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ABSTRACT

Vehicles are a major source of transportation greenhouse gas emissions and the need to accurately quantify and monitor transportation-related emissions from vehicles is nowadays essential. Vehicle emissions are complex functions to be approximated in practice due to many variables affecting their outcome. The aim of this research is to study factors affecting different types of vehicle emissions on Egyptian roads. Models were calibrated using vehicle emissions records collected in the period 2018/2019 and data were recorded in the field for eight types of vehicles. Emission data were classified into three categories according to the fuel type (Diesel, Natural Gas, and Petrol Vehicles). A comparative analysis of various statistical modelling techniques was used to predict vehicle emission rates as a function of six independent variables for vehicle emissions. The Linear Regression Model with Link Function of a Log was found to be the best generalized regression model to represent the correlation between CO_2, CO and NO_X emissions for Diesel vehicles, whereas the Linear Regression Model with Link Function of Identity was a good representative for the relationship of HC emission for Diesel vehicles. Natural Gas and Petrol vehicle emissions (CO_2, CO, HC, and NO_X) were best represented with the Linear Regression Model with Link Function of Log. Amongst the studied independent variables, changes in the ambient pressure (P) and numbers of rotations per minute for vehicle engine (RPM) were found to be directly proportional with gas emission for all the three types of vehicles in this study. In addition to these factors, increase of emissions from Diesel vehicles was also related to increasing vehicle speed (V), ambient temperature (T) and relative humidity (RH), whereas emissions from Natural Gas and Petrol vehicles were found to increase also with road grade (G) (both), and ambient temperature (T) (Natural Gas only).

Keywords: Vehicle emissions; Diesel vehicles; Natural gas vehicles; Petrol vehicles; Multi-factor emission modelling

1. Introduction

The Egyptian road network carries a variety of vehicle types including petrol, diesel, and gas motor vehicles. The rate of increase of vehicles jumped from 2.2% in the period 2000/2005 to 6.1% in the period of 2005/2010, which was not balanced by an adequate expansion of the existing road network. This causes congestions and consequently a general increase of vehicle emissions [1]. The transport sector in Egypt contributes with large amount of gaseous pollutant emissions such as nitrogen oxides (NO_X), carbon monoxide (CO), non-methane organic compounds (NMOC), and Sulphur dioxide (SO_2) [1]. Globally, research showed that transport sector share with an increasing portion from 2010 to 2018, it is responsible for about 14% (8.3 $GtCO_2eq$), as opposed to the energy systems sector (34%; 20 $GtCO_2eq$), industry (24%; 14 $GtCO_2eq$), agriculture, forestry and other land uses (AFOLU) (21%; 12 $GtCO_2eq$) and the operation of buildings (6%; 3.3 Gt CO_2eq) from greenhouse gas (GHG) emissions [2].

This figure suggested more strict policies to mitigate car dependence, with the inclusion of demand management policies and innovation on technologies [3], [4], [5].

Mei et al. [6] measured the exhaust CO, HC, and NOx emissions from five typical light-duty vehicles with a portable emissions measurement system under real driving conditions, and analyzed the relationships between emission characteristics of regulated gaseous pollutants and operating conditions including speed, acceleration, and vehicle specific power. It was found that road conditions had an important impact on regulated gaseous emissions, especially for HC emissions from both light-duty passenger cars and light-duty diesel trucks. CO, NOx, and HC emissions from the test vehicles on urban roads were found to increase by approximately 1.1–1.5 times, 1.2–1.4 times, and 1.9–2.6 times, respectively, compared with those on suburban and highway roads.

Nobili [7] analyzed how highway geometric design affects fuel consumption and CO_2, NOx, HC, and CO emissions. As a result, several regression models were calibrated to estimate fuel consumption and emissions on an entire homogeneous road segment. Results showed that fuel consumption and CO_2, NO_X, HC, and CO emission rates are strongly affected by the sum of the absolute deflection angle divided by the sum of the length of the horizontal curves, curvature change rate (CCR_C) and the average horizontal radius (AR). Fuel consumption and CO_2, NO_X, and HC emission rates increase as CCR_C increases and AR decreases.

A complete modeling framework to estimate road traffic microscopic pollutant emissions from easily obtainable macroscopic road topology and traffic information was proposed by De Nunzio et al. [8]. Models were able to predict driving behavior and pollutant emissions as a function of simple macroscopic features.

Liu et al. [9] analyzed the influencing factors of road transport carbon emissions under a "human-vehicle-environment" perspective. The analysis showed that the type of oil has the greatest impact on emissions. For natural gas oil, the emission of one unit of combustion is 0.329 kg more than that of the same unit of diesel combustion. The service life of vehicles is the main influencing factor of road passenger vehicle emissions, due to a decrease of the fuel combustion efficiency. The influence of the proportion of secondary trunk roads on the emissions is mainly related to the acceleration/deceleration cycles becoming more frequent the longer the vehicle at low speed. Increase of vehicle load is also a main factor affecting directly the emission of road passenger vehicles.

Static, kinematics, and dynamics characteristics affects fuel consumption and consequently fuel vehicle emissions. As the vehicle weight and dimensions increase, vehicle emissions increase accordingly. In addition, it has been observed that vehicles with automatic transmissions emit more than manual ones. Similarly, vehicles with more power accessories emit more than vehicles with less power accessories [10]. Weather conditions also affect fuel consumption. In detail, fuel consumption and emissions increase at low temperatures and with high-speed winds due to aerodynamic losses [10]. For example, in Europe, fuel consumption in winter exceeds that in summer by about 15 to 20 percent [5]. Furthermore, emission models must be evaluated with multiple vehicle types, to consider the effects of own characteristics and emission properties from a larger set of vehicles in a more comprehensive manner [3], [9], [11].

Barth et al [6] established a methodology to utilise both traffic sensors and microscopic data for the estimation of emissions. However, this method neglects road geometry characteristics and cannot be used for roads without loop detectors. Models based on this methodology consider conditions established in laboratory dynamometer driving tests and were capable to estimate various types of emissions [12].

Driving behavioral factors are relatively complex to monitor and require use of improved model and methods as well as statistical analyses. Shirmohammadi [13] used a cluster-based analysis to investigate into driving behaviors and driving skills in a large sample of tourists of different age. Specific subgroups of drivers from safe drivers to unskilled and relatively unsafe drivers were identified. Based on annual intentional and unintentional accidents and fines, the clusters were therefore ranked, evaluated and analyzed statistically. The results indicated that unsafe and offensive behaviour is associated with accident events whilst safest and not harmful events are linked to the safe and skillful cluster.

Shirmohammadi and Hadadi [14] investigated into the effect of behavioral and physiological measures for predicting driver's drowsiness. Aim was to develop an intelligent transportation system such as fuzzy logic for preventing fatal traffic accidents by evaluating the lack of driver's arousal level. Drowsy states of drivers were predicted by means of the multinomial logistic regression model. The authors found that the most predicted behavioral measure is the neck bending angle (vertical). Fuzzy logic also showed that driver's sleep behavior is affected in unsuitable weather, such as rainy conditions.

Sturm et al [15] described three modeling techniques to relate emissions with driving behavior, streets conditions, and vehicle-miles travelled (VMT). Parameters considered were traffic volume, traffic characteristics, vehicle kinematics (cruising, idling, accelerating or decelerating), and vehicle condition (starting temperature, speed, RPM, trip length, frequency of trips). In addition, vehicle parameters (vehicle model and year, maintenance schedule, engine type and size, emission control devices, accrued mileage, fuel-delivery system), and the fuel characteristics (type, volatility, chemical composition) were also studied and tested. Moreover, driver behavior, local weather conditions, and land topography were considered.

Emission models have considered a variety of emission factors (EFs). Marsden et al. [16] considered vehicle speed, acceleration, deceleration, cruising speed, idle condition, state of repair of vehicle, emission control devices to estimate carbon monoxide emissions. They proved that vehicle-exhaust emissions depend strongly on the fuel-to-air ratio. They proved also that CO_2 increase with very high and very low speeds. In addition, they proved that the traffic characteristics especially traffic volume affect with large amount CO and PM emission and with small amount CO_2 emissions [7].

Hallmark [17] found in their research study that driving characteristics in term of speeds at intersections are affected by queue position, lane volumes, incidents, percent of heavy vehicles, and posted link speed. Consequently, these factors affect emissions. Emissions also depend on driver's characteristics such as experience, gender, physical condition, and age. Aggressive driving style raise emission rates compared to usual driving [17].

It is worth mentioning that, as the range of temperature extremes increase per day, emission amount increases in that day in both regional and urban traffic. Also, in winter the amount of emissions is 50% more than summer [18].

In an earlier attempt by Int Panis et al [19] to model instantaneous traffic emissions with traffic speed limit, they found that the speed management impact on vehicle emissions is not related to traffic, vehicles and fuel characteristics. They concluded that the active speed management had no significant influence on the number of emissions. On a later stage, Int Panis et al [20] determined PM, NOx, and CO_2 emission reductions as a result of speed management applied policies in Europe. Authors compared the impact of urban (microscopic) and regional (macroscopic) modeling approaches.

Ya-Wen and Chi-Hung [21] studied the effect of the vehicle model year on the average vehicle emissions. They concluded that relatively old vehicles model year are high emitters and contribute significantly to total traffic emissions. On the other hand, they found also that the model year is not affected by the site characteristics on the emission of CO, HC, and NO. Consequently, they developed a model to relate speed and acceleration of vehicles with (CO, HC and NOx) emissions. They stated that CO and HC increase with speed changing from 15 to 32 km/h. However, with the further change of speed from 32 to 53 km/h, CO and HC concentrations were observed to drop slightly. Authors also found that the CO and HC concentrations decrease with increasing acceleration.

Nesamani et al [22] proposed another model that can estimate a set of emission characteristics with link speed. The model was developed using multiple linear regression analysis using a microscopic traffic simulation model. Results showed that the proposed models performed better than current practice especially if traffic sensor data are available as model input.

Boriboonsomsin and Barth [23] studied the effect of the longitudinal road grade on the vehicle fuel consumption and the carbon dioxide emissions. Experimental results proved that this factor has lower effects on the fuel consumption rates compared to light-duty vehicles in both short and long-distance travels.

Zhang [24] explored the model to relate road grades and three traffic emissions, namely, CO, HC, and NO_X. The author used polynomial regression through the SPSS software. Results showed that the R^2 of CO, HC, and NO_X were 0.9855, 0.8433, and 0.9099, respectively, proving fine goodness of fit of correlations for the three traffic emissions with road grades.

Shu et al [25] tried to estimate a best fit multiple linear regression model to relate CO_2 emissions with allocation factors (e.g., population density, urban area, income, road density) together. Authors concluded that the population density affects vehicle CO_2 emissions, i.e., if the population density increases, this increases the CO_2 emissions.

The Environmental Protection Agency (EPA) set National Ambient Air Quality Standards (NAAQS) for six common air pollutants, i.e., ozone, particulate matter (PM), carbon monoxide (CO), nitrogen oxides (NO_X), Sulphur dioxide (SO_2) and lead (Pb). These are commonly known as "criteria pollutants". Significant portions of mobile source emissions are composed mainly of three of these criteria pollutants primarily CO, NO_X, PM and one other class of pollutants volatile organic compounds (VOCs) [26].

Abou-Senna [27] developed traffic volume curves which to predict emissions per mile. Therefore, total emissions were based on a link or group of links with a specific volume or flow rate at different parameter settings. The author used a forward stepwise regression approach including Volume, Speed, Trucks, Grade, and Temperature. Other two-way factor interactions included Speed-Grade and Trucks-Grade in addition to two quadratic effects for the Volume and Speed factors.

Ko [28] documented that as rate of change of curvature of vertical curve "K" increased, the fuel consumption decreased while traveling on the curves. The fuel consumption and CO_2 emissions decrease as K increases.

Vehicle age and type are major factors in emission modelling, as it typically constraints many elements related to the emission generation. These include vehicle engine technology (increased efficiency, etc.), emission control technology (catalytic converters, etc.) in addition to the maintenance history of the vehicle [25].

David [29] projected models to predict CO_2 emission rates depending on the vehicle type. These models considered the Curvature Change Rate (CCR) of the homogeneous road segment, the average speed profile (V_m), and the standard deviation of the average vehicle speed (σV_m) as the explanatory variables. The author concluded that all these variables affect CO_2 emissions, and these models can be used during the road design and operational stage. In detail, it was found that CO_2 emission rates increases when the CCR index increases.

Harikishan [30] developed a simple exponential regression model between vehicle average speed and vehicle emissions of HC, CO and NO_X. The author checked how the default MOVES emission rates could be successfully replaced for the model to be used in India.

Within this context, traffic emissions are affected by several variables, which can be categorised as travel-related factors, highway characteristics, vehicle characteristics, environmental and weather conditions, and other factors. On the other hand, emissions from motor vehicles are highly dependent on number of trips and distance travelled, speed, acceleration, and traffic volumes.

Research reported in this paper is envisioned considering major findings, methodological directions, and prospects from the above-mentioned studies. A fully comprehensive experimental and statistical investigation of critical factors (i.e., road, environment, driver, and traffic), and their effect on traffic emissions per vehicle types has been therefore developed by a comparative analysis of various statistical techniques.

2. Problem Statement and Research Objectives

The excessive increase of the number of vehicles in Egypt results in a more vehicle milled travelled and consequently more emissions. This contributes increasing air pollution with a clear environmental impact and a cascade effect on climate change dynamics. In this scenario, understanding sources and scale of pollution by traffic emission and the way these are interrelated to road, environment. driver and traffic characteristics are crucial for a more comprehensive data analysis, problem assessment and the provision of mitigation actions. To achieve significant predictions, transport planners need to investigate combinations of different scenarios for various amount of vehicle emissions. A model is therefore required to estimate different emissions as a function of significant related factors. To achieve this aim, a main objective of this research is to estimate the best model to relate emissions with a range of different contributing factors. Factors considered in this paper include roadway characteristics, vehicle characteristics, environmental characteristics and driving behavior. The study focuses on vehicle emission measurements of CO_2 (g/s), CO (mg/s), HC (mg/s), and NO_X (mg/s). Six independent variables were selected in this research (vehicle speed, longitudinal profile grade, ambient temperature, ambient pressure, ambient relative humidity and numbers of rotations per minute for vehicle engine) which affect directly the vehicle emissions for the vehicles' categories investigated in this study. This study is directed to provide a better understanding of critical factors for vehicle emissions, and it is not intended to examine the direct environmental effects of the pollutant emissions on the atmosphere and the anthroposphere.

3. Methodology

This section presents the methodology and techniques which were applied in this research, data sources utilized in the modeling method, and the mathematical approaches for the estimation of vehicle emission relationships with the dependent variables. A short description of these items is listed in the following sections. Research methodology can be summarized in Fig. 1

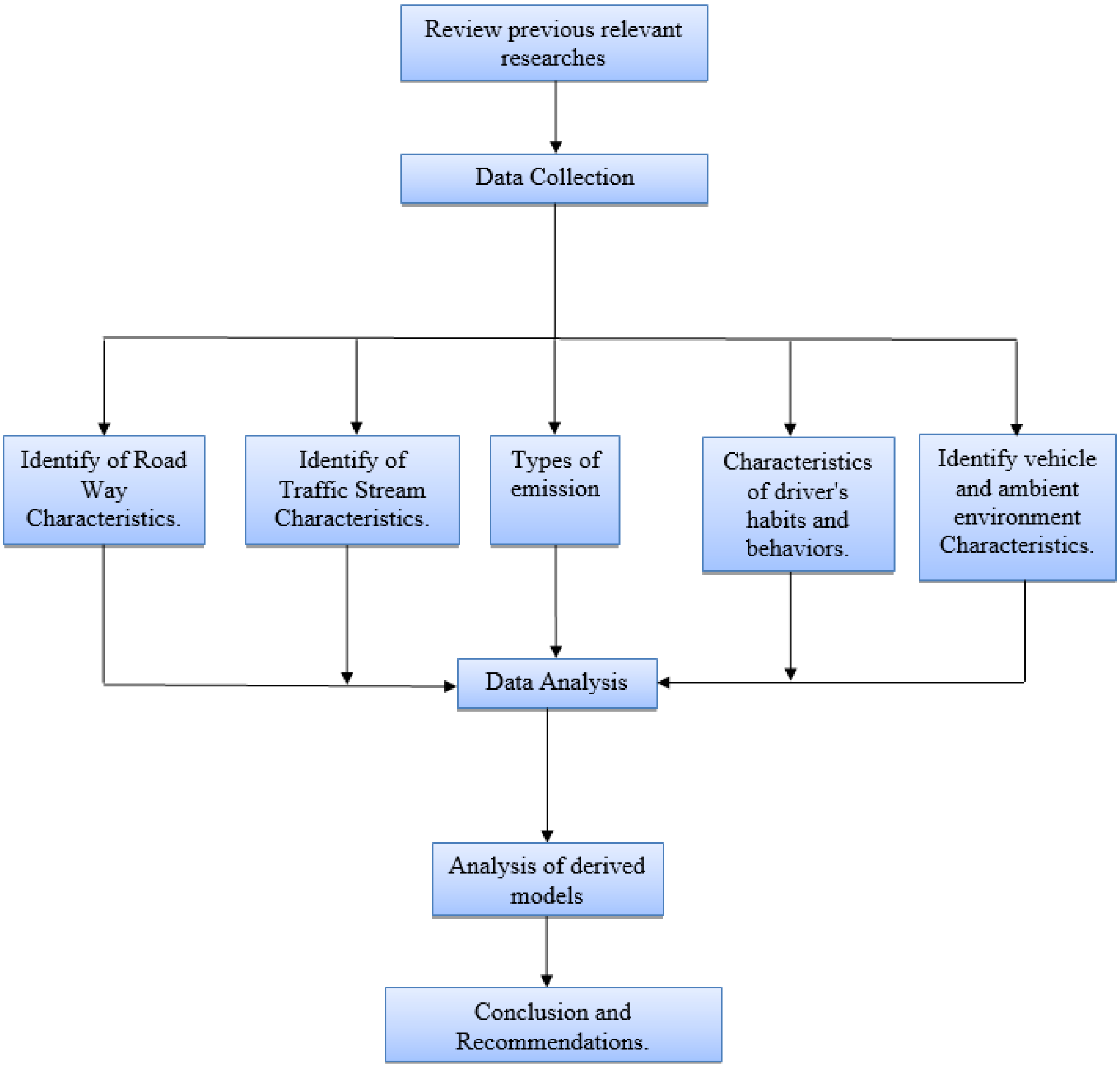

Fig. 1. The research Methodology.

3.1. Data Description

In this research, the available data for vehicle emissions were obtained from the Egyptian Environmental Affairs Agency (EEAA) recorded in (November 2017). An on-board Portable Emission Measurement System (PEMS) as indicated in Fig. 2 was used to collect the data of continuous emissions (time frequency steps of 1s) and the vehicle speed variation in real-life conditions at any travelled location [31].

Fig. 2. Portable Emission Measurement System (PEMS) used in this research.

These data are returned in terms of look-up tables for microscopic emission rate measurements (CO_2 [g/s], CO [mg/s], HC [mg/s], and NO_X [mg/s]), Temperature, Pressure, Relative Humidity, Numbers of Rotations per Minute for Vehicle Engine and Vehicle Speed. The raw data were collected during various driving cycles for each individual vehicle. Table 1 reports the main typological features and information on emission data collected for the eight vehicles used in this research.

A total reading of 48489 of vehicle emission exhaust were recorded for the eight vehicles. A bar chart with number of emission readings for each vehicle is indicated in Fig. 3.

Table 1

Vehicle data brand, engine capacity, model year, fuel type and usage (EEAA, 2017).

Fuel Type	Car No	Car Brand	Usage	Readings per Car	Total no. of Readings	Engine Capacity (CC)	Model Year	Usage
Diesel	1	Mercedes	Bus	2,685	19,082	6,000	2,006	Bus
	2	Chevrolet	Minibus	12,169		4,500	2,009	Minibus
	3	Toyota	Microbus	4,228		2,500	2,010	Microbus
Natural Gas	4	Daewoo	Bus	6,041	10,327	6,000	2,010	Bus
	5	Foton	Microbus	4,286		2,500	2,013	Microbus
Petrol	6	Speranza	Taxi	6,557	19,080	1,600	2,010	Taxi
	7	Isuzu	Private Car	7,326		2,000	1,989	Private Car
	8	Jeep Cherokee	Private Car	5,197		3,700	2,008	Private Car

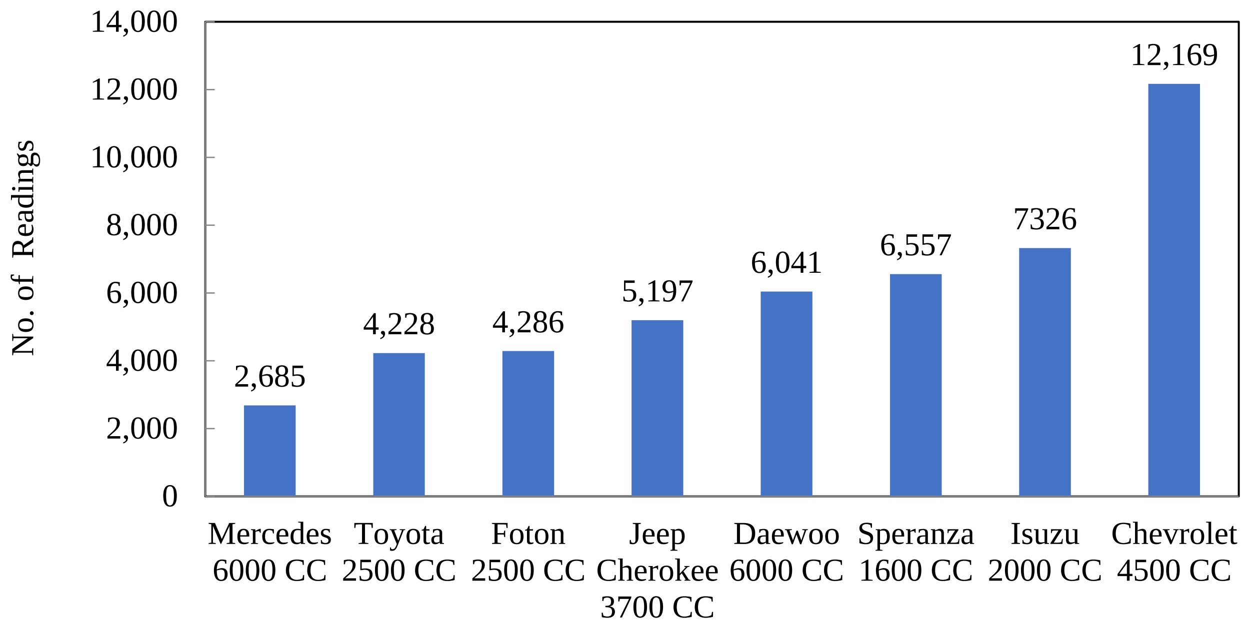

Fig. 3. Emission readings for each vehicle utilized in this study (EEAA, 2017).

3.1.1. Data Classification

The eight vehicles were classified into three categories according to the fuel type. The first was for Diesel Vehicles and included a Mercedes Bus, a Chevrolet Minibus, and a Toyota Microbus. The second category was for Natural Gas Vehicles containing a Daewoo Bus and a

Foton Microbus). The last category was for Petrol Vehicles and included a Speranza Taxi, an Isuzu Private Car, and a Jeep Cherokee Private Car. The total number of emission exhaust per vehicle category is illustrated in Fig. 4.

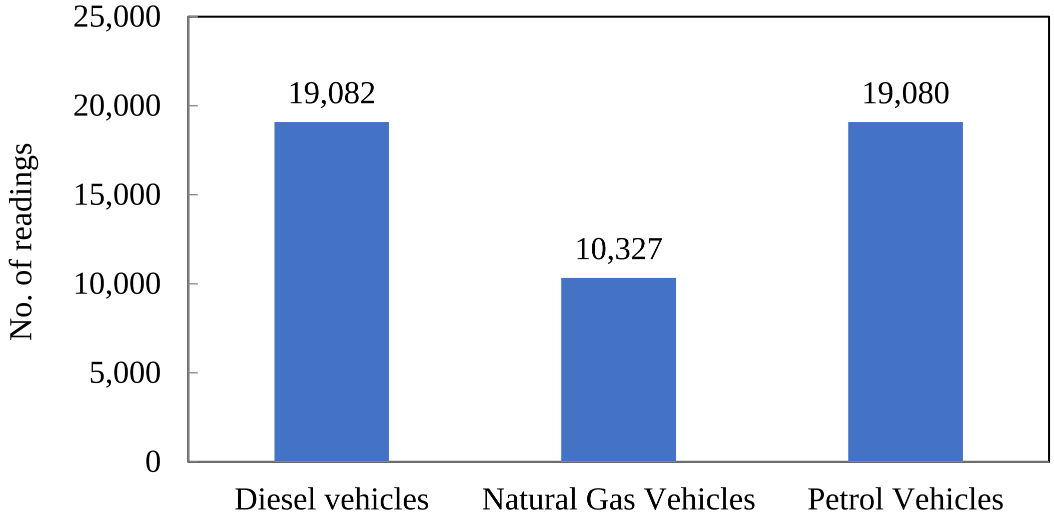

Fig. 4. Total emission readings for each vehicle category (EEAA, 2017).

3.1.2. Dependent Variables

In previous research it was found that the main important vehicle emissions exhaust to represent dependent variable measurements were CO_2 [g/s], CO [mg/s], HC [mg/s], and NO_X [mg/s]. In view of this, these parameters were taken as dependent variables in this study.

3.1.3. Independent Variables

Six independent variables were selected in this research which directly affect vehicle emissions. It is known that a designated design speed is essential in highway geometric design, as it is used to establish a variety of design features [30]. However, driver's interpretation of the road geometry and its interaction with the traffic flow is a prominent factor that must be accounted for. To this effect, vehicle speed (V) was identified as a key element of travel-related factors effect on vehicle emissions in this research, linking designated speed profiles with drivers' perception of the appropriate design speed. Considering average speed-flow relationship conditions and their inverse proportionality, V was also accounted as a representative parameter for traffic characteristics. The longitudinal road grades (G) were selected to study the effect of the highway characteristics on vehicle emissions. However, as the study has been done in the urban area, the longitudinal grade was usually less than 3%. Numbers of rotations per minute for vehicle engine (RPM), ambient temperature (T), ambient pressure (P) and ambient relative humidity (RH) were selected to study the effect of vehicle characteristics and weather conditions on vehicle emission, as reported in Table 2.

Table 2

Dependent Variables.

No.	Variables	Symbol	Units
1	Vehicle Speed	V	Kilometer Per Hour (KPH)
2	Profile Grade	G	Percentage (%)
3	Ambient Temperature	T	Celsius (C^o)
4	Ambient Pressure	P	kilopascal (kPa)
5	Ambient Relative Humidity	RH	Percentage (%)
6	Numbers of Rotation Per Minute for Vehicle Engine	RPM	Value

3.2. Generalized Linear Emission Models

Generalized Linear Models were introduced by [32] in an attempt to make the assumptions of traditional regression models more realistic and suit real-life conditions more effectively. The generalized linear model is a regression model, in which the dependent variable follows one of the probability distributions belonging to the exponential family. These models are considered less restrictive than the traditional regression models. Generalized linear models are based on a set of assumptions as follows:

1- The dependent variables are not required to follow the normal distribution, but an exponential distribution is assumed to follow.

2- The variation is not required to be constant, and Heteroscedasticity is allowed.

3- It is not required that the between the dependent variable/the independent variables relationship must be linear. However, it assumes that a linear relationship exists between the Link Function and the independent variables. Therefore, some non-linear models can be reconciled using generalized linear models.

4- Random errors are independent and they are not required to follow a moderate distribution.

5- Parameters are estimated using the Maximum Likelihood Estimation (MLE) method as well as the Ordinary Least Squares (OLS) method.

Generalized models have been used in many applications as important statistical methods in the analysis and construction of models. The generalized linear model differs from the linear regression model in that the expected value of the response variable is replaced by the link function ($g(\mu) = \eta$), where η is a linear syntactic of the explanatory variables. The main objective of using the link function is to stabilise the error variance. The general formulation for generalized linear models is as follows:

$$Y_i = g(X_i \beta_i) + \varepsilon_i \qquad (1)$$

where:

X_i: represents the set of independent variables affecting the value of the dependent variable Y_i.

g: is the correlation function. This function is used to illustrate the relationship between the expected value of the response variable and the explanatory variables.

ε_i: is a random error representing the unexpected variables.

Y_i: is the dependent variable. This is a random variable that follows one of the Exponential Family distributions, including the following:

- Normal distribution.

- Gamma distribution.
- Poisson distribution.
- Binomial distribution.
- Negative Binomial distribution.
- Inverse Gaussian distribution.
- Tweedy distribution.

The components of the Generalized Linear Model

The Generalized Linear Model consists of three components, namely:

1- Random component means the distribution followed by the dependent variable Y, where in generalized models it is assumed that the dependent variable follows one of the exponential distributions.

2- Systematic Component (Linear Predictor) (η) means the set of parameters (β) and the set of explained variables (x_1, x_2... x_n), and then ($\eta = X_i{}^{\wedge T}\beta$). This component represents the regular element.

3- The Link Function is a function used to link the random component to the systematic component, and it is used to indicate the relationship between the expected value of the dependent variable and the linear predictor. The Link Function is denoted by the symbol (g).

Where:

$$\eta_i = g(\mu_i)$$

$$\eta i = X_i^T \beta$$

$$g(\mu_i) = X_i^T \beta$$

Four model types of generalized linear regression models have been used to test the study hypotheses as follow:

1- Linear Regression with Link Function of Identity.

2- Linear Regression with Link Function of Log.

3- Gamma Regression with Link Function of Log.

4- Tweedy Regression with Link Function of Log.

4. Simple Regression Analysis

Simple Regression Analysis gives the correlation between each dependent variable representing vehicle emission measurements (CO_2 [g/s], CO [mg/s], HC [mg/s], and NO_X [mg/s]) for the three categories according to fuel type and the seven selected independent variables.

4.1. Diesel Vehicle Emissions

The correlation between dependent variables of Diesel Vehicle emission measurements (CO_2 [g/s], CO [mg/s], HC [mg/s], and NO_X [mg/s]) and independent variables were discussed. Table 3 provides a summary for a single regression of diesel vehicle emissions. Relationships were ranked based on the Adjusted R^2 value. In detail, a threshold of 0.500 was selected to identify poor vs good relationships.

Table 3

Simple regression analysis for diesel vehicles.

	Dependent Variable	Independent Variables	Adjusted R^2	Equation	Relation
Diesel Vehicles	1- CO_2 Emission for Diesel Vehicles	V	0.594	$CO_2 = 0.176 \cdot V - 0.002 \cdot V^2$	Good
		G	0.084	$CO_2 = 0.016 \cdot G + 0.048 \cdot G^2$	Poor
		T	0.523	$CO_2 = 0.162 \cdot T - 0.003 \cdot T^2$	Good
		P	0.521	$CO_2 = 0.023 \cdot P$	Good
		RH	0.528	$CO_2 = 0.128 \cdot RH - 0.001 \cdot RH^2$	Good
		RPM	0.638	$CO_2 = 0.002 \cdot RPM + 1.761E\text{-}7 \cdot RPM^2$	Good
	2- CO Emission for Diesel Vehicles	V	0.374	$CO = 0.330 \cdot V + 0.038 \cdot V^2$	Poor
		G	0.019	$CO = 0.737 \cdot G + 0.426 \cdot G^2$	Poor
		T	0.169	$CO = 2.761 \cdot T - 0.051 \cdot T^2$	Poor
		P	0.163	$CO = 0.003 \cdot P^2$	Poor
		RH	0.18	$CO = 1.798 \cdot RH - 0.025 \cdot RH^2$	Poor
		RPM	0.272	$CO = 0.008 \cdot RPM + 1.802E\text{-}5 \cdot RPM^2$	Poor
	3- HC Emission for Diesel Vehicles	V	0.729	$HC = 0.870 \cdot V - 0.008 \cdot V^2$	Good
		G	0.116	$HC = -0.028 \cdot G + 0.309 \cdot G^2$	Poor
		T	0.688	$HC = 0.503 \cdot T - 0.004 \cdot T^2$	Good
		P	0.686	$HC = 0.001 \cdot P^2$	Good
		RH	0.671	$HC = 0.992 \cdot RH - 0.015 \cdot RH^2$	Good
		RPM	0.818	$HC = 0.008 \cdot RPM + 1.771E\text{-}6 \cdot RPM^2$	Good
	4- NO_X Emission for Diesel Vehicles	V	0.649	$NO_X = 1.497 \cdot V - 0.020 \cdot V^2$	Good
		G	0.094	$NO_X = 0.100 \cdot G + 0.381 \cdot G^2$	Poor
		T	0.539	$NO_X = 0.877 \cdot T - 0.011 \cdot T^2$	Good
		P	0.54	$NO_X = 0.175 \cdot P$	Good
		RH	0.533	$NO_X = 1.033 \cdot RH - 0.012 \cdot RH^2$	Good
		RPM	0.644	$NO_X = 0.014 \cdot RPM - 1.036E\text{-}7 \cdot RPM^2$	Good

Single regression showed a strong relation between CO_2 emission with the independent variables RPM, V, T, P and RH whereas a poor relation was found with the profile road longitudinal grade G. The latter condition could be explained by a rather contained value of the longitudinal road grade, i.e., lower than 3%, leading to the assumption of prevailing flat grade conditions for the investigated road sections. This is in line with studies showing that, under uncongested conditions, operations on longitudinal gradients of 3% maximum slope have limited effect on passenger car speeds compared to operations on level terrain [33]. Table 3 showed a poor correlation between CO emission of diesel vehicles and all the independent variables. HC and NO_X emissions report the same trend as CO_2 emission with the independent variables, a strong relation with the independent variables RPM, V, T, P and RH whereas a poor relation with profile road grade G.

4.2. Natural Gas Vehicle Emissions

Table 4 provides a summary of single regression for Natural Gas Vehicles dependent variables emission measurements (CO_2 [g/s], CO [mg/s], HC [mg/s], and NO_X [mg/s]). The independent variables, Single regression, showed a strong relationship between CO_2 emissions with the independent variables RPM, T, P and RH, whereas a poor relation with vehicle speed V and road profile grade G was observed.

A poor relationship between CO emission for natural gas vehicles and all independent variables, HC emission, showed a better representative for the relation with the independent variables. NO_X emission had a good relationship with the independent variables, RPM, T and RH. Poor relation with vehicle speed V, pressure P and road profile grade G was observed.

Table 4

Simple regression analysis for natural gas vehicles.

	Dependent Variable	Independent Variables	Adjusted R^2	Equation	Relation
Natural Gas Vehicles	1- CO_2 Emission for Natural Gas Vehicles	V	0.463	$CO_2 = 0.413 \cdot V - 0.007 \cdot V^2$	Poor
		G	0.103	$CO_2 = 0.050 \cdot G + 0.185 \cdot G^2$	Poor
		T	0.623	$CO_2 = 0.217 \cdot T + 0.009 \cdot T^2$	Good
		P	0.555	$CO_2 = 0.745 \cdot P^2$	Good
		RH	0.694	$CO_2 = 0.569 \cdot RH - 0.011 \cdot RH^2$	Good
		RPM	0.793	$CO_2 = 0.002 \cdot RPM + 5.463E\text{-}7 \cdot RPM^2$	Good
	2- CO Emission for Natural Gas Vehicles	V	0.214	$CO = 0.733 \cdot V - 0.01 \cdot V^2$	Poor
		G	0.052	$CO = 1.086 \cdot G + 0.418 \cdot G^2$	Poor
		T	0.303	$CO = 2.680 \cdot T - 0.062 \cdot T^2$	Poor
		P	0.181	$CO = 0.097 \cdot P$	Poor
		RH	0.446	$CO = - 0.538 \cdot RH + 0.021 \cdot RH^2$	Poor
		RPM	0.189	$CO = 0.011 \cdot RPM - 2.474E\text{-}6 \cdot RPM^2$	Poor
	3- HC Emission for Natural Gas Vehicles	V	0.402	$HC = 1.810 \cdot V - 0.024 \cdot V^2$	Poor
		G	0.078	$HC = 1.176 \cdot G + 1.010 \cdot G^2$	Poor
		T	0.412	$HC = 1.532 \cdot T - 0.021 \cdot T^2$	Poor
		P	0.411	$HC = 0.271 \cdot P$	Poor
		RH	0.423	$HC = 1.742 \cdot RH - 0.024 \cdot RH^2$	Poor
		RPM	0.482	$HC = 0.018 \cdot RPM - 8.502E\text{-}7 \cdot RPM^2$	Poor
	4- NO_X Emission for Natural Gas Vehicles	V	0.407	$NO_X = 4.891 \cdot V - 0.076 \cdot V^2$	Poor
		G	0.067	$NO_X = 2.379 \cdot G + 2.087 \cdot G^2$	Poor
		T	0.508	$NO_X = -3.835 \cdot T + 0.139 \cdot T^2$	Good
		P	0.432	$NO_X = 0.006 \cdot P^2$	Poor
		RH	0.527	$NO_X = 6.965 \cdot RH - 0.134 \cdot RH^2$	Good
		RPM	0.615	$NO_X = 0.028 \cdot RPM + 5.061E - 6 \cdot RPM^2$	Good

4.3. Petrol Vehicle Emissions

Table 5 represents the correlation between dependent variables of Petrol Vehicle emission measurements (CO_2 [g/s], CO [mg/s], HC [mg/s], and NO_X [mg/s]) and independent variables. Single regression showed a poor relation between CO_2 emissions with all independent variables except RPM variable. A poor relation between CO, HC and NO_X emissions for Petrol vehicles and independent variables was observed.

Table 5

Simple regression analysis for petrol vehicles.

	Dependent Variable	Independent Variables	Adjusted R^2	Equation	Relation
Petrol Vehicles	1- CO_2 Emission for Petrol Vehicles	V	0.437	$CO_2 = 0.108 \cdot V - 0.001 \cdot V^2$	Poor
		G	0.083	$CO_2 = 4.850E\text{-}5 \cdot G + 0.053 \cdot G^2$	Poor
		T	0.392	$CO_2 = 0.042 \cdot T + 0.001 \cdot T^2$	Poor
		P	0.383	$CO_2 = 0.018 \cdot P$	Poor
		RH	0.384	$CO_2 = 0.057 \cdot RH$	Poor
		RPM	0.696	$CO_2 = 2.020E\text{-}7 \cdot RPM^2$	Good
	2- CO Emission for Petrol Vehicles	V	0.229	$CO = 9.391 \cdot V - 0.086 \cdot V^2$	Poor
		G	0.022	$CO = 2.001 \cdot G + 3.164 \cdot G^2$	Poor
		T	0.197	$CO = 10.066 \cdot T - 0.164 \cdot T^2$	Poor
		P	0.191	$CO = 0.015 \cdot P$	Poor
		RH	0.215	$CO = 11.290 \cdot RH - 0.170 \cdot RH^2$	Poor
		RPM	0.222	$CO = 0.153 \cdot RPM - 2.887E\text{-}5 \cdot RPM^2$	Poor
	3- HC Emission for Petrol Vehicles	V	0.293	$CO = 0.568 \cdot V - 0.005 \cdot V^2$	Poor
		G	0.029	$CO = - 0.065 \cdot G + 0.197 \cdot G^2$	Poor
		T	0.252	$CO = 0.696 \cdot T - 0.013 \cdot T^2$	Poor
		P	0.248	$CO = 0.001 \cdot P^2$	Poor
		RH	0.253	$Co = 0.522 \cdot RH - 0.007 \cdot RH^2$	Poor
		RPM	0.273	$CO = 0.007 \cdot RPM - 9.377E\text{-}7 \cdot RPM^2$	Poor
	4- NO_X Emission for Petrol Vehicles	V	0.153	$NO_X = 0.119 \cdot V + 0.002 \cdot V^2$	Poor
		G	0.016	$NO_X = 0.064 \cdot G + 0.139 \cdot G^2$	Poor
		T	0.089	$NO_X = - 0.009 \cdot T + 0.007 \cdot T^2$	Poor
		P	0.084	$NO_X = 0.050 \cdot P$	Poor
		RH	0.082	$NO_X = 0.141 \cdot RH - 0.001 \cdot RH^2$	Poor
		RPM	0.205	$NO_X = 1.104E\text{-}6 \cdot RPM^2$	Poor

5. Statistical Analysis

The combined effect of multiple parameters can contribute to increase or decrease vehicle emissions, as opposed to considering the effect of individual parameters only. To this extent, Multiple Regression Models represent effective analysis tools to evaluate the combined effect of these parameters on vehicle emissions. Generalized Linear Models are used to analyze the relationship between a single dependent variable of vehicle emission measurements (CO_2 [g/s], CO [mg/s], HC [mg/s], and NO_X [mg/s]) and several independent variables.

5.1. Results of Diesel Vehicle Emission Models

Table 6 represents a summary of the relation between Diesel vehicle emission measurements (CO_2 [g/s], CO [mg/s], HC [mg/s], and NO_X [mg/s]) and the independent variables. The best model is the one returning lowest values of the goodness of fit indicators and the largest R–Square value.

Table 6

Generalized linear models for Diesel Vehicles.

	Dependent Variable	Generalized Linear Regression Models			
		Linear Regression with Link Function of Identity	Linear Regression with Link Function of Log	Gamma Regression with Link Function of Log	Tweedie Regression with Link Function of Log
Diesel Vehicles	1– CO_2 Emission	$CO_{2\ (D)}$ = 0.001* RPM + 0.061* RH + 0.028*G $R^2 = 0.59$	Log $CO_{2\ (D)}$ = 0.02*RH + 0.007*G* G $R^2 = 0.589$	Log $CO_{2\ (D)}$ = 0.02*RH + 0.012*G $R^2 = 0.587$	Log $CO_{2\ (D)}$ = 0.02*RH + 0.011* G $R^2 = 0.588$
	2– CO Emission	$CO_{(D)}$ = 0.1169*RPM + 0.1137*V + 0.1217*G $R^2 = 0.748$	Log $CO_{(D)}$ = 0.001*RPM + 0.032*V + 0.021*P + 0.068*G $R^2 = 0.875$	Log $CO_{(D)}$ = 0.001*RPM + 0.018*V + 0.018*P + 0.039*G $R^2 = 0.618$	Log $CO_{(D)}$ = 0.001*RPM + 0.020*V + 0.021*P + 0.045*G $R^2 = 0.778$
	3– HC Emission	$HC_{(D)}$ = 0.007*RPM + 0.197*V + 0.282*G $R^2 = 0.664$	Log $HC_{(D)}$ = 0.016* V + 0.014*P +0.030*G $R^2 = 0.684$	Log $HC_{(D)}$ =0.001* RPM + 0.012* V + 0.024*T + 0.002*P + 0.019*G $R^2 = 0.558$	Log $HC_{(D)}$ = 0.001* RPM + 0.014*V + 0.029*T + 0.021*G $R^2 = 0.629$
	4– NO_X Emission	$NO_{X\ (D)}$ = 0.012* RPM $R^2 = 0.284$	Log $NO_{X\ (D)}$ = – 0.005*V + 0.064*T $R^2 = 0.418$	Log $NO_{X\ (D)}$ = 0.0001*RPM – 0.005*V + 0.064*T $R^2 = 0.36$	Log $NO_{X\ (D)}$ = – 0.006*V +0.06*T $R^2 = 0.398$

5.1.1. CO_2 Statistical Analysis for Diesel Vehicles

Analysis of statistics using the generalized regression models showed that all used generalized regression models had given acceptable account a goodness of fit with acceptable percent of correlation R^2 value. The results showed that Linear regression model with Link Function of Identity (LRMLFI) was the best generalized regression model as it had accounted a goodness of fit with a highest percent of correlation, R^2 = 59 %.

$$CO_{2\,(D)} = 0.001 \cdot RPM + 0.061 \cdot RH + 0.028 \cdot G \quad (2)$$

5.1.2. CO Statistical Analysis for Diesel Vehicles

The relation between Diesel vehicle emission CO [mg/s] and independent variables were investigated by four models of generalized linear regression models. All used generalized regression models have given acceptable account for a goodness of fit with a high percent of correlation R^2 values. The Linear Regression Model with Link Function of Log (LRMLFL) was the best as it accounted a goodness of fit with the highest percent of correlation R^2 = 87.50%.

$$\text{Log } CO_{(D)} = 0.001 \cdot RPM + 0.032 \cdot V + 0.021 \cdot P + 0.068 \cdot G \quad (3)$$

5.1.3. HC Statistical Analysis for Diesel Vehicles

HC [mg/s] emissions for Diesel vehicles were investigated by four models of generalized linear regression models. All used generalized regression models have given acceptable account for a goodness of fit with a high percent of correlation R^2 value. The Linear Regression Model with Link Function of Log (LRMLFL) was the best model in view of the highest percent of correlation, R^2 = 68.40%.

$$\text{Log } HC_{(D)} = 0.016 \cdot V + 0.014 \cdot P + 0.030 \cdot G \quad (4)$$

5.1.4. NO_X Statistical Analysis for Diesel Vehicles

Analysis of statistics using the generalized regression model by different types of models shows that the linear regression model with Link Function of Identity (LRMLFI) and Gamma, Tweedie Regressions with Link Function of Log were not appropriate to analyze NO_X emissions for diesel vehicles. The Linear Regression Model with Link Function of Log (LRMLFL) models provided better results, as it accounted for a goodness of fit with an acceptable percent of correlation R^2 = 41.80%.

$$\text{Log } NO_{X\,(D)} = -\,0.005 \cdot V + 0.064 \cdot T \tag{5}$$

5.2. Results of Natural Gas Vehicle Emission Models

Four models of generalized linear regression models were used to investigate the relationship between Natural Gas vehicle emission measurements (CO_2 [g/s], CO [mg/s], HC [mg/s], and NO_X [mg/s]) and each independent variable, as reported in Table 7.

Table 7

Generalized linear models for Natural Gas Vehicles.

		Generalized Linear Regression Models			
	Dependent Variable	Linear Regression with Link Function of Identity	Linear Regression with Link Function of Log	Gamma Regression with Link Function of Log	Tweedie Regression with Link Function of Log
Natural Gas Vehicles	1– CO_2 Emission	$CO_{2\,(N)}$ = 0.004*RPM – 0.103*V + 0.004*P R^2 = 0.638	Log $CO_{2\,(N)}$ = – 0.013*V + 0.011*P R^2 = 0.604	Log $CO_{2\,(N)}$= 0.001*RPM – 0.018*V + 0.009*P R^2 = 0.545	Log $CO_{2\,(N)}$ = 0.001* RPM – 0.019*V + 0.026*T R^2 = 0.593
	2– CO Emission	$CO_{(N)}$ = – 0.148*V + 0.467*RH + 0.812*G R^2 = 0.544	Log $CO_{(N)}$ = 0.064*RH + 0.042*G R^2 = 0.630	Log $CO_{(N)}$ = – 0.014*V + 0.015*P + 0.033*RH + 0.034*G R^2 = 0.418	\Log $CO_{(N)}$ = – 0.007*V + 0.077*RH + 0.065*G R^2 = 0.531
	3– HC Emission	$HC_{(N)}$ = 0.014*RPM + 0.16*RH + 0.581*G R^2 = 0.320	Log $HC_{(N)}$ = 0.004*V + 0.046*T + 0.021*RH + 0.029*G R^2 = 0.347	Log $HC_{(N)}$ = 0.004*V + 0.043*T + 0.019*RH + 0.02*G R^2 = 0.338	Log $HC_{(N)}$ = 0.004*V + 0.043*T + 0.02*RH + 0.023*G R^2 = 0.340
	4– NO_X Emission	$NO_{X\,(N)}$ = 0.045*RPM + 0.23*V + 0.586*P – 2.288*RH + 1.104*G R^2 = 0.487	Log $NO_{X\,(N)}$ = 0.009*V + 0.043*P – 0.038*RH + 0.009*G R^2 = 0.480	Log $NO_{X\,(N)}$= 0.001*RPM + 0.007*V + 0.043*P – 0.051*RH + 0.026*G R^2 = 0.413	Log $NO_{X\,(N)}$ = 0.001*RPM + 0.007*V + 0.043*P – 0.047*RH + 0.019*G R^2 = 0.448

5.2.1. CO_2 Statistical Analysis for Natural Gas vehicles

Analysis of statistics using the generalized regression models showed that all used generalized regression models returned acceptable account for a goodness of fit with a good percent of correlation R^2 value. The results showed that the Linear Regression Model with Link Function of Identity (LRMLFI) was the best generalized regression model, as it accounted for a goodness of fit with the highest percent of correlation R^2 = 63.80%.

$$CO_{2\,(N)} = 0.004 \cdot RPM - 0.103 \cdot V + 0.004 \cdot P \tag{6}$$

5.2.2. CO Statistical Analysis for Natural Gas vehicles

CO [mg/s] emission for Natural Gas vehicles were investigated by four models of generalized linear regression models. All used generalized regression models provided acceptable account for a goodness of fit with a high percent of correlation R^2 value. This excludes the Tweedie Regression with Link Function of Log model (TRMLFL), which was found not suitable in analyzing CO [mg/s] emissions for Natural Gas vehicles.

The Linear Regression Model with Link Function of Log (LRMLFL) was the best model as it was given the highest percent of correlation R^2 = 63% with account a goodness of fit values.

$$\text{Log } CO_{(N)} = 0.064 \cdot RH + 0.042 \cdot G \tag{7}$$

5.2.3. HC Statistical Analysis for Natural Gas vehicles

Analysis of statistics using the generalized regression model by different types of models shows that the Linear Regression with Link Function of Identity (LRMLFI), the Gamma Regression with Link Function of Log (GRMLFL) and the Tweedie Regression with Link Function of Log (TRMLFL) were not appropriate in analyzing HC emissions for Natural Gas vehicles. The Linear regression model with Link Function of Log (LRMLFL) provided the best model of regression, as it accounted for a goodness of fit with an acceptable percent of correlation R^2 = 34.70%.

$$\text{Log HC}_{(N)} = 0.004\cdot V + 0.046\cdot T + 0.021\cdot RH + 0.029\cdot G \tag{8}$$

5.2.4. NO_X Statistical Analysis for Natural Gas vehicles

The Linear Regression Model with Link Function of Log (LRMLFL), the Gamma regression with Link Function of Log (GRMLFL) and the Tweedie Regression with Link Function of Log (TRMLFL) were found not suitable in analyzing NOx emissions for Natural Gas vehicles. The results showed that the Linear regression model with Link Function of Identity (LRMLFI) was the best generalized regression model as it accounted for a goodness of fit with an acceptable percentage of correlation R^2 = 48.70%.

$$NO_{X\,(N)} = 0.045\cdot RPM + 0.23\cdot V + 0.586\cdot P - 2.288\cdot RH + 1.104\cdot G \tag{9}$$

5.3. Results of Petrol Vehicle Emission Models

The relation between Petrol vehicle emission measurements (CO_2 [g/s], CO [mg/s], HC [mg/s], and NO_X [mg/s]) and each independent variable was investigated by four models of generalized linear regression models, as reported in Table 8.

Table 8

Generalized linear models for Petrol Vehicles.

	Dependent Variable	Generalized Linear Regression Models: Linear Regression with Link Function of Identity	Linear Regression with Link Function of Log	Gamma Regression with Link Function of Log	Tweedie Regression with Link Function of Log
Petrol Vehicles	1– CO_2 Emission	$CO_{2\,(P)}$ = 0.001*RPM – 0.015*V + 0.014*G R^2 = 0.501	Log $CO_{2\,(P)}$ = –0.006*V + 0.010*G R^2 = 0.497	Log $CO_{2\,(P)}$= –0.006*V + 0.008*G R^2 = 0.498	Log $CO_{2\,(P)}$ = –0.006* V + 0.007*G R^2 = 0.496
	2– CO Emission	$CO_{(P)}$ = 3.523*V + 0.682*P + 5.428*G R^2 = 0.45	Log $CO_{(P)}$ = 0.020*V + 0.047*P + 0.042*G R^2 = 0.451	Log $CO_{(P)}$ = 0.027*V + 0.116*T +0.011*P + 0.033*G R^2 = 0.42	Log $CO_{(P)}$ = 0.027*V+ 0.045*P + 0.046*G R^2 = 0.442
	3– HC Emission	$HC_{(P)}$ = 0.198*V + 0.043*P + 0.139*G R^2 = 0.61	Log $HC_{(P)}$ = 4.254E-5*RPM + 0.015*V + 0.017*P + 0.014*G R^2 = 0.51	Log $HC_{(P)}$ = 0.022*V + 0.014*P R^2 = 0.42	Log $HC_{(P)}$ = 6.817E-5*RPM + 0.020*V + 0.015*P + 0.017*G R^2 = 0.45
	4– NO_X Emission	$NO_{X\,(P)}$ 0.004*RPM + 0.095*V – 0.087*RH + 0.157*G R^2 = 0.22	Log $NO_{X\,(P)}$ = 0.024*V – 0.004*RH + 0.062*G R^2 = 0.37	Log $NO_{X\,(P)}$ = 0.001*RPM + 0.018*V – 0.008*RH + 0.041*G R^2 = 0.36	Log $NO_{X\,(P)}$ = 0.001*RPM + 0.019*V – 0.006*RH + 0.043*G R^2 = 0.365

5.3.1. CO_2 Statistical Analysis for Petrol vehicles

Analysis of statistics using the generalized regression models showed that all used generalized regression models returned an acceptable account for a goodness of fit with an acceptable percentage of correlation R^2 value. The results showed that the Linear Regression Model with Link Function of Identity (LRMLFI) was the best generalized regression model providing an acceptable percentage of correlation R^2 = 50.1%.

$$CO_{2\,(P)} = 0.001 \cdot RPM - 0.015 \cdot V + 0.014 \cdot G \quad (10)$$

5.3.2. CO Statistical Analysis for Petrol vehicles

CO [mg/s] emissions for Petrol vehicles were investigated by four models of generalized linear regression models. The Linear Regression Model with Link Function of identity (LRMLFI), the Gamma Regression with Link Function of Log (GRMLFL) and the Tweedie Regression with Link Function of Log (TRMLFL) were not found appropriate in analyzing CO emissions for Petrol vehicles. The Linear Regression Model with Link Function of Log (LRMLFL) was the best model as it returned an acceptable percentage of correlation, R^2 = 45.10%, with account for a goodness of fit values.

$$\text{Log CO}_{(P)} = 0.020 \cdot V + 0.047 \cdot P + 0.042 \cdot G \tag{11}$$

5.3.3. HC Statistical Analysis for Petrol vehicles

Analysis of statistics using the generalized regression model by different types of models shows that the Gamma Regression with Link Function of Log (GRMLFL) and the Tweedie Regression with Link Function of Log (GRMLFL) were not appropriate to analyze HC emissions for Petrol vehicles, whereas the Linear Regression with Link Function of Identity (LRMLFI) and the Linear Regression Model with Link Function of Log (LRMLFL) provided acceptable regression models. Results showed that the Linear Regression Model with Link Function of identity (LRMLFI) was the best generalized regression model as it accounted for a goodness of fit with an acceptable percent of correlation R^2 = 61%.

$$\text{HC}_{(P)} = 0.198 \cdot V + 0.043 \cdot P + 0.139 \cdot G \tag{12}$$

5.3.4. NO_X Statistical Analysis for Petrol vehicles

The Linear Regression Model with Link Function of Identity (LRMLFI), the Gamma Regression with Link Function of Log (GRMLFL) and the Tweedie Regression with Link Function of Log (TRMLFL) were not suitable in analyzing CO emissions for Petrol vehicles NO_X [mg/s]. Emissions for Petrol vehicles were investigated by four models of generalized linear regression models. The Linear Regression Model with Link Function of identity (LRMLFI), the Gamma Regression with Link Function of Log (GRMLFL) and the Tweedie Regression with Link Function of Log (TRMLFL) were not appropriate in analyzing NO_X emissions for Petrol vehicles. The Linear Regression Model with Link Function of Log (LRMLFL) was the best model as it returned an acceptable percentage of correlation $R^2 = 37\%$ with account for a goodness of fit values.

$$\text{Log } NO_{X\,(P)} = 0.024 \cdot V - 0.004 \cdot RH + 0.062 \cdot G \tag{13}$$

6. Conclusion, Recommendations and Future Research

In this research, road, environment, driver, and traffic factors affecting different types of vehicle emissions on Egyptian roads were studied. Vehicle emission records collected in the period 2018/2019 for eight types of vehicles were used for model calibration. Emission data were classified according to the fuel type into three categories (Diesel, Natural Gas, and Petrol Vehicles). A comparative analysis of various statistical modelling techniques was used to predict vehicle emission rates as a function of the identified independent variables.

The following conclusions were drawn based on the results and analyses carried out in this study.

- For Diesel vehicles it was generally found that the increase of vehicle speed (V), ambient temperature (T), ambient pressure (P), ambient relative humidity (RH) and the numbers of rotations per minute for vehicle engine (RPM) increase the emissions. These variables showed a good relationship with CO_2, HC and NO_X emissions, whereas a poor relationship was found with the profile road grade (G), as the average vertical gradient for the selected roads was comparable to prevailing flat grade conditions.
- For Natural Gas vehicle emissions:

- overall analyses indicate that the increase of ambient temperature (T), road grade (G), ambient pressure (P) and the numbers of rotations per minute for vehicle engine (RPM) lead to increasing vehicle emissions.
- CO_2 emissions showed a good representative relationship with ambient temperature (T), ambient pressure (P), ambient relative humidity (RH) and numbers of rotations per minute for vehicle engine (RPM), whereas a poor relationship was found with vehicle speed (V) and profile road grade (G).
- NO_X emissions showed a good representative relationship with ambient temperature (T), ambient relative humidity (RH) and numbers of rotations per minute for vehicle engine (RPM). Conversely, a poor relation was showed for vehicle speed (V), ambient pressure (P) and profile road grade (G).

- For Petrol vehicle emissions:
    - overall analyses indicate that the increase of numbers of rotations per minute for vehicle engine (RPM), ambient pressure (P) and road grade (G) are the main elements affect the vehicle emissions mostly.
    - CO_2 emissions showed a good representative relationship with numbers of rotations per minute for vehicle engine (RPM). However, a poor relation was observed with vehicle speed (V), ambient temperature (T), ambient pressure (P), ambient relative humidity (RH) and profile road grade (G).
- Poor correlation was observed between the following pollutant/vehicle types against all the independent variables:
    - CO emissions of Diesel vehicles;
    - CO and HC emissions of Natural Gas vehicles;
    - CO, HC and NO_X emissions of Petrol vehicles.

It is recommended to apply the Generalized Linear Regression Model with Link Function of Log (LRMLFL) and that with Link Function of Identity (LRMLFI) technique for vehicle emissions. These were found the best generalized regression models to represent the correlation between different vehicle emission independent variables, RPM, RH, G, V, P, and T with a correlation R^2 ranging between 34.70% and 87.50%.

The environmental impact of heavy-duty vehicles cannot be neglected in the modeling process. It should be modelled separately based on engine types. Awareness should be also increased amongst drivers in terms of vehicle emission causes and how to be constantly in focus to safeguarding the environment.

Future research could task itself to study the effect on vehicle's emissions of additional driver behavioral variables, e.g., acceleration and deceleration, as well as road geometric properties, e.g., cross-section characteristics, and direct factors related to variability of traffic conditions.

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Conflict of interest

On behalf of all authors, the corresponding author states that there is no conflict of interest.

Data availability

Data will be made available upon request.