at the entire amount of societal savings. As a result, for fuel efficiency to be beneficial to society, the vehicle's price should either remain constant as its fuel economy improves, or the vehicle's fuel efficiency should at the very least compensate for its higher price. When vehicles operate in less congested areas, they achieve significant gains in fuel efficiency. Meanwhile, increased fuel consumption and emissions are caused by traffic congestion on city roads (Bigazzi,

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2019; Rui-Qiang et al., 2019; Xie et al., 2017; Yao et al., 2021). As a consequence, lowering mobility exhaust emissions should be a primary concern in transportation systems (Karaoğlan et al., 2019).

In the short term, road traffic management concerns the control of road user movement to make the most use of existing road networks. In the 1950 s and 1960 s, traffic management was primarily concerned with vehicle traffic problems in local regions and making the greatest use of resources, which meant to increase safety and operating efficiency (higher capacity, less delays, etc.) (Xie et al., 2017; Yao et al., 2021). By applying insufficient trade-off analysis methods, traffic engineers attempted to address the practical challenges produced by conflicts between individual objectives of safety and operational efficiency. The problem of fuel consumption and automotive congestion has arisen as demand for autos has expanded, and the notion of traffic lights has also been introduced. Traffic lights, that are being used to govern vehicles at intersections, direct and regulate the flow of vehicles at road junctions. Since traffic lights significantly affect the maneuver of vehicles, it also significantly influences the fuel consumption especially in the period of signal change where drivers need to take decisions of either stopping or accelerating to clear the intersection. Therefore, fuel consumption issue must be examined in the context of total traffic system management, which necessitates the development of models for both fuel consumption and traffic operational characteristics (delay, number of stops, speed, and so on) (Vicente and J.J.I.T.o.s., 1992).

When traffic light turns into yellow, drivers should decide whether to stop or accelerate to cross the intersection safely. If the drivers come to a stop at a red light, they must stay stopped until the signal turns green (Tang et al., 2017). In another common traffic signal setting, a flashing green is introduced before the yellow signal indication aiming at informing the driver of the end of the green interval and introducing the start of the yellow signal indication, which is the gate to the red interval. Since the 1980 s, flashing green lights have been used in the city center and provincial highways in many parts of the world (Shen and Wang, 2015; Tang et al., 2015; Tang et al., 2016) such as Qatar and other Arab Gulf countries. Because drivers must determine whether to stop or proceed through an intersection until the green light turns red, the change from green to yellow influences driving behavior. The presence of a flashing green indicator means that the green signal is about to expire. In this case, drivers usually have more time to evaluate the situation and take a decision whether to stop or proceed through the signalized intersection due to them realizing when the yellow light will turn on (Shen and Wang, 2015; Tang et al., 2015; Tang et al., 2016). If flashing green is not used drivers will be aware that the green signal will expire when the yellow signal begins (Shen and Wang, 2015; Tang et al., 2015; Tang et al., 2016). However, drivers sometimes do not have the needed time to fully stop in some situations, so they decide to speed up and go through the stop line at the onset of the red signal (Akcelik, 1981). The effect of flashing green on fuel consumption at intersections will be the focus of this research. Previous research, on the other hand, has primarily focused on the effects of intersection control such as signalization on traffic safety, as intersections are the scene of numerous types of crashes. When the green signal is activated, the queue is discharged. The discharge rate gradually increases to a maximum flow rate before remaining constant until the queue is emptied or the green interval has expired, accordingly.

The bulk of research on the influence of flashing green lights on road safety are mainly concerned with traffic safety. According to (Shen and Wang, 2015; Tang et al., 2015; Tang et al., 2016), employing flashing green reduced the incidence of right-angle collisions and the proportion of red-light breaches. On the other hand, they revealed an increase in the number of rear-end incidents. Drivers participated in (Tang et al., 2017) were shown short movies depicting various circumstances on crossroads using flashing green settings, examining their behaviors when the traffic light turns from green to red. The flashing green generated an earlier decision reaction from the drivers, as well as a larger percentage of improper stopping decisions. With the flashing green light, the pattern of halting and crossing decisions implies a larger chance of rear-end incidents than without the flashing green signal. Similar results were observed in a driving simulator study from the state of Qatar indicating that the flashing green setting could enlarge the length of the indecision zone and hence more inconsistent stopping behaviors (Hussain et al., 2020). Based on studies in Switzerland, Austria, and Germany (Rakauskas et al., 2010), the stopping behavior of cars during signals in both situations with and without flashing green was studied and modelled. According to the study, the frequency of early stops was enhanced in the flashing green settings, which minimizes the danger of crashes from the right angle. The flashing green, on the other hand, generates a larger decision zone in Austria, which creates ambiguity and may lead to an increase in rear-end collisions. Shen and Wang (Akcelik, 1981) compared the behavior of drivers before and after the flashing green in China. The findings show that flashing green is an efficient approach in avoiding skipping yellow signals. However, only using flashing green would not enhance junction safety, albeit it will offer additional information to drivers. In Shanghai, China, the effect of flashing green on problem zone behavior at high-speed junctions with inadequate yellow intervals were explored by Tang, et al. in (Shen and Wang, 2015; Tang et al., 2015). By lowering the frequency of problem zone type I, flashing green signals may be effective in averting right-angle accidents.

Moreover, the notion of eco-driving has gained popularity in recent years. “Eco-driving” is a term used to explain how automobiles may be used to save energy. In addition to the benefits of saving energy, eco-driving can also be beneficial for safety, driver’s awareness and comfort, as well as traffic efficiency. One of the most critical advantages of eco-driving is not only it is a low-cost technology, but also from it being friendly for the environment and can decrease pollution. Several previous studies assessed the efficacy of eco-driving technology using driving simulator data such as (Tang et al., 2016) and (Tang et al., 2017). They have argued that eco-driving is promising and can decrease fuel consumption and emissions. The resulted behavior produces more eco-efficient driving, and according to (Rakauskas et al., 2010) and (van der Voort et al., 2001), if the system is properly designed, it can instruct what actions drivers need to take, as well as when to take that actions. For example, instant feedback shows how much emissions increase when greater accelerator power is applied, which means more thorough understanding of eco-driving behavior. Flashing green treatments displays the remaining green time for drivers, which is similar to eco-driving technology. In this study, we explored the effect of two traffic signal settings: control condition and flashing green treatment on fuel consumption of vehicles passing through signalized intersections. To the best of our knowledge, this study is the first of its kind investigating the fuel consumption for the two abovementioned traffic signal settings.

2. Dataset and methods

The conducted experiment took place at the driving simulator laboratory of Qatar Transportation and Safety Center, Qatar University (Hussain et al., 2019; Almallah et al., 2021). Time, longitudinal position, speed, acceleration, and other data was acquired by a driving simulator located at the center (Hussain et al., 2020). Most traffic accidents take place at intersections (Hussain et al., 2020); therefore, the design of the simulator resembles such traffic intersections in Doha, Qatar. Sixty-six holders of valid Qatari driving license participated in this experiment. The experiment included various driving intersection scenarios. In this study, we’ll refine our focus to two scenarios. The first scenario takes place at the indecision zone (labeled as S1), where there is usually a high probability to cross the red light. The second scenario took place at the stopping zone, where the driver must stop to avoid crossing the red light (labeled as S2). The controlled parameter that mainly distinguishes these two scenarios is the distance of the vehicle from the stopping line, which is 80 m for indecision zone scenario (S1) and 95 m for the stopping zone scenario (S2). Drivers were also exposed to two different signal treatments for each driving scenario: control condition (labeled as T0) in which the signal indication sequence is green/flashing-yellow/red, and flashing green condition (labeled as T1) in which the signal indication sequence is green/flashing-green/flashing-yellow/red. While the former has a sequence of green, yellow, and red; the latter has the sequence of green, flashing green, yellow, and red. The experiment was designed in such a way that most of the drivers will end up in the decision zone at the first scenario; in contrary to the second scenario where only the aggressive drivers are expected to end up there. More details on the dataset can be found in (Hussain et al., 2020).

3. Methods

Vehicle's fuel consumption is severely affected by the road design, road treatments, and road scenarios a driver comes across; therefore, to alleviate fuel consumption we need to study what circumstances are likely to affect fuel consumption. To find Fuel consumption, we used two fuel consumption models, namely, the Virginia Tech Comprehensive Power-Based Fuel Consumption Model (VT-CPFM) (Rakha et al., 2011) and COPERT model (Ali et al., 2021).

3.1. VT-CPFM model

As a microscopic fuel consumption model, VT-CPFM depends on instantaneous vehicle power. VT-CPFM was developed to avoid the need for calibrating specific parameters from field testing or simulators and to avoid producing the bang-bang control effect. It can avoid the bang-bang control as it has a second-degree polynomial relationship with vehicle specific power (VSP). Moreover, the model can be applied on publicly available data, which makes it feasible to be used in any geographical location. The model was also tested for different vehicle types including light- and heavy-duty vehicles (Rakha et al., 2011; Wang and Rakha, 2017), and buses (Edwardes and Rakha, 2014). More details on the model and how it can be implemented can be found in (Rakha et al., 2011).

First, power can be calculated using the following Eq. (1):

$$P(t_i) = \left(R(t_i) + \frac{1.04ma(t_i)}{3,600\eta_d}\right)*v(t_i) \quad (1)$$

where:

$P(t_i)$ = power at time step t_i (kW), m = vehicle mass (kg), $a(t_i)$ = vehicle acceleration at time step t_i (m/s^2), $v(t_i)$ = vehicle speed at time step t_i (km/h), η_d = parameter of driveline efficiency, and $R(t_i)$ = force of resistance at time step t_i (N).

$R(t_i)$ can be computed using the following Eq. (2):

$$R(t_i) = \frac{\rho}{25.92}C_D C_h A_f v(t_i)^2 + 9.8066m\frac{C_r}{1,000}(c_1 v(t_i) + c_2) + 9.8066mG(t_i) \quad (2)$$

where:

ρ = air density (1.2256 kg/m^3 at sea level and 15 °C), C_D = coefficient of vehicle drag (unitless),

C_h = factor to correct for elevation, A_f = area of vehicle frontal (m^2), $G(t_i)$ = grade of roadway at time step t_i, and c_r, c_1, and c_2 = parameters for rolling resistance (unitless) (Rakha et al., 2011).

Fuel consumption (*FC*) is then computed applying Eq. (3). More details on the needed parameters and their values can be found in (Rakha et al., 2011).

$$FC(t_i) = \begin{cases} \alpha_0 + \alpha_1 P(t_i) + \alpha_2 P(t_i)^2 \forall P(t_i) \geq 0 \\ \alpha_0 \forall P(t_i) < 0 \end{cases} \quad (3)$$

where:

α_0, α_1 and α_2 are constants to account for vehicle-specific calibration in the model.

3.2. COPERT model

COPERT model (Ali et al., 2021) was also used to estimate the vehicle's fuel consumption and to compare results with VT-CPFM. Two different equations are used to calculate fuel consumption from the speed profile of vehicles. Eq. (4) is used to calculate fuel consumption whilst the vehicle is moving; whereas Eq. (5) is used when the vehicle is stationary. Eq. (6) shows the total fuel consumption.

$$FC_{ma} = \begin{cases} \frac{217 + 0.253V + 0.00965V^2}{1 + 0.096V - 0.000421V^2} ifV \geq 4.5km\Big/h \\ 0 ifV < 4.5km/h \end{cases} \quad (4)$$

$$FC_{sa} = \begin{cases} 0 ifV \geq 4.5km/h \\ 0.361 \times \Delta t ifV < 4.5km/h \end{cases} \quad (5)$$

$$FC_{total} = FC_{ma} \times \Delta d + FC_{sa} \times fueldensity \quad (6)$$

where FC_{ma} is the fuel consumption on vehicle's moving activity in g/km, FC_{sa} is the fuel consumption on vehicle's stationary activity in *ml*, FC_{total} is the total consumed fuel in g, Δt in seconds is the time difference between the two data samples, Δd in km is the distance difference between the two data samples, V is the vehicles' velocity in km/h, and $fueldensity = 0.77g/ml$.

The data of the sixty-six drivers is then turned into a vector that contains information about: the scenarios, the treatments, the total fuel consumption at the intersection, the driver ID, and the intersection ID. Table 1 shows a sample data for the driver with ID = 1 at each one of the four intersections, where drivers experienced a combination of each one of the two scenarios (S) and two treatments (T).

3.3. GLME model

Generalized linear mixed-effects (GLME) model (as in Bolker *et al.* (Bolker et al., 2009) was used to investigate if there is a significant disparity in the results between the two signal treatments. GLME generally characterizes the relationship between independent variables and a response variable that resulting from data, which is not normally distributed. The relationship is characterized using coefficients that change with grouping variables. GLME models are extension to generalized linear models (GLM) for group summarized data. Moreover, when the response variable for the data is not normally distributed, GLME represents a generalized version of linear mixed-effects models (LME).

The term mixed-effects model represents the model composition of fixed-effects and random-effects terms. A linear regression is used as the fixed-effect term, whereas the random-effects terms are experiments drawn from random populations and are attributed to deviations between groups at which are likely to affect the response. The fixed-effects model has no pre-defined distributions; on the other hand, the random-effects model does, as follows:

$$y_i|b\ Distr\left(\mu_i, \frac{\sigma^2}{w_i}\right) \quad (7)$$

$$g(\mu) = X\beta + Zb + \delta \quad (8)$$

where y is an $n \times 1$ response vector, and y_i is its i $^{\text{th}}$ element, b is the random-effects vector, *Distr* is a specified conditional distribution of y given b, μ is the conditional mean of y given b, and μ_i is its element, σ^2 is the dispersion parameters, w is the effective observation weight vector, w_i is the weight for observation i, $g(\mu)$ is a link function that defines the relationship between the mean response μ and the linear combination of the predictors, X is an $n \times p$ fixed-effects design matrix, β is a $p \times 1$ fixed-effects vector, Z is an $n \times q$ random-effects design matrix, b is a $q \times 1$ random-effects vector, and δ is a model offset vector. The equation for the mean response μ is

Table 1
Sample data of one drive at four intersections that covers the combination of the two treatments (T) and two scenarios (S).

Total Fuel (g)	T	S	Driver ID	Intersection 1	Intersection 2	Intersection 3
32.72	Control	Indecision	1	0	0	0
32.21	F-green	Indecision	1	1	0	0
30.46	Control	Stopping	1	0	1	0
30.32	F-green	Stopping	1	0	0	1

$$\mu = g^{-1}(\eta) \tag{9}$$

Where g^{-1} is the inverse of the link function $g(\mu)$, and $\hat{\eta}_{ME}$ is the linear predictor of the fixed and random effects of the generalized linear mixed-effects model, as follows:

$$\eta = X\beta + Zb + \delta \tag{10}$$

4. Analysis and results

We present the analysis and results of investigating the effect of two signal treatments with two scenarios on fuel consumption using the two models: VT-CPFM and COPERT. Specifically, two treatments were investigated, namely, T0, which is the control condition, and T1, which is the condition with the traffic lights of flashing green (like some countries including Qatar). We also studied the two abovementioned scenarios, namely, S1 and S2. Table 2 shows the scenarios, treatments, and the intersections where the experiment was implemented. These junctions are located in series; nevertheless, they were not all studied in the same session. S1 and S2 were performed in two separate sessions that both include T0 and T1 which are located at different location for each scenario.

We used the two models (i.e., VT-CPFM and COPERT) to calculate the fuel consumption for each driver at each intersection. In particular, we calculated the accumulated fuel consumption starting from 300 m before the intersection up until 200 m after clearing from the intersection. Then we applied the GLME on two distribution models normal and log-normal. We used Maximin Projection Learning (MPL) as a fitting method for GLME to extract the effect of the two scenarios (i.e., S1 and S2) and the two treatments (i.e., T0 and T1) on the fuel consumption of the different drivers. Eq. (11) shows the formula for normal GLME distribution model, whereas Eq. (12) shows the formula for log-normal GLME distribution model.

$$TotalFuel \cong 1 + T + S + (1|Intersection) + (1|Driver) \tag{11}$$

$$Log(TotalFuel) \cong 1 + T + S + (1|Intersection) + (1|Driver) \tag{12}$$

where T is the treatment, S is the scenario.

Table 3 and Table 5 show the models fit statistics for the normal and log-normal GLME model distributions, respectively. Table 4 and Table 6 show the fixed effect coefficients (95% CIs) for the normal and log-normal GLME model distributions, respectively.

Results showed that the Log Likelihood of the VT-CPFM model is −612.19 and −31.89, while the Log Likelihood of the COPERT is −559.76 and 285.74, for the normal and log-normal GLME, respectively. Based on this information, we can conclude that the second model has a higher Log Likelihood than the first model. Having a model with a higher log likelihood indicates a better fit to the data. However, in our case it indicates that COPERT model is less complex than VT-CPFM, which means it does necessarily reflect the real world. COPERT model is based on average speed, which makes it easier to be fitted using GLME model.

As shown in the results, the p-value for T1 (flashing-green setting) was found to be less than 0.05 and its coefficient is negative, which means that T1 has a statistically significant correlation with the total fuel consumption and produced significantly less fuel consumption than in T0. However, S1 was found to have a p-value more than 0.05, which means that S1 has no clear effect on the total fuel consumption, which means we found no significant difference between the total fuel consumption of drivers with respect to their position at the decision zone. This confirms that while proceeding the decision zones, the decisions taken by drivers to stop or proceed when the traffic signal changes have significant effect on the safety near signalized intersections but has no clear effect on fuel consumption according to the results of this study.

Fig. 1 shows the speed profiles and the average speed profile for the drivers who have experienced T0 and T1 at S1 and has experienced T0

Table 2
Locations of the studied scenarios and treatments.

Intersection	Location (km)	Scenario	Treatment
1	0.7	S1 (Indecision)	T0 (Control)
2	3.2	S2 (Stopping)	T1 (F-green)
3	1.77	S2 (Stopping)	T0 (Control)
4	10.7	S1 (Indecision)	T1 (F-green)

Table 3
Model fit statistics for normal GLME distribution model.

FC Model	AIC	BIC	Log Likelihood	Deviance
VT-CPFM	1234.4	1252.1	−612.19	1224.4
COPERT	1131.5	1152.7	−559.76	1119.5

Table 4
Fixed effect coefficients (95% CIs) for normal GLME distribution model.

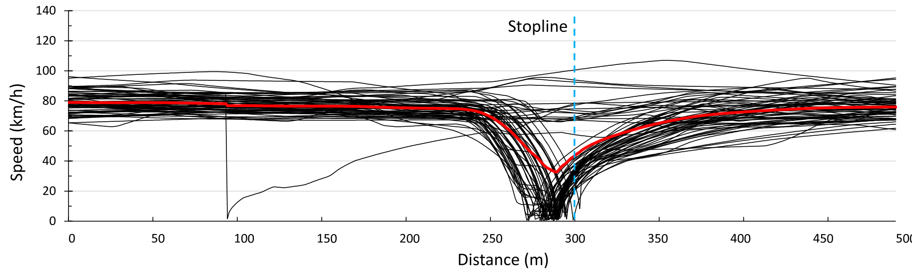
Coefficient	Estimate	SE	sStat	p-value
VT-CPFM				
Intercept	10.40	0.29	34.87	<0.001
T1	−0.27	0.31	−0.87	<0.001
S1	0.75	0.31	2.40	0.170
COPERT				
Intercept	29.33	0.24	117.7	<0.001
T1	−1.97	0.25	−7.85	<0.001
S1	0.24	0.25	0.97	0.330

Table 5
Model fit statistics for log-normal GLME distribution model.

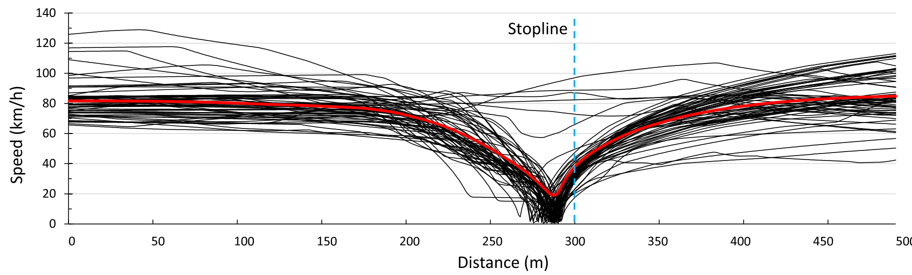
FC Model	AIC	BIC	Log Likelihood	Deviance
VT-CPFM	73.78	91.48	−31.89	63.78
COPERT	−559.48	−538.26	285.74	−571.48

Table 6
Fixed effect coefficients (95% CIs) log-normal GLME distribution model.

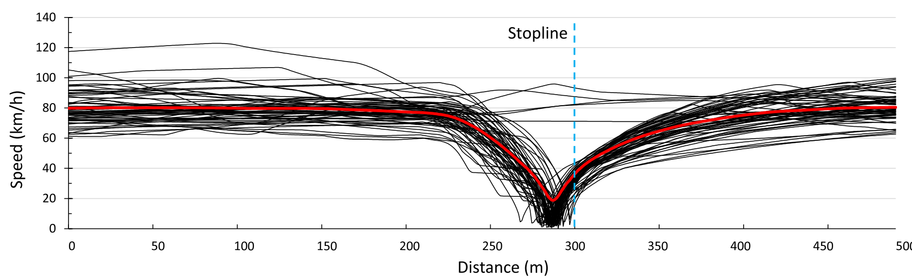
Coefficient	Estimate	SE	sStat	p-value
VT-CPFM				
Intercept	3.12	0.28	45.23	<0.001
T1	−0.13	0.31	−3.76	<0.001
S1	0.26	0.31	1.63	0.040
COPERT				
Intercept	3.37	0.01	377.91	<0.001
T1	−0.07	0.01	−7.77	<0.001
S1	0.01	0.01	1.36	0.180



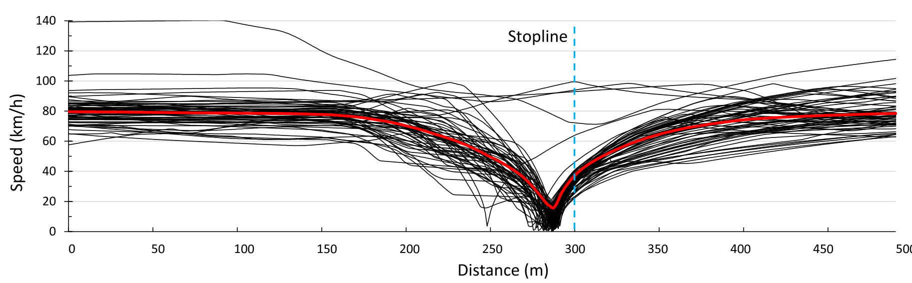
(a) Control condition (T0) at indecision zone scenario (S1)



(b) Flashing green condition (T1) at indecision zone scenario (S1)



(c) Control condition (T0) at stopping zone scenario (S2)



(d) Flashing green condition (T1) at stopping zone scenario (S2)

Fig. 1. Speed profiles of drivers, where red line is the average and black lines are speed for each driver.

and T1 at S2 shown at (a), (b), (c), and (d), respectively. The speed profiles in Fig. 1(b) and 2(d) shows that flashing green signal indication has created a relatively more optimal deceleration pattern with a gradual decrease in the speed than that at Fig. 1(a) and 2(c). This behavior cost less fuel than making more abrupt braking events as in the case of control condition (Rakha et al., 2011; Wang and Rakha, 2017; Edwardes and Rakha, 2014; Muñoz-Organero and Magaña, 2013). On average, T1 produced lower fuel consumption than T0. The averages of fuel consumptions for drivers traveling through T0 were about 65.31 g and 58.93 g for VT-CPFM and COPERT models, respectively. The average fuel consumption for drivers traveling through T1 were about 62.53 g and 54.94 g for VT-CPFM and COPERT models, respectively. Summary statistics of the results are shown in Table 7. In fact, results sound reasonable when drivers see a flashing green (i.e., T1), they are made aware that the traffic signal is turning red ahead of time. Thus, they either speed up a little to cross the intersection in time, or they early start decelerating, which creates a more optimal deceleration pattern.

Table 7
Summary statistics of the results.

Model	VT-CPFM		COPERT	
Treatment	T0	T1	T0	T1
Mean	65.31	62.53	58.94	54.94
Median	64.36	62.21	60.52	54.00
Standard Deviation	11.71	10.93	3.52	3.80
Skewness	0.17	0.10	−1.09	0.27
Range	48.53	45.63	13.86	12.69
Minimum	45.77	41.88	49.87	49.84
Maximum	94.30	87.51	63.74	62.53
Sum	4310.73	4127.08	3889.83	3626.08

On the other hand, in T0, where there is no flashing green, drivers are less likely to be informed when the traffic would become red. Thus, they tend to have a higher possibility to aggressively accelerate at the intersection or make an abrupt braking to stop. Although the reduction of fuel consumption that results from eco-driving is more likely to be much higher, flashing green can have similar impact to eco-driving in displaying the remaining green time and therefore producing a relatively less fuel consumption if compared with control condition.

4.1. VT-CPFM model vs COPERT model

In this section, we will compare the results of VT-CPFM model and COPERT model. Fig. 2 shows the results of fuel consumption for the two models by the two treatments (i.e., T0 and T1). Fig. 2(a) shows the difference of resulted fuel consumption for VT-CPFM and COPERT for T1, and Fig. 2(b) shows the difference for T1. Results for T0 and T1 showed that VT-CPFM, as a microscopic model, was able to incorporate the instantaneous distribution of driver's kinematic values including their speed and acceleration. The VT-CPFM model can avoid the bang-bang control as it has a second-degree polynomial relationship with the vehicle specific power (VSP). In contrast, COPERT, as a macroscopic model, was found to underestimate the fuel consumption, which is consistent with previous studies (Gebisa et al., 2021; Martins, 2016). COPERT is considered as a model that is based on average speed, which means it fails to consider the instantaneous distribution of driver's kinematic values (Ahn and Rakha, 2008). The COPERT model is not capable to be consistent with driving cycle's dynamics, which leads to an underestimation of localized high fuel consumption rates (Martins, 2016).

5. Conclusion

This paper explored the impact of two different traffic signal settings on fuel consumption using a dataset gathered through an experiment using the driving simulator at Qatar Transportation and Traffic Safety Center, Qatar University. We calculated the total fuel consumption at the vicinity of certain intersections, where the considered traffic signal settings took place, using two models: VT-CPFM and COPERT models. Subsequently, we applied GLME model on normal and log-normal distributions to study the correlation between the fuel consumption and the two traffic signal settings. Results showed that by displaying the remaining green time, flashing green signal indication setting is similar to eco-driving and has a relatively lower average fuel consumption at signalized intersections than control condition. As the drivers become aware ahead of time when the green signal indication will be terminated and the red signal indication will start, eventually they either speed up a little to cross the intersection in time, or they early start decelerating, which creates a more optimal deceleration pattern. We also compared between the two fuel consumption estimated methods: VT-CPFM and COPERT models. We found that VT-CPFM resulted in more realistic results as it was able to consider the instantaneous distribution of driver's kinematic values including their speed and acceleration. However, COPERT underestimates the fuel consumption as it relies on average numeric values rather than the instantaneous changes in driver's movement including speed and acceleration.

Author contribution

The authors confirm contribution to the paper as follows: study conception and design: All Authors; data collection: Q. H., and W. A.; analysis and interpretation of results: All Authors; draft manuscript preparation: All Authors. All authors reviewed the results and approved the final version of the manuscript.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence

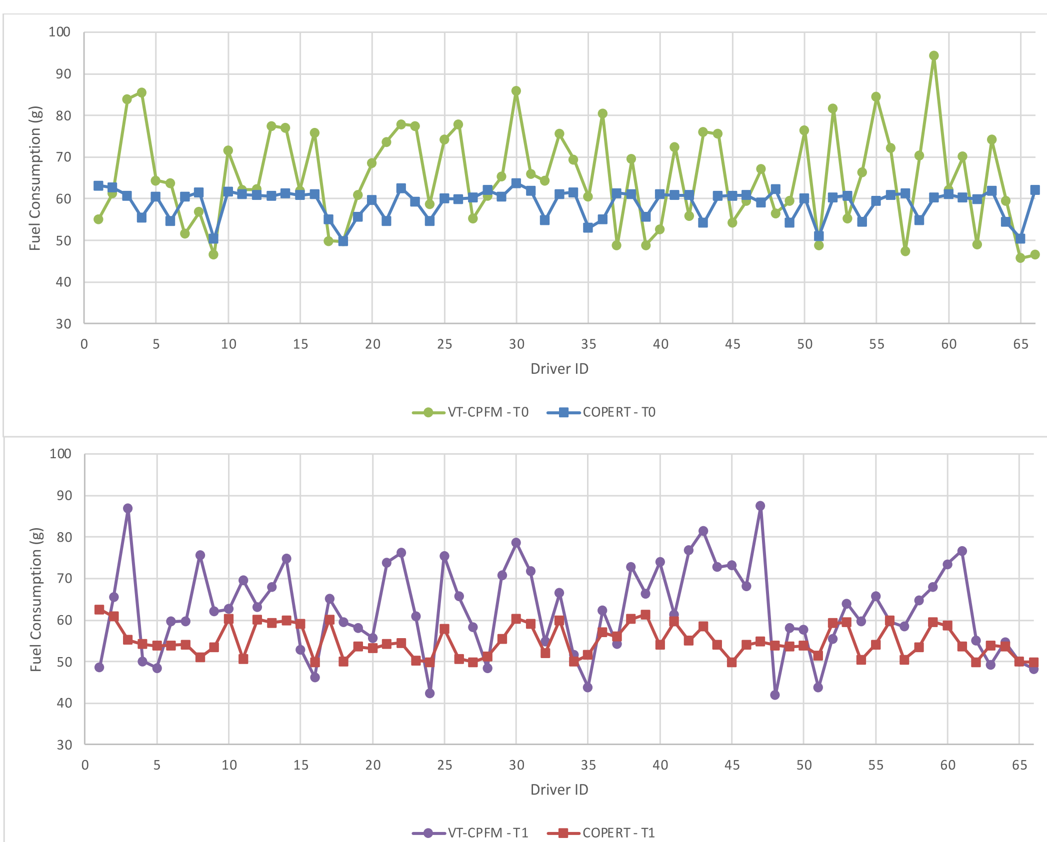


Fig. 2. Fuel consumption results using the models and by the two treatments.

the work reported in this paper.

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