Evaluation of Spark Ignition Engine Emission Logistic Regression Model

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***Abstract*— The transport sector is expected to be responsible for about 75% of carbon emission by the year 2020 and therefore reducing transport sector carbon emissions will be crucial for stabilizing atmospheric concentrations of greenhouse gases (US EPA, 2002). The research therefore, sought to establish the major contributing factors and develop logistic regression model based in their category, usage and engine operating parameters. The sample size was 384 petrol vehicles randomly selected. The key observations included vehicle usage, compression pressure, ignition angle, engine speed, spark plug gap, and vehicle category. The key variables examined for emission were CO, HC, CO_2, excess air factor (lambda) and factors that influence emissions. Logistic regression model was fitted to determine the probability of tested vehicles failing emission tests based on the test variables. The mean vehicle usage ranged between 14328 km/yr and 19640 km/yr and the lowest compression pressure, 6.8 bar was recorded in the non-catalytic vehicles manufactured before 1986. Both categories of non-catalytic vehicles operated at rich mixture. Logistic regression model showed that the coefficient of the engine parameters namely; vehicle usage, compression pressure, ignition angle, engine speed, spark plug gap and lambda were statistically significant in contributing to the probability of failing or passing of a vehicle. The null hypothesis of no significant regression was strongly rejected for all categories of vehicles at 5% significance level.**

***Index Terms*— Vehicle emissions, emissions factors, regression model**

I. INTRODUCTION

Vehicles emissions, which occur near ground level and in densely populated areas, cause much greater human exposure to harmful pollutants in the immediate locality than do emissions from source such as power plants that are situated at elevated levels and farther away from dense populated centres. In addition vehicle exhaust particles being small and numerous can be expected to have considerable health impacts. Pollution abatement in the transport sector is therefore becoming more important factor in urban air quality management strategies (Kojima and Lovei, 2001; Gwilliam *et al*, 2004). Real-world vehicle emissions are highly variable. Several factors account for the variability in emissions in different vehicles and the amount of environment damage caused (Shehata and Razek, 2008). However, due to relatively higher average temperatures, poor fuel quality, poor vehicle maintenance culture and high proportion of old vehicles, the level of emissions from mobile sources are usually high (Subramanian *et al*., 2007; Kojima and Lovei, 2001; Mulaku and Karuiki, 2001; Whitelegg and Hag, 2003;Bin, 2003; Choo *et al*, 2007).

As vehicles age and accumulate mileage, their emissions tend to increase. This is both a function of normal degradation of emissions controls of properly functioning vehicles, resulting in moderate emissions increases, and malfunction or outright failure of emissions controls on some vehicles, possibly resulting in very large increases in emissions, particularly CO and HC (Wenzel, 1999; Washburn *et al*, 2001; Bin, 2003). However, exhaust emission as a function of age and mileage accumulation can vary depending on vehicle maintenance culture. A more accurate way of determining the influence of the two variables in exhaust emission is by considering vehicle annual usage. This is obtained by dividing total mileage accumulated by vehicle age (US EPA, 2002, BAQ, 2002).

A. Vehicle models

Some vehicle models are simply designed and manufactured better than others. Some vehicle models and engine families are observed to have very low average emissions while others exhibit very high rates of emissions control failure (Caton, 2003; Bureau of Automotive Repair, 2003). The design of a particular emissions control system affects both the initial effectiveness and the lifetime durability of the system, which in turn contributes to a model- specific emissions rate (Fomunung, 2000).

B. Maintenance and tampering

The degree to which owners maintain their vehicles by providing tune-ups and servicing according to manufacturer schedules can affect the likelihood of engine or emissions control system failure and therefore tailpipe emissions. Outright tampering with vehicles, such as removing fuel tank inlet restrictors to permit fueling with leaded fuel that will degrade the catalytic converter or tuning engines to improve performance, can have a large impact on emissions (Wenzel *et al*, 2000, Bureau of Automotive Repair, 2002; Bin, 2003). Early inspection and maintenance (I/M) programs relied on visual inspection to discourage tampering. The advent of sophisticated on-board computers and sensors has greatly reduced the incentive to improve vehicle performance through tampering. In fact, tampering with the sophisticated electronics installed on today's vehicles will likely reduce performance as well as increase emissions. Requirements for extended manufacturer warranties have led to vehicle designs that are less sensitive to maintenance, at least within the warranty period. Nonetheless, there is evidence that maintenance can still affect real-world emissions from new vehicles, at least on some models (Michalek *et al*., 2004; Bin,

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2003; Choo *et al*, 2007). Improper maintenance or repair can also lead to higher emissions (Michalek *et al.*, 2004; Bureau of Automotive Repair, 2003). The cumulative effects of hard driving or 'misuse" of a vehicle can also increase emissions. For example, prolonged high power driving, such as repeated towing of a trailer up mountain grades, leading to high engine temperatures can cause premature damage to catalytic converter, resulting in dramatic increase in emissions (Osborne, 2007).

Washburn *et al*, 2001). There are many emissions control components that can malfunction or fail. Some of these malfunctions are interpreted; for instance, the onboard computer of a vehicle with a failed oxygen sensor may command a constant fuel enrichment, which can eventually lead to catalyst failure. Different component malfunctions result in very different emissions consequences. In general, malfunctioning vehicles with high CO emissions tend also to have high HC emissions, while vehicles with high NOx emissions tend to have relatively low CO and HC emissions (Wenzel *et al,* 2000; Bureau of Automotive Repair, 2002).

II. Logistic regression models

Logistic regression models explain the probability of an event occurring given certain input variables. The models have been used in vehicles emission analysis to explain the probability of vehicles emission characteristics when certain emission input variables are given. The Radian HEP model (Assanis *et al.*, 2003) is a logistic regression model with input variables that include vehicle type, model year, catalytic converters, odometer readings and type of fuel system. Many of the variables have been identified in the literature as being correlated with high emitting vehicles (Osborne, 2007; Choo *et al*, 2007). For examples, vehicle characteristics such as vehicle age (model year, odometer readings (mileage), fuel type and fuel system have identified with higher emission or higher failure rates (Osborne, 2007; Kahn, 1996; Washburnn *et al*, 2001; Bin, 2003). Other technology based relationships that have been explored in logistic regression modelling include those between the failure rates and repairs of specific emissions control systems components such as catalyst, oxygen sensors or exhaust recirculation (EGR) and high emission (Prucka *et al*., 2010; Mohammadia *et al.*, 2007; Choo*et al*, 2007).

However, the models developed dependent on vehicle characteristics and emission test variables and they can only be used on vehicles with the same characteristics with the vehicles used in model development (Choo *et al*, 2007). This study therefore adopted the approach to develop a logistic model to determine which of the engine input variables vehicle usage, compression pressure, ignition angle, engine speed and spark plug gap contributed to vehicles passing or failing exhaust emission tests based on KS 1515 standards. The identified variables were further used to non-linear regression models to explain the effects of the engine operating parameters on engine performance and emission characteristics.

III. MATERIALS AND METHODS

A. *Determination of factors that affect exhaust emissions*

Vehicle category, vehicle usage and engine operating parameters were used as measures of emission levels. Vehicle usage was calculated by dividing mileage by age while age was calculated from the date of manufacture as indicated in the log book and mileage accumulation was obtained directly from the odometer. For vehicles whose odometer stopped working, mileage accumulation was calculated from a regression model develop by US EPA (US EPA, 2002).

$$\text{Accumulated use (km)} = 489\times(\text{Yrs before Kenya}) + 19023\times(\text{Yrs in Kenya}) - 458.3\times(\text{Yrs in Kenya})^2 \quad (2.1)$$

Exhaust emission tests were determined using AGS-200 exhaust gas analyzer with the engine warm and enrichment devices not operating. The engine was required to remain idling and was not subjected to any significant electrical loading. The exhaust system was ensured to be free from any leakage. For exhaust gases, the test criterion was based on KS1515-2000 specifications, where the tested vehicles were expected to meet individual gas limits. The limits for CO were given as 4.5%, 3.5%, 0.5% and 0.2% for non-catalytic vehicles before 1986, non-catalytic vehicles between 1986 and 2002, catalytic vehicles between 1986 and 2002 and catalytic vehicles after 2002 respectively. HC limits were 1200 ppm for non-catalytic vehicles before 1986, non-catalytic vehicles between 1986 and 2002, while 250 ppm and 200 ppm for catalytic vehicles between 1986 and 2002 and catalytic vehicles after 2002 respectively. The limit for air excess factor lambda (λ) was only considered for catalytic vehicles between 1986 and 2002 and catalytic vehicles after 2002 which was taken as 1.00 ± 0.03. However, the overall test results of pass or fail was based on CO limits.

(i) Non-catalyst test

Temperature and engine speed probe was connected to the engine to obtain the temperature and engine speed readings as shown in Fig. 3.3. Exhaust gas analyzer probe was also fitted in the exhaust pipe to determine the proportions of carbon monoxide (CO), hydrocarbon (HC), carbon dioxide (CO_2) and air/fuel ratio in the exhaust gas over a period of 5 seconds at idle speed. If the vehicle met the CO requirements at its normal idling speed but failed the HC, the HC levels were checked at high idle speed of 2000 rpm.

(ii) Catalyst test

Carbon monoxide (CO), hydrocarbon (HC) and lambda were measured at fast idle speed and CO checked again at idle speed. The 1st Fast idle speed test was done by raising the engine speed to the vehicle specific fast idle speed mostly between 2500-3000 rpm and maintained for 30 seconds. CO, HC and air/fuel ratio values were recorded in the last 5 seconds as Basic Emission Test (BET) results. If the vehicle failed the 1st idle speed additional engine pre-conditioning was done by running the engine between 2000-3000 rpm for 3 minutes or until all emissions were within limits. After engine pre-conditioning, 2nd fast idle speed were done by repeating the procedure of 1st fast idle test. This was followed by catalyst stabilization which required the vehicle specific fast idle speed be maintained for 30 seconds. Finally the engine was allowed to idle for 30 seconds and during the last five seconds, the CO readings were recorded.

(iii) Compression pressure

All the spark plugs were removed from the engine cylinder head and the throttle valve was blocked wide open to ensure that maximum amount of air enters into the cylinders. Then the compressor adaptor was screwed into the spark plug hole of cylinder number 1 as shown in Fig. 3.3. To protect the coil on high voltage, the primary lead from the negative terminal of the coil was disconnected. On electronic system, the positive lead to the control unit was disconnected. The throttle was held wide open as starter motor was operated to crank the engine through the four compression stroke. The needle moved around to indicate the maximum compression in the cylinder. The same procedure was repeated for the rest of the cylinders.

(iv) Ignition angle

Ignition angle was determined by use of stroboscope as shown in Fig. 3.4. The stroboscope lead was connected to number 1 spark plug cable when the engine running at idle speed. Each time number 1 plug fired, the stroboscope flashed. This happened so quickly that when the light was pointed at the crankshaft pulley appears to stand still. A value in degrees corresponding to a mark in the pulley was recorded.

(v) Spark plug gap

Spark plug gap was measured using thickness gauge (feeler gage). All spark plugs were removed from the engine and their gap checked and recorded for every vehicles.

B. *Data Analysis*

Data were coded and then entered into Microsoft Excel and Statistical Analysis System (SAS) version 9.0 for analysis. Data cleaning was done and frequencies were run. Cross tabulation was done to look for differences and relationship among variables. Descriptive analysis was carried out on vehicles characteristics and associated factors using t-test. Chi-squire test was done to determine exhaust emission levels at 5% level of significance. Logistic regression model was fitted on tested results and factors associated with it namely; vehicle usage, compression pressure, ignition angle, engine speed and spark plug gap.The fitted logistic regression model was in the form;

$$\ln(Y) = \ln\left(\frac{\pi}{1-\pi}\right) = \beta_0 + \beta_1 U + \beta_2 P_c + \ldots + \beta_6 \lambda \quad (2.2)$$

where $\hat{\pi}$ =Prob($Y=y/U = x_1, P_c = x_2, \ldots, \lambda = x_6$) = $\left(\frac{e^{\beta_0+\beta_1 x_1+\ldots+\beta_6 x_6}}{1+e^{\beta_0+\beta_1 x_1+\ldots+\beta_6 x_6}}\right)$

Y=Test results
U = Vehicle usage
P_c= Compression pressure
θ = Ignition angle
S = Engine speed
G = Spark plug gap
λ = Lambda
β_i = parameter coefficient

The fitted logistic model effectiveness was assessed by overall model evaluation, statistical teats on the regression and the individual estimation parameters. The statistical test for the logistic regression coefficients was implemented using the Wald Chi-square. Standards engine performance equations were used to analyze engine performance characteristics from the parameters, while non-linear regression models were used to predict engine performance and emission based on engine operating parameters.

IV. RESULTS AND DISCUSSION

A. *Probability of the engine parameters affecting test results*

Equation 3.3 was used to determine the probability of a vehicle failing the test criteria when the parameters x_1, x_2, x_3, x_4, $x_5$and x_6. The hypothesis tested was that the likelihood that a vehicle fails the test was related to; Y=Test results vehicle usage, compression pressure, ignition angle, engine speed and spark plug gap. The independent variable was the test results while vehicle usage, compression pressure, ignition angle, engine speed, spark plug gap and lambda were the predictors/explanatory variables. The test results were coded as 1=Fail and 2=Pass, the vehicle categories were coded as 1=Non-catalytic before 1986, 2=Non-catalytic between 1986 and 2002, 3=Catalytic between 1986 and 2002 and 4=Catalytic after 2002. The model Parameter estimates are presented in Table 4.4. Some variables like fuel type, body type and transmission type were excluded in the model as there was no theoretical justification to include them (Barghi and Safavi, 2011).The estimated parameters were used to test the probability of the vehicle failing emission tests were related to vehicle usage, compression pressure, ignition angle, engine speed and spark plug gap. From the table, the probability values suggests that the coefficients β_0, β_1, $\beta_2, \beta_3, \beta_4$ and β_5 apart from β_6 were not statistically significant at 5% significance level for vehicles manufacture before 1986, while $\beta_1, \beta_2, \beta_3$, β_5 and β_6 were statistically significant at 5% for non catalytic vehicles manufactured between 1986 and 2002. Also β_1 and β_3 were significant at 5% for catalytic vehicles manufactured between 1986 and 2002, while β_1 and β_2 were significant for catalytic vehicles after 2002.

According to the fitted model, the log of odds of a vehicle failing the test is positively related to vehicle usage, ignition angle and spark plug gap and negatively related to compression pressure and lambda for non-catalytic vehicles manufactured between 1986 and 2002, while positively related to vehicle usage and ignition angle for catalytic vehicles between 1986 and 2002. Also the odds of vehicles failing was negatively related to vehicle usage and compression pressure for catalytic vehicles after 2002. In other words, the bigger the values for the positive variables, the higher the chances the vehicle failing the test, while the smaller the values for the negative variables the higher the chances the vehicle failing the test. In overall vehicle usage and compression pressure influenced test results more than the other parameters. Lambda also influenced the test results for non-catalytic vehicles. This is because vehicle usage is a function of normal degradation of emission controls of properly functioning vehicles, resulting moderate emission increase (Gaeta, *et al.*, 2011). Compression pressure and fuel metering can be affected by lack of proper inspection and maintenance which may result in long intervals of vehicle service. Long service intervals affect vehicle lubricants properties resulting in increase wear which affects compression pressure and fuel metering (Ebrahimi,*et al.*, 2012; Bin 2003).

Table 3.1: Parameter estimate for logistic Regression model

Vehicle Category	parameter	Estimate	Std Error	P-value
Non-catalytic	β_0	464.6	223.1	0.9550
before 1986	β_1	-0.00112	0.00057	0.8292
	β_2	-15.7825	4.6535	0.7238
	β_3	-0.8071	4.2222	0.9734
	β_4	-0.0706	0.0074	0.9243
	β_5	34.6242	13.1	0.9462
	β_6	- 16.5329	4.5352	0.0013
Non-catalytic	β_0	-57.5845	41.6393	0.1667
between 1986 and 2002	β_1	0.000037	0.000021	0.0777
	β_2	-1.7190	0.0328	0.0001
	β_3	0.00956	0.00049	0.0535
	β_4	0.1411	0.0111	0.2057
	β_5	18.8360	4.2141	0.0001
	β_6	-4.2119	1.3919	0.0025
Catalytic	β_0	523.0	267.5	0.1547
between 1986	β_1	0.000207	0.000077	0.0073
and 2002	β_2	-1.3152	0.4773	0.3733
	β_3	0.0372	0.0022	0.0928
	β_4	1.4733	0.09831	0.1340
	β_5	-28.1704	6.0589	0.2797
	β_6	2.9545	0.634	0.6511
Catalytic	β_0	17.9671	2.073	0.9307
after 2002	β_1	-0.00018	0.00010	0.0733
	β_2	-10.1167	4.4870	0.0242
	β_3	0.2216	0.0542	0.6827
	β_4	0.0553	0.0078	0.1818
	β_5	-20.4581	2.6836	0.1068
	β_6	-27.0092	0.5935	0.4411

3.2Evaluations of the fitted Logistic models

The model effectiveness was assessed by overall model evaluation, statistical tests on the regression and the individual estimated parameters. The overall model was performed by examining the null model (intercept only model) and the fitted logistic regression model. The null model provides a baseline because it contains no predictors. A logistic model is said to be a better fit if its diagnostics are smaller than those of the intercept-only model. Consequently, the fitted logistic model has a better fit than the null model. This is proved by the Akaike Information Criterion (AIC), Likelihood ratio and Schwarttz Criterion (SC) tests, all of which yield similar conclusion. In all the cases, fitted logistic model minimized the AIC and SC while maximized the likelihood ratio relative to the null model. The tests are presented in the Table 4.5.

Table 3.2: Overall model evaluation

Vehicle category	Criterion	Intercept only	Intercept and Covariates
Non-catalytic before 1986	AIC	17.090	12.017
	SC	18.586	20.996
	-2 Log L	15.090	0.017
Non-catalytic 1986-2002	AIC	230.804	121.547
	SC	234.067	141.124
	-2 Log L	228.804	109.547
Catalytic 1986-2002	AIC	164.169	55.529
	SC	166.997	72.499
	-2 Log L	162.169	43.529
Catalytic After 2002	AIC	47.475	38.613
	SC	48.971	47.598
	-2 Log L	45.475	26.613

The statistical test for the regression coefficients was implemented using the Wald Chi-square statistic for the three criteria. The results are presented in the Table; 3.3;

Table 3.3: Wald Chi-square table

Vehicle category	Test	Chi-Square	df	P-value
Non-catalytic before 1986	Likelihood Ratio	15.0723	5	0.0101
	Score	11.3850	5	0.0443
	Wald	0.30250	5	0.9976
Non-catalytic 1986-2002	Likelihood Ratio	119.2569	5	0.0001
	Score	93.9806	5	0.0001
	Wald	45.1628	5	0.0001
Catalytic 1986-2002	Likelihood Ratio	118.6399	5	0.0001
	Score	83.0424	5	0.0001
	Wald	18.9953	5	0.0019
Catalytic after 2002	Likelihood Ratio	18.8611	5	0.0020
	Score	14.5865	5	0.0123
	Wald	8.5413	5	0.1288

The null hypothesis of no significant regression was strongly rejected for both categories of vehicles manufactured between 1986 & 2002 by the three tests at 5% significance level. For non-catalytic vehicles before 1986 and catalytic vehicles after 2002, the regression model was also considered to be significant despite the fact that the Wald statistic failed to reject the hypothesis of no significance in regression. In overall, the combination of independent variables (vehicle usage, compression pressure, ignition angle, idle speed and spark plug gap) significantly contributed to the probability of failure or pass for the vehicles studied.

V. Conclusion

Logistic regression model showed that the coefficient of the engine parameters namely; vehicle usage, compression pressure, ignition angle, engine speed, spark plug gap and lambda were statistically significant in contributing to the probability of failing or passing of a vehicle. The assessment of the logistic model showed better fit as fitted model minimized the AIC and SC while maximizing the likelihood ratio relative to the null model. The null hypothesis of no significant regression was strongly rejected for all categories of vehicles at 5% significance level.

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