Aggregated Metrics to Assess Fuel Consumption in Freight Fleets

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Abstract

Vehicle-Fleet´s Managers require to identify relevant aggregate metrics to monitor the performance of their vehicles and drivers. The chosen metric should help in the decision making process of programs relative to the vehicle maintenance, drivers awarding, vehicle routing, fleet renovation, among others. It is well known that fuel consumption is around half of the operative cost of vehicular fleets. However, fuel consumption depends of several factors, such as, vehicle weight, load, route, vehicle technology, road conditions, driving patterns, traffic, among others. Therefore fuel consumption by itself is not an appropriate metric for these purposes. The situation worsen for the case of freight transportation where companies usually have a large diversity of vehicles capacities and technologies and cover many different routes.

We hypothesized that fuel consumption, measured as l/km-gross ton, is the metric to follow. To test this hypothesis, a monitoring campaign was developed on a non-homogenous fleet of 50 heavy-duty freight vehicles, with nationwide operation, in a country with large variations in altitude (0-3500 masl), during two months of normal operation. Fuel consumption behavior was analyzed with several options of performance metrics. Results indicated that for cases when vehicles are almost always fully loaded, specific consumption measured in [l/km – curb ton] also works for these purposes.

Keywords

Fuel consumption, assessment metrics, freight fleets.

1 Introduction

Fuel consumption's cost represents a large portion of transportation companies' variable costs. In Latin America, for example, it accounts to about 50% for domestic transit transportation companies (Huertas et al, 2018). For this reason, vehicle fleet's management focus its attention in monitoring, controlling and improving the fuel consumption of their units, and relating these values to both, vehicle's and driver's performance.

Planning decisions on transport operations such as vehicle maintenance, drivers awarding schemes, and vehicle routing, need to take into consideration fuel consumption data, especially when such activities are to be seen in terms of money. So the most common approach is to assume that cost is linearly proportional to fuel consumption and this one is "only" proportional to traveled distance (de Abreu e Silva et al, 2015); so a measure of fuel consumption given in l/km is enough, disregarding the influence of factors that can affect fuel consumption.

Factors influencing fuel consumption can be classified into strategic, tactical and operational levels. For transport fleets, the strategic factors refer to those that are inherent to long term decisions such as vehicle fleet, vehicle technology, fleet renovation, driver's profile, and type of fuel or power feeding. According to Walnum and Simonsen (2015), these are among the factors with greater influence on fuel consumption in heavy-duty freight transport. Among the tactical factors, which are those that can be updated in from a monthly to yearly basis, are mainly fleet size, driving cycles, and routes. Finally, operational factors are those tightly related to driving itself, route conditions, and driver's behavior such as speed, engine speed, acceleration, breaking, slope, positive kinetic energy, load, route assignment, among others. These are the most common factors considered in fuel consumption estimation models (Huertas et al, 2017). There exists also a vast literature in fuel consumption estimation models that consider factors at different levels at the same time (de Abreu e Silva et al, 2015). Analytic models to estimate fuel consumption, such as multivariate regression models, have been proposed to measure the impact of driving behavior, usually after the implementation of eco-driving programs, to feed driver's performance evaluation, training programs and reward programs, among others (Barla et al, 2017, Díaz et al, 2017).

However the practical application of these models require to have available the specific (and most of them, operational short-term or even instantaneous) significant variables information. So, for planning and prediction purposes, transport companies end up combining expected or planned values with history data as input for their estimation models.

In this work, we hypothesized that fuel consumption, measured as l/km-gross ton, is the metric to follow for planning purposes, since it is the metric that behaves the most independent as possible of many of the influencing factors, and thus, final fuel estimations can be then computed only with aggregated data that reflect the fleet's operation level.

2 Materials and Methods

To test our hypothesis, the behavior of four fuel consumption metrics are analyzed with data obtained from a monitoring campaign on a non-homogeneous fleet of heavy-duty freight vehicles, with nationwide operation, in a country with large variations in altitude (0-3500 meters above sea level) during two months of normal operation. In this section we present the metrics used in this study and a full description of the monitoring campaign.

2.1 Fuel Consumption Metrics

Fuel efficiency is a form to estimate thermal efficiency of the combustion engine of a vehicle. In transports, fuel efficiency is expressed as *fuel economy* that states the ratio of two variables, the distance traveled per fixed unit of fuel consumed by the vehicle in volume, mass or energy. It is expressed as kilometer per liters (km/l) in SI units or miles per US gallon (MPG) in British Imperial System. If this value is high the vehicle is more economic (EPAa and EPAb, 2018). A second form to express fuel efficiency uses the reciprocal, this is, *fuel consumption*, in units of fuel per fixed distance, which is expressed as liters per kilometer (l/km) in SI (EPAb, 2018, EPAc, 2018, NRC, 2011). It can be varied to l/100 km or other consistent SI units depending on the scale of the analysis. Another measure of fuel efficiency is the *specific fuel consumption* which is a measure of how efficiently the fuel supplied to the engine is used to produce power (Heywood, 1989). It is defined as the fuel flow rate in mass (or volume, in some cases) of fuel used per unit power output. The low value of specific fuel consumption shows a more efficient vehicle. It is expressed in gr/kW-hr in SI units or in pound/HP-hr in British Imperial System. This measure is mostly used to analyze instantaneous behavior of the vehicle, as in a tests on dynamometer or road tests.

In this study, four metrics to express fuel efficiency are analyzed: fuel consumption measured in (a) Fe1: liters per 100 km (l/100km), (b) Fe2: liters per 100 km per gross (or total) weight in tons (l/100km-t); (c) Fe3: liters per 100 km per load's weight, or per transported tons (l/100km-tt); and (d) Fe4: liters per 100 km per curb (or empty vehicle weight) in tons (l/100 km-et). Letters "t" and "e" are put before t (tons) to help distinguish the last two metrics.

FE1: fuel consumption in liters per 100 km (l/100 km). As stated before, it is the classic measure of fuel efficiency, interchangeable with fuel economy, and comparable with the technical specifications of vehicles (although they assume empty vehicles). Useful for estimation of total costs, since in the operation, the distances traveled are known. It is used in evaluations of Eco-driving programs (Liimatainen, H., 2011, Ayyildiz et al, 2017) and fuel consumption mathematical models (Duarte et al, 2017, Zhou et al, 2016).

FE2: fuel consumption in liters per 100 km per ton of total weight (l/100 km-t). Also referred as gross weight, total weight includes the weight of the vehicle plus accessories and the load. This metric is sometimes used in transport freight. It is useful to measure the effects of technological improvements in vehicles, by making the unit independent of the total weight, since the mass is included in most of the components that define the demand for energy (power demand).

FE3: fuel consumption in liters per 100 km per ton of load transported (l/100 km-tt). (Díaz et al, 2017) have used this metric to evaluate the effectiveness of eco-driving programs in freight transport. Despite being so scarcely used, it is very useful from the logistical point of view for decision making of fleet capacity and load efficiency, since fuel efficiency can be seen as a constant parameter proportional to distance and to load to be transported.

FE4: fuel consumption in liters per 100 km per ton of curb (or empty) weight (1/100 km-et). Authors have not seen this metric literature reports applying this metric. However, it can be very useful for fleet type assignment decisions, since fuel efficiency can be seen as a constant parameter proportional to the type of vehicle (characterized by its curb weight) to be assigned to a route with a specific distance.

2.2 Description of fleet and data acquisition process.

The freight fleet: 19 trucks of a Latin American manufacturer company that owns a larger fleet were chosen to take the sample with the following characteristics: Vehicles followed an instrumentation process with its corresponding calibration, the vehicles follow the same maintenance program, the experienced drivers drove the same vehicles, the sample was taken from a continuous period of two months. In this research, we only keep track of the total load weight without distinguishing the type of product being transported, since analyses are performed at an aggregate level. Vehicle specifications and the sample composition are summarized in Table 1.

A "trip": This study only considers trips corresponding to a "duty travel"; which could be matched with transport orders. This means, trips with freight movement with known load, known origin and known destination. Thus, raw data from the logging system was selected and grouped into (loaded) trips. This explains the high utilization rates recorded in Table 1.

Data Collection: The system used to log vehicle data is a vehicle display output (VDO) Mix Telematics FM 3306 Communicator®, an in-vehicle onboard computer with standard controller area network (CAN) communication protocol and with a main electronic module of the vehicle, a web interface, an internal global positioning system (GPS) receiver and a 3G modem for data transmission. This system is able to gather data from more than 70 vehicle variables simultaneously at a frequency of 1 Hertz.

Table 1. Vehicle specifications and sample composition

Vehicle	T2	S2	M3	M5_1	M5_2
Type	Medium-duty Turbo	Medium-duty	Heavy-duty	Heavy-duty	Heavy-duty
Engine	Isuzu 4HK1-TCS Turbo	J08E-UD	Cummins ISM 320V	Cummins ISM 410	Cummins ISX 450
Class	C5	C4	C7	C8	C8
Year	2012	2012	2012	2012	2008
Gross weight (tons)	10.40	16.93	39.3	49.1	54.54
Curb weight (tons)	5.52	7.73	15.3	17.1	17.46
Capacity (tons)	7	9.2	24	34	32
Descriptive statistics					
Number of vehicles	4	1	4	9	1
Trips (%)	9.47	36.74	20.83	27.65	5.30
Average load (t)	7.01	8.85	19.81	30.42	31.22
Std deviation load (t)	2.14	1.08	4.73	5.11	4.35
Vehicle utilization (%)	100.14	96.20	82.54	89.47	97.56

Routes: During the study time horizon, the operation registered the delivery of products in 67 routes (origin-destination paths), 12 of which accounted for 80% of the total load. Figure 1 shows the frequency of these routes (# routes), the total load transported, and the average distance of the routes. In general, the average distance is 574.6 km, the median is 523.8 km, and the standard deviation is 205.3 km. Only 3 trips were on routes with less than 50 km with 0.7% of total load, and 11 trips carrying 5.6% of the total load were on routes with more than 1000 km.

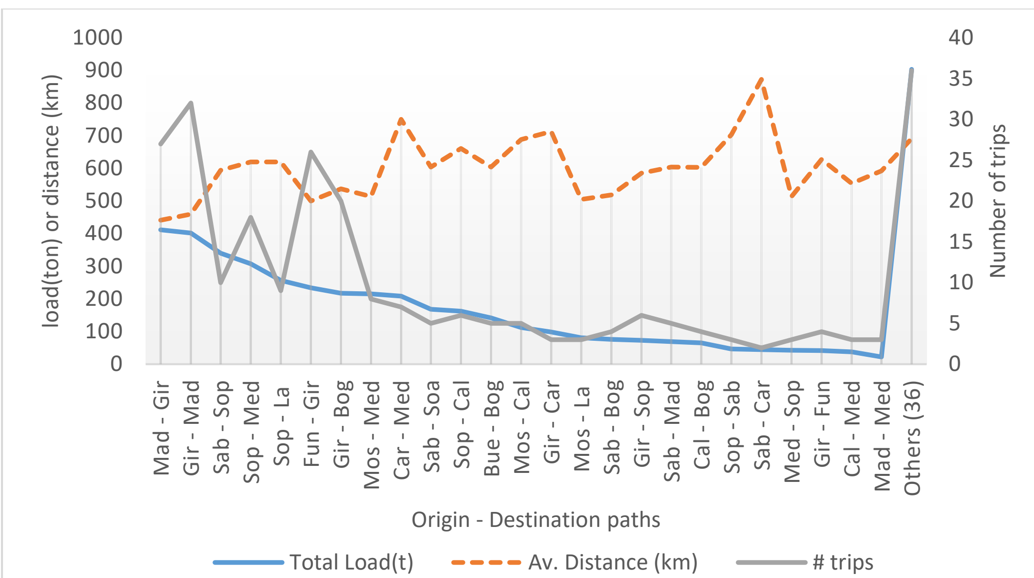


Figure 1. Routes behavior: load, distance and frequency per origin – destination path

Data Preprocessing: A double check process was performed: (a) doubtful points due to inconsistencies in the reports were eliminated, and (b) tests were carried out to identify outliers which were later deleted. The test used is the Grubbs standard (from Minitab) with $\alpha = 5\%$. Out of 277 trips that constituted the original sample, 264 were finally analyzed.

3 Fuel consumption behavior under the four metrics' perspective

Fuel consumption behavior of the fleet described above is analyzed in this section through the four metrics described in section 2.1. An ideal fuel consumption metric to be used for planning purposes should be one which value is the most independent as possible of many of the fuel consumption influencing factors. This is actually the meaning of what an "input parameter" is for planning and operational prescriptive models. So an ideal metric should: (a) be the expected value of a unique normal distribution, and (b) be uncorrelated of the influencing factors.

3.1 Normality analysis

Figures 2a and 2b shows the normality probability plots and the histograms with a 95% normal fit of the four metrics, respectively. From these figures we can observe that FE1 (in l/100km) is the distribution that is least distributed normally. They suggest the presence of stratification, this is, at least two different populations (or distributions) altogether. The other three metrics appear to be normal, except for the behavior at the tails.

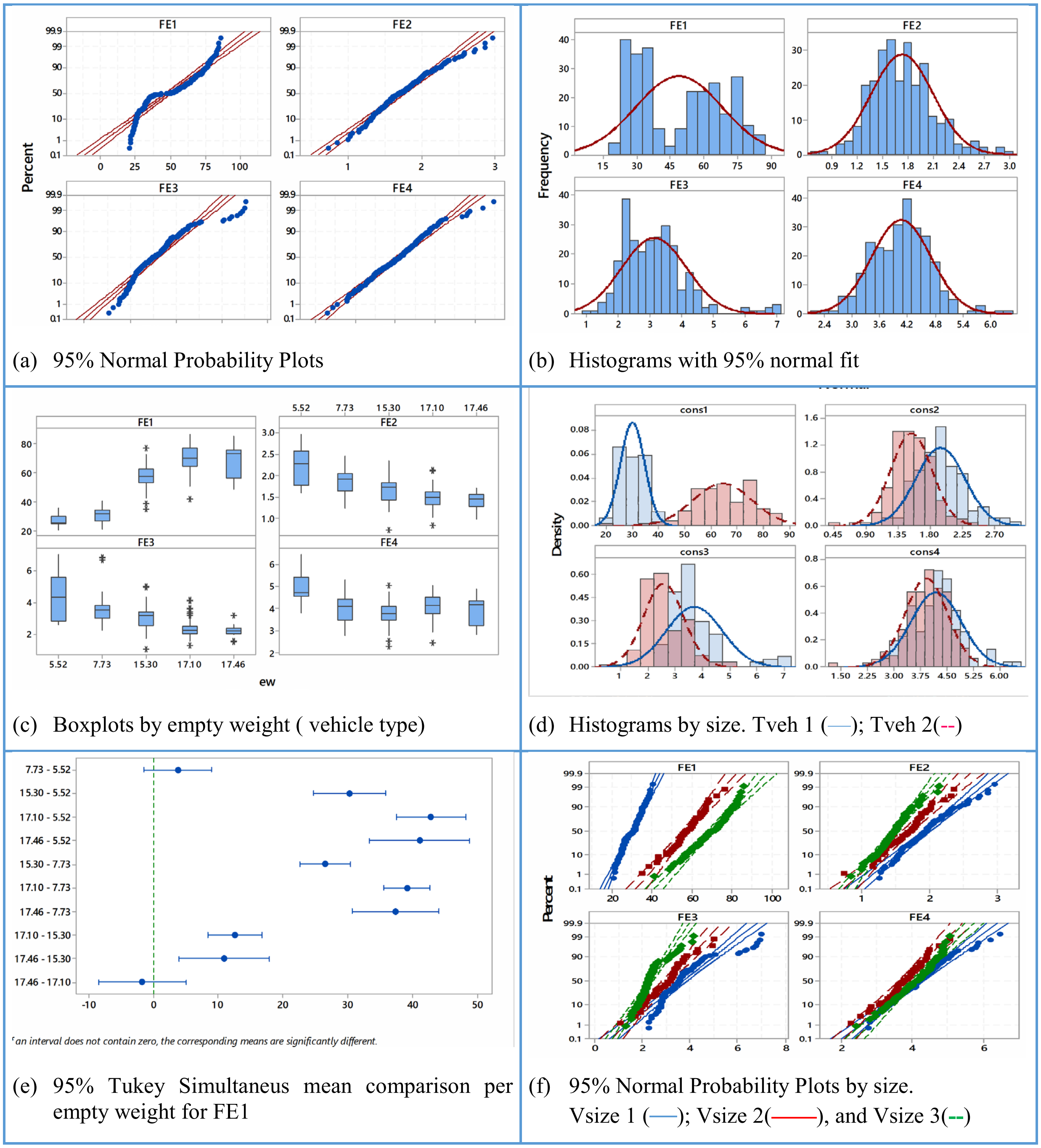
Table 2 presents basic statistics on the metrics and the p_values from the Anderson-Darling (AD) tests for normality. The row "All" shows the results for the entire set of trips. Small values on p indicate non-normal distributions. From this information and with a chosen $\alpha = 0.05$, we can observe that the only metric that "passes" the normality test is FE4 (l/100km-et).

Since fuel consumption is highly dependent on mass, we decided to divide the sample by vehicle's empty weight. This is almost equivalent to divide per vehicle's type. Figure 2c shows the box plots of these divisions. As it can be observed, the graph for FE1 suggests at least two different groups, one for small vehicles and other for medium and large vehicles. In addition, we observe the presence of several outliers in all metrics, especially in FE3, highly biased distributions for the larger vehicles, and high variability in smaller vehicles, especially for FE3 and FE4.

Table 1. Descriptive statistics and normality test's *p* values (case 1)

	N	Variable	FE1	FE2	FE3	FE4
All	264	Average	49.02	1.74	3.14	4.07
		Std. Dev.	19.32	1.02	0.37	0.65
		P_value	<0.005	0.007	<0.005	0.178
Vsize1	122	Average	30.30	1.95	3.73	4.21
		Std. Dev.	4.60	0.34	1.01	0.71
		P_value	<0.005	0.051	<0.005	0.064
Vsize2	55	Average	57.58	1.67	3.05	3.77
		Std. Dev.	8.20	0.30	0.76	0.54
		P_value	0.438	0.267	0.102	0.438
Vsize3	87	Average	69.87	1.48	2.36	4.07
		Std. Dev.	9.24	0.23	0.53	0.54
		P_value	0.186	0.277	<0.005	0.210

Based on this, histograms presented in Figure 2d shows the distributions of the groups of data: blue for smaller vehicles and pink for larger vehicles. Clearly, there are two different distributions for FE1 and on the contrary, two very similar distributions for FE4. Therefore, we performed a 95% Tukey Simultaneus mean comparison for FE1 for all 5 types of vehicles (measured as empty weight). The confidence intervals of the mean grouped by vehicle size (Figure 2e) indicate that the two small sizes and the two larger sizes have the same mean, respectively; suggesting the presence of three groups, so an Analysis of Variance and the Tuckey paired differences test were applied (with $\alpha = 0.05$) to stratify the population. The ANOVA (not shown) had a p value of 0.000 and an $R^2_{adj} = 86.31\%$, when the factor is empty weight. As seen in Figure 2e and in Table 3, the Tuckey test suggests three groups, so a new ANOVA was done using the vehicle size (Vsize) as a factor with three levels: 1, 2 and 3. Again we obtained a p_value = 0 and an $R^2_{adj} = 86.10\%$, very similar to the previous one, which means that it is not necessary to know the exact weight of the vehicle but just its type (of size). Based on this, the sample was divided into three groups according to size; size 1 (Vsize 1) that includes vehicles T2 and S2, size 2 (Vsize 2) with vehicles M3 and size 3 (Vsize 3) with M5 vehicles. Figure (2f) shows their distributions and fits to normality.



(a) 95% Normal Probability Plots

(b) Histograms with 95% normal fit

(c) Boxplots by empty weight (vehicle type)

(d) Histograms by size. Tveh 1 (—); Tveh 2(--)

(e) 95% Tukey Simultaneus mean comparison per empty weight for FE1

(f) 95% Normal Probability Plots by size. Vsize 1 (—); Vsize 2(——), and Vsize 3(--)

Figure 2. Distribution of the four measures of fuel efficiency.

Table 2. 95% Tuckey comparison tests for FE1 per empty weight and FE4 per vehicle size

<table>
<tr><th>Empty weight</th><th>n</th><th>FE1 Mean (t)</th><th>FE1 95% IC (t)</th><th>Tuckey groups</th><th>Veh. size</th><th>FE4 Mean (t)</th><th>FE4 99% IC (t)</th></tr>
<tr><td>5.52</td><td>25</td><td>27.35</td><td>(24.534, 30.164)</td><td>A</td><td rowspan="2">1</td><td rowspan="2">4.21</td><td rowspan="2">(4.0635, 4.3570)</td></tr>
<tr><td>7.7</td><td>97</td><td>31.06</td><td>(29.634, 32.492)</td><td>A</td></tr>
<tr><td>15.3</td><td>55</td><td>57.58</td><td>(55.68, 59.47)</td><td>B</td><td>2</td><td>3.76</td><td>(3.5446, 3.9817)</td></tr>
<tr><td>17.1</td><td>73</td><td>70.15</td><td>(68.50, 71.80)</td><td>C</td><td rowspan="2">3</td><td rowspan="2">4.07</td><td rowspan="2">(3.8989, 4.2464)</td></tr>
<tr><td>17.46</td><td>14</td><td>68.39</td><td>(64.63, 72.16)</td><td>C</td></tr>
</table>

Table 2 also shows basic statistics on the variables and the p_values from the AD normality tests for the three vehicle size groups. Because of the multimodal behavior on FE1, the fits for the whole sample are not good. However, they improve when data is divided by vehicle size. FE2 and FE4 are the distributions that fit to normality for the three vehicle sizes. FE3 do not distributes normally except for vehicle size 2.

Regarding FE4, we can see that when data is estratified by vehicle size they belong to very similar distributions, although the Tukey test still distinguishes the three groups with $\alpha = 0.01$. The ANOVA has an $R^2_{adj} = 6.21\%$ which suggests an independence of this variable from the weight level of the vehicle (Vsize).

Finally, Figure 2f suggests that: (i) the fuel economy (FE1) can be tracked by groups of similar vehicle size. (ii) Fuel economy measured in l/100 km-ton of empty vehicle (FE4) could be used as a "unique" FE metric to track the whole fleet, and most importantly, as a input parameter to estimate transportation costs, when decisions about load or/and vehicle size (or type) are taken in consideration. (iii) Extreme values are always present. The specific conditions of these behaviors should be studied further, since there are plenty of operating conditions that can booster them (e.g. vehicle maintenance needs, driver behavior, particular traffic conditions, etc.)

3.2 Consumption descriptive variables

We were interested in examining decision variables that can be controlled at the aggregate level, from the point of view of a typical logistics operation. Variables such as slope of the route, positive kinetic energy, acceleration time, speed, idle time, positive acceleration, driving (or driver) errors, etc. are frequently used to describe or estimate fuel consumption. However, these variables depend on the driver, the route and the traffic of the moment, and are measured instantaneously and are not necessarily controllable by planners. The fact that FC depends on all these "instantaneous" variables is what supports that the eco-driving training programs continue to be strongly considered as a topic of interest in the literature (Diaz et al, 2017, Huertas et al, 2018)

From the logistic point of view, the decision variables that were considered as of interest are: vehicle's empty (or curb) weight, vehicle's load capacity, vehicle's size (categorical variable with three levels), load, vehicle's gross weight, route, route's total distance, and load factor (LF).

In this study, load factor (LF) is measured as the ratio between empty weight and total (or gross) weight, which is a value between 0 and 1; thus, the lower the value, the fuller the truck is. For example: LF ~ 0.5 is for a truck carrying as much load as its empty weight; LF ~ 0.33 is for a truck carrying as much cargo as twice its empty weight; and LF = 1 means that the truck is empty.

A correlation analysis was first performed between each FC metric and each of the logistics variables selected. The Pearson correlation coefficient r and the p_value when testing the null Hypothesis $H_0\!: r = 0$ are shown in Table 3. In addition, correlation between the logistics variables were calculated. Naturally, those variables related to weight (total, weight, empty weight, vehicle size, and load) resulted with correlations between 0.90 and 0.99. This explains the similar results obtained in Table 4, for correlations of these variables with the four metrics.

From Table 3, it can be observed that the first three metrics are highly correlated with all of the variables, except for Distance, and FE4 has very low or none correlation with all variables. This shows the independence of the metric FE4 from the logistics variables. Table 3 also shows that fuel efficiency is, in general, independent of the traveled distance. The positive sign in FE1 indicates the positive relation between fuel consumption and weight. FE2, FE3, FE4 have negative correlation with fuel consumption. This indicates that greater weight suggests a lower metric value, since they reflects consumption per ton.

Table 3. Correlation table r

Variable	FE1		FE2		FE3		FE4	
	r	p	r	p	r	p	r	p
Empty weight	0.922	0.000	-0.598	0.000	-0.592	0.000	-0.224	0.000
Load	0.881	0.000	-0.679	0.000	-0.734	0.000	-0.083	0.178
Total weight	0.913	0.000	-0.668	0.000	-0.705	0.000	-0.130	0.035
Vehicle size	0.915	0.000	-0.573	0.000	-0.593	0.000	-0.113	0.068
Load factor	-0.604	0.000	0.648	0.000	0.857	0.000	-0.117	0.057
Distance	0.016	0.794	-0.312	0.000	-0.213	0.000	-0.313	0.000

Table 4 shows the determination coefficient R^2 of simple regression models for the four metrics with each variable. R^2 indicates the proportion of the variation of the metric that is explained by the variable. Again, FE4 is not explained by any of the variables. Table 4 also shows the p_values of the Anderson-Darling normality tests. Low values for p means that the residuals are not normally distributed and therefore, the regression models for the three first metrics are not adequate to explain the metrics.

Table 4. R^2 for simple regression models

Variable	FE1		FE2		FE3		FE4	
	R^2	p(AD)	R^2	p(AD)	R^2	p(AD)	R^2	p(AD)
Empty weight	0.850	0.031	0.358	0.263	0.350	<0.005	0.050	0.180
Load	0.776	<0.005	0.461	0.020	0.539	<0.005	0.007	0.237
Total weight	0.834	0.005	0.446	0.026	0.497	<0.005	0.017	0.243
Load factor	0.365	<0.005	0.420	0.015	0.734	<0.005	0.014	0.072
Vehicle size	0.837	0.090	0.328	<0.005	0.352	<0.005	0.013	0.222
Distance	0.000	<0.005	0.097	<0.005	0.045	<0.005	0.098	0.192

4 Conclusions

Unlike the original hypothesis, that FE3 would be the most independent metric to be followed, results showed that no significant differences were observed between FE2 and FE3. More importantly, results showed that FE4 is the metric that though not identically, is the most similarly normally distributed. In addition, the fact that the R^2_{adj} of FE4 of the ANOVA for all the logistics variables studied are so low (below 10%) can be interpreted as this metric is the most "dimensionless" or more "independent" of the operational factors that are controllable at a logistic planning level. This suggests that it is a good option to take it as an input parameter in logistic models such as vehicle routing, resource allocation, among others. For the studied case, the fuel consumption parameter is 4.07 l/100km-et with a standard deviation of 0.65. This value should be multiplied by the curb weight of the selected vehicle and the distance to be assigned to travel in a given route to estimate fuel consumption and then its cost.

The most dimensionless fuel consumption metric that is distributed normally and that applies to the entire data set is FE4 (l /100km-empty vehicle weight (tons)).

It worth highlight that a single variable help to explain 85% of FE1 variation, which is the empty weight of the vehicle. With very close R^2_{adj} the total weight also explains FE1. This similarity is consistent with the high correlation between both variables and probably because practically all recorded trips carried a load close to their capacity. However, if the load were more variable, the total weight would be expected to better explain the FE1. This claim could not be validated with the available data.

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Biographies

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