

AN INVESTIGATION OF FUEL-CONSUMPTION FOR HEAVY-DUTY VEHICLES BASED ON THEIR DRIVING PATTERNS

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Abstract

With the growing energy requirements, it is important to understand the impacts of driving patterns on fuel-consumption. This study is aimed at investigating the quantification effects of driving patterns such as distance travelled, instantaneous speed, hard braking, hard accelerating, and engine idle timings on fuel-consumption of heavy-duty vehicles. The telematics data from a leading logistics firm in Thailand was collected for three different types of vehicles (i.e., 6-W NGV, 18-W NGV, and 18-W-Diesel) over a period of two months. Stepwise regression modeling approach was employed to predict fuel-consumption. The results showed that average error between the predicted and measured fuel-consumption was 12.02%, 7.07% and 12.85% for 6-W NGV, 12-W NGV, and 12-W Diesel vehicles, respectively. This research study shows that regression modelling can be used to observe the quantification impacts of real-world driving patterns in heavy-duty vehicle on fuel-consumption.

Keywords: Fuel-consumption, Fuel-modeling, Driving patterns, Heavy-duty vehicles, Regression

Introduction

With the advances in technology, world is moving towards globalization. The need to save fuel is ever increasing with growing demand of fuel in the transportation sector. According to the reports published by the International Energy Agency (IEA), transportation sector is using more than the quarter of the total fuel produced (Borger and Mulalic, 2012). It has been estimated that in 2035, global transport sector would be using 60 million barrels of fuel daily amounting 61% of the total fuel-production. The energy requirements are ever increasing in recent times because of higher demand

of logistics operations. The statistics of the share of energy consumption by type of fuel are shown in Figure 1, which shows that oil accounts for 31% of the total energy requirements (EIA, 2012).

The development of fuel-control strategies is inevitable for controlling the rising demand of fuel consumption in the transportation sector. Fuel-modeling is one of the tools to quantify the effect of driving patterns on fuel-consumption. It can serve a purpose to revise the driving styles for efficient and effective optimized logistics operations.

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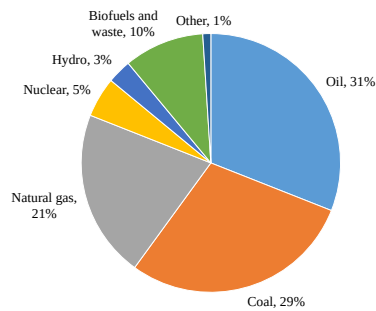


Figure 1. The share of energy consumption by fuel type in 2013.

In a wider standpoint, fuel-modeling can be categorized in three major types based upon the inclusion of the driving parameters scale and scope of the study conducted. These fuel-modeling strategies are mainly macro, meso, and micro modeling approaches. Macro-modeling spans when fuel modeling for a larger area and relatively longer period of time (i.e., longer than one month) is required. Meso-modeling approach incorporates speed as an important input parameter for predicting fuel-consumption. The typical meso-modeling approaches from the literature are as under (Song *et al.*, 2013).

- 1) Fuel models based on correction factor
- 2) Fuel models based on Vehicle Special Power (VSP) bin distribution

However, micro-modeling approach includes different statistical techniques incorporating regression and derivation of driving patterns based on power requirements. Different researchers used different techniques for the estimation of fuel-consumption but the basic parameters incorporated were; speed, acceleration, traffic conditions and vehicle characteristics (Bratt and Ericsson, 2000; Ericsson, 2000a, 2000b, 2001; Nutramon and Supachart, 2009; Ando and Nishihori, 2012; Song *et al.*, 2013; Mensing *et al.*, 2014; Chi *et al.*, 2015; Braun and Rid, 2017; Stillwater *et al.*, 2017). However, it has been investigated that the amount of fuel-consumed is largely dependent upon some of the factors, which are called driving parameters (Ericsson, 2001). It's evident from the literature that the impacts of some of the independent driving parameters such as instantaneous speed, acceleration, deceleration, traffic conditions, and road grade are significant on fuel-consumption (Ericsson, 2000a; Ericsson, 2001) investigated the impacts of sixty-four (64) different driving parameters and concluded that nine (9) of them have statistically significant impacts on fuel-consumption. Other researchers, (Frey *et al.*, 2007; Wang and Rakha, 2017) suggested that the impacts of accelerating patterns are sensitive to the fuel-

consumption, which is an essential parameter in fuel-modeling. Similarly, different road conditions and vehicle characteristics have significant effect on fuel-economy. For example, different driving styles accounts for up to 30% change in fuel-consumption in urban roads and 20% in high speed arterial roads outside of the residential routes (Ma *et al.*, 2015). Another study, Voort *et al.* (2001) developed an isoline fuel map based on regression technique using vehicle speed, acceleration, and fuel-consumption as input parameters for fuel-modeling. (Ahn *et al.*, 2002) estimated fuel-consumption with instantaneous speed (km/h) and acceleration (m/s^2) as input parameters by regression VT_micro modeling approach. He investigated that different acceleration values (1.8, 0.9, 0.0 and -0.9 m/s^2) have different impacts on fuel-consumption with same speed parameter. He also concluded that acceleration patterns have greater impact on fuel-consumption as compared to deceleration patterns. Similarly, vehicle characteristics such as frontal area, shape and engine type also have significant contribution in fuel-consumption (Ganti *et al.*, 2010).

By keeping in view of the above-mentioned literature, most of the researchers included speed and acceleration as determining parameters for fuel-consumption estimation. According to author's knowledge, none of the researcher have investigated the quantification impacts of hard braking, hard accelerating, and engine idle time on fuel-consumption prediction. It was hypothesized that aggressive driving behavior will leads to extra fuel-consumption. In other words, a greater number of hard braking, hard acceleration and more engine idle time means more fuel-consumption. These hypothesis are basis on the findings of the previous studies which offer similar insights with different variables (Lattemann *et al.*, 2004; Groelke *et al.*, 2018; Borek *et al.*, 2020). The basic intent of this study is to check, how change in driving behaviors in heavy-duty vehicles leads to change in their fuel-consumption? In this research study, stepwise regression modeling approach is practiced in order to quantify the effects of distance travelled, instantaneous speed, hard braking, hard accelerating, and engine idle timing in predicting fuel-consumption. The study of these impacts is very important in moderating driving styles which optimize fuel consumption.

Methodology

In this study, the quantification impacts of distance travelled, instantaneous speed, hard braking, hard accelerating, and engine idle timing are investigated

using Stepwise regression modeling (micro modelling technique). The hard braking and hard accelerating incidents are recorded in each time fuel-filling. The data were collected from one of the leading logistics firm in Thailand. The name of the logistics firm is not mentioned in the manuscript to maintain the anonymity of the firm. Three different types of vehicles; 6-Wheeler Natural Gas Vehicles, 18-Wheeler Natural Gas Vehicles, and 18-Wheeler Diesel Vehicles, were included in this research study. The data was collected using Controlled Area Network (CAN) technology installed in the study vehicles for a period of two months. The data contained the information of latitude, longitude, distance, speed, fuel-consumption, number of hard braking, number of hard accelerating. Hard braking and hard accelerating are recorded as incidents using SECONLINE software used by the company for driver's management systems. SECONLINE records hard braking and hard accelerating as incidents if the speed of the vehicle changes more than the set values Equation (1) and Equation (2) in one second time interval. The data was recorded in the suburbs of the Bangkok city and driving patterns were calculated from real-world driving patterns. Fuel-consumption was predicted by stepwise regression and equations with acceptable accuracies were selected. Modeling was done very carefully and only those parameters having statistically significant impact ($p\text{-value} < 0.05$)

on fuel-consumption were included in predicted models. Another criterion to select the model was the best fitting of the data ($R^2\text{-value}$).

Measures

Based on the literature review discussed above, the defined driving parameters were calculated from the telematics data collected over a period of two months from August to September of 2017. Before discussing the details of the driving parameters, their descriptive statistics are explained in the following Table 1.

For example, some of the researchers used speed as one of the determining factor for fuel-consumption prediction. (Bratt and Ericsson, 2000; Ericsson, 2000a, 2000b, 2001; Nutramon and Supachart, 2009; Ando and Nishihori, 2012; Song *et al.*, 2013; Mensing *et al.*, 2014; Chi *et al.*, 2015; Braun and Rid, 2017; Stillwater *et al.*, 2017) This study included instantaneous speed as one of the determinant parameters for fuel-consumption estimation. It has been suggested that an optimal speed control can possibly save fuel up to 12% if unnecessary hard braking and hard accelerations are avoided (Turri *et al.*, 2017). Another study by (Kamalanathsharma and Rakha, 2016) investigated that fuel-efficiency from 5 to 30% can be achieved if vehicles hard braking, hard acceleration, cruising and engine idle episodes are optimized and reduced. Similar findings have suggested that reduction in hard braking and hard acceleration can reduce the fuel consumption from 5.28 to 9.02%, respectively (Borek *et al.*, 2020). However, different previous studies (Table 2) used different thresholds to define a hard braking and a hard accelerating in different contexts. There is no explicit rule to set specific values of acceleration as hard braking and hard accelerating incidents. Most of the studies set these values based on their own understanding and criterion.

As evident from Table 2, each study used different values of acceleration to record hard braking and hard accelerating incidents. Also,

Table 1. Terms used in this study along with their description.

Terms	Description
v	Instantaneous speed of vehicle (km/h)
Δs	Change in distance travelled (km)
Δt	Change in time interval (sec)
v_f	Final speed (km/h)
v_i	Initial speed (km/h)
I_t	Engine idle time (%)
H_a	Number of hard braking
H_b	Number of hard accelerating

Table 2. Set values of acceleration change as hard braking and hard acceleration incidents.

Paper	Threshold value (m/s ²)	Types of incidents	Vehicle
(Ando and Nishihori, 2012)	1.962	Hard acceleration	Toyota city cars
	(-1.962)	Hard braking	
(Rolim <i>et al.</i> , 2014)	3.04 - 4.41	Hard acceleration	Cars
	- (3.33 - 4.41)	Hard braking	
(Rutty <i>et al.</i> , 2013)	2.97	Hard acceleration	Gasoline and hybrid cars
	- 3.47	Hard braking	
(Staubach <i>et al.</i> , 2014)	3.5	Hard acceleration	Dynamic car simulator
	-3.5	Hard braking	
(Klauer <i>et al.</i> , 2009)	2.943	Hard acceleration	Cars
	-2.943	Hard braking	

different vehicle types have varying values as set incidents and none of the researchers have used these parameters as determinant for fuel-consumption prediction in heavy-duty vehicles. For convenience, we define hard braking and hard accelerating incidents in such a way;

- 1) If the speed of vehicle changes less than or equal to 6 km/h in 1 sec (hard braking)
- 2) If the speed of vehicle increases more than or equal to 8 km/h in 1 sec (hard acceleration)

The reasons for differentiating values of hard braking and hard acceleration incidents from previous researchers are;

1) According to author's knowledge, no previous study has studied heavy-duty vehicles in defining these incidents.

2) Because of more inertia values, it is assumed that it would take much force to accelerate and stop heavy-duty vehicles, so set values of these parameters are smaller as compared to other researchers.

3) It is believed that it is easy to accelerate the vehicle as compared to deceleration within specified period of time, so the set value of hard acceleration is more as compared hard braking.

The mathematical demonstrations of hard braking and hard accelerating incidents are shown as follows;

$$H_b = \frac{v_f - v_i}{t} \geq -1.66 \text{ m/s}^2 \quad (1)$$

$$H_a = \frac{v_f - v_i}{t} \geq 2.22 \text{ m/s}^2 \quad (2)$$

The negative sign at the right side of Equation (1), shows that there is decrease in speed with respect to initial speed (negative acceleration). Stepwise regression modeling approach was used to investigate above-mentioned parameters.

Procedure

There were several meetings arranged with the researchers and company management. In first meeting, the company management was informed of the scope and objectives of the study conducted. The company management was requested to set the values of change in acceleration (hard braking and hard accelerating) according to the requirement of the study, suggested by the researchers. Initially all of the driving parameters; instantaneous speed, distance travelled, hard braking, hard accelerating, and engine idle time were included as input parameters for fuel-consumption prediction. However, the stepwise regression modeling was performed using MS-excel to find the best possible model including only those driving parameters which have statistically significant impacts on fuel-consumption. The percentage (%)

errors were calculated between the calculated and predicted fuel-consumption.

Model Development

Human behavior is very complex and difficult to comprehend because of its non-linear and dynamic nature. With all given same conditions, it's hardly possible to produce same results from human behavior. Increased fuel demand has urged the researchers to model driving styles of drivers for better fuel-consumption results. Modeling of effective fuel-usage prediction models is very necessary for moderating effective driving styles in real-world driving patterns.

The main purpose to conduct this study is to investigate the quantification impacts of above-mentioned driving parameters (section 2.1) on fuel-consumption. The data used for the fuel-consumption prediction was obtained from one of the leading logistics (trucking) company in Thailand. The obtained parameters were used to model the fuel-consumption of heavy-duty vehicles. Stepwise regression modeling approach was used for analysis purposes because of its less complexity and ease of inputting values of parameters if required. In this modeling approach, the impacts of input variables ($X_1, X_2, X_3 \dots X_n$) are measured for dependent variable (Y). Stepwise regression modeling approach is based on the values of correlation coefficients. The mathematical form of the simplified regression equation is shown as follows:

$$Y = \beta_0 + \beta_1 \Sigma s + \beta_2 \Sigma (s * v) + \beta_3 \Sigma (s * v^2) + \beta_4 \Sigma H_b + \beta_5 \Sigma H_a + \beta_6 \Sigma I_t + \varepsilon \quad (3)$$

Where;

Y is dependent variable (fuel-consumption) (kg/km, liter/km);

s is distance travelled (km);

v is instantaneous speed (km/h);

H_b is number of hard braking per 100-km;

H_a is number of hard accelerating per 100-km;

I_t is engine idle time in one time fuel-filling (minutes);

$\beta_0, \beta_1 \dots \beta_6$ are coefficient parameters; and ε is random component (rest of the model);

This stepwise regression modeling was done using Microsoft excel and two indices were used to check the validity of the proposed models. The *R-value* gives the information of how best the data is fitted, and *p-value* manifest if the input variable is statistically significant or not, which can be used for modeling purposes. The analysis was carried out and the best fit describing models with acceptable accuracies were chosen. Results showed that the regression equations have the potential to predict

fuel-consumption within acceptable accuracies and difference between predicted (modelled fuel-consumption) and actual (measured fuel-consumption) is minimal.

Results

This study investigated the quantification impacts of driving patterns (distance travelled, instantaneous speed, number of hard braking, number of hard accelerating, and engine idle timing) have been investigated us stepwise regression modeling technique. The driving parameters from real-world driving patterns which are statistically significant ($p\text{-value} < 0.05$) are included in the modeling process. The percent (%) error between the modelled (predicted) fuel-consumption and actual (measured) fuel-consumption lies between 12.02% and 12.85% for 18W-NGV and 18W-Diesel vehicles, respectively. Two important indices for the selection of the predicted models are $R^2\text{-value}$ and $p\text{-value}$. $R^2\text{-value}$ manifest how best the data is fitted, while $p\text{-value}$ shows if the parameter is statistically significant or not. The regression equation for 6W-NGV trucks takes the following form:

$$Y = 0.0129 * v * s - 0.0002 * v^2 * s + 1.5461 * H_b + 0.0365 * I_t \quad (4)$$

According to Equation (4), the parameters which have statistically significant impacts on fuel consumption are; instantaneous speed, distance travelled, number of hard braking, and engine idle time. It can be inferred from Equation (4), the fuel-consumption will increase by 1.5461 times with an additional hard braking provided that all other parameters remain unchanged. The findings of this study are in agreement with the findings of the previous studies which indicated that aggressive driving behavior increases the fuel-consumption (Borek *et al.*, 2020; Lattemann *et al.*, 2004). It can also be indicated that an increase in engine idle time will lead to increased fuel-consumption if all other input variables remain same. Similar investigations have been made by (Zhang and Zhuan, 2013; Groelke *et al.*, 2018) for heavy-duty vehicles. The fuel-consumption will increase by 0.0365 times with an additional minute of engine idle time, provided that all other parameters do not change. A very high value of R^2 (0.9789) shows that these parameters are best fit to predict the amount of fuel-consumption. However, the R^2 value between the modelled and predicted fuel-consumption is 0.8573, which indicate that they are in good agreement with each other with an average error of 12.02%.

The model Equation (5) include distance travelled, instantaneous velocity, hard braking, and engine idle timing as input parameters for the determination of fuel-consumption. The regression equation of 18-W NGV takes the following form:

$$Y = 0.4618 * s - 0.0001 * v^2 * s + 0.7332 * H_b + 0.0073 * I_t \quad (5)$$

The results of regression Equation (5) can be explained in the following manner; the fuel-consumption will increase by 0.4618 times with an additional travel of 1-Km if all other parameters do not change. In the same way, increased number of hard braking will also result in more fuel-consumption. As evident from Equation (5), an additional hard braking incident would result in 0.7332 Kg of fuel-consumed if all of driving parameters remain same. In the similar manner, an additional engine idle timing of one minute, would result in 0.0073 Kg of additional fuel-consumption if all other variables do not change. Again, these results have similar findings as suggested by the previous studies which indicated that additional idle time can increase the fuel-consumption (Lattemann *et al.*, 2004; Kamalanathsharma and Rakha, 2016; Groelke *et al.*, 2018). The scatter plot between the predicted (modelled) and measured (actual) fuel-consumption is shown in Figure 2 and Figure 3. The $R^2\text{-value}$ between the modelled and measured fuel-

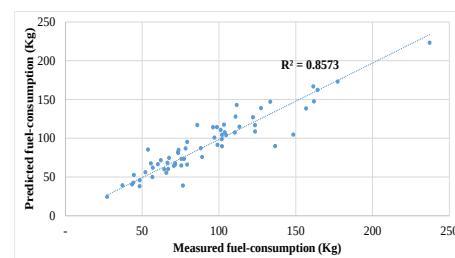


Figure 2. Measured Vs. predicted fuel-consumption of 6W-NGV vehicles.

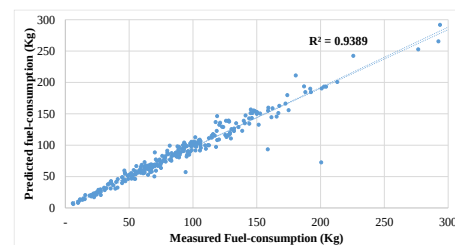


Figure 3. Measured Vs. predicted fuel-consumption of 18W-NGV vehicles.

consumption is 0.9389. It ascertains that there is a good fit of data with an average error of 7.70%.

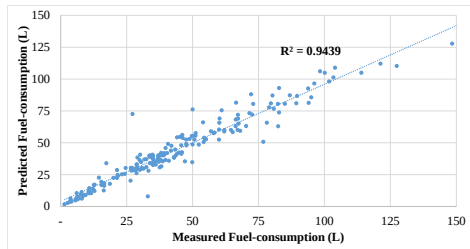


Figure 4. Measured Vs. predicted fuel-consumption of 18W-diesel vehicles.

The regression equation for 18-W Diesel vehicles can be illustrated in the following manner. This model Equation (6) contain distance travelled, instantaneous velocity, and hard braking as determining variables for fuel-consumption prediction.

$$Y = 0.4335 * s - 0.0102 * v * s + 0.0001 * v^2 * s + 0.4290 * H_b \quad (6)$$

The results of regression equation for 18-W Diesel vehicles can be explained in the manner. There would be an additional consumption of 0.4335 Kg of diesel if vehicle travel an additional 1-Km distance provided that all other parameters are not changed. It has been reported that an additional traveling of distance leads to extra fuel-consumption which is not fuel-efficient (Borek *et al.*, 2020). In the same manner, more number of hard braking incidents means more fuel-consumption (Zhang and Zhuan, 2013). As determined from above model Equation (6), an additional hard braking incident would lead to extra fuel-consumption of 0.4290 provided that all other variables are not changed. The high R^2 -value (Figure 4) shows a very good fit between modelled (predicted) and measured (actual) fuel-consumption with an average error of 12.85%. So, it can be inferred from scatter plot (Figure 4) that stepwise regression modeling has the potential to predict fuel-consumption in real-world driving styles.

Discussions and Conclusion

This study was conducted to understand the impacts of real-world driving patterns on fuel-consumption. It was meant to comprehend how different driving habits of accelerating, braking and engine idle timing affect fuel-consumption. However, it has been inferred from above-mentioned models

Equation (4), (5) and (6) that these driving variables are much important to understand fuel-consumption patterns. The driving parameters have statistically significant impact of fuel-consumption. The results of this study can be used to moderate driving behaviors of drivers for efficient and sustainable driving styles. These regression equations with acceptable accuracy (R^2 -value>60) (Chi *et al.*, 2015) have potential to predict fuel-consumption while driving pattern parameters were estimated in different real-world driving conditions for NGV and diesel vehicles. These regression models are not only important for the determination of fuel-consumption but also can be used to develop energy control strategies for heavy-duty vehicle drivers. The analyzed results manifested that fuel-consumption was mainly dependent upon different proportions of instantaneous speed (positive and negative sign in equations), distance travelled, hard braking and engine idle timing.

Limitations and Future Work

It is important to mention that some of the significant fuel-consumption parameters are not included in this study. As it has been observed from the results that the prediction of the models is slightly underestimated when the fuel consumption is high. This can be attributed because of the fact that there might be some other factors as well which influence the rate of fuel consumption. These parameters might include the road infrastructure characteristics and environmental conditions. The information of road gradient, payload on the vehicle, configuration of traffic signals on trip routes, and engine conditions may improve the accuracy of the proposed models. The inclusion of engine rotation speeds and vehicle characteristics can also make a positive consonance for improved prediction of results. The data was much scattered, so the accuracy of the proposed models maybe attributed to the quality of the data. One of the possible reasons for slight underestimation can be attributed due to outliers and some randomness in the data, which affect the precision in prediction.

For continuation of this study, some more driving parameters such as vehicle engine condition, road grade, traffic conditions and payload information would be included for more detailed analysis and improved results. These driving parameters, which are inevitable for fuel-modeling would be included for better results prediction.

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