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RESEARCH IN ENVIRONMENTAL PLANNING AND MANAGEMENT

Estimating the urban environmental impact of gasoline-ethanol blended fuels in a passenger vehicle engine

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Abstract

A large portion of urban emissions in developing countries come from old gasoline vehicles driven in metropolitan areas. The present study aimed to develop models to estimate the environmental impact of different contents of gasoline and ethanol mixtures (pure gasoline; 25, 50, 75% ethanol blended to gasoline; and 100% ethanol) in a flex-fuel engine. We tested the blended fuel using three different speeds and recorded the GHG emissions and engine output data. The data mining approach was used to develop environmental impact predictive models. The ethanol content in gasoline; the engine rotational speed 900, 2000, and 3000 rpm; and λ were used as attributes. The classification target was the environmental impact concerning the CO_2 emission ("low," "average," and "high"). We employed the Random forest algorithm to develop predictive models. The mean values of CO_2 concentrations for all studied fuel content were above 2.47% of the volume. The trees' models (accuracy 73%, κ =0.61) showed three alternatives for predicting the environmental impact based on the ethanol blend, the engine rotation, λ, and the air-fuel ratio. Such models might help policymakers develop educational campaigns to reduce short- and medium-term urban commuter traffic pollution in countries that lack suitable urban transportation.

Keywords Alternative fuel · Ethanol · Combustion · Spark-ignition engine · Pollution control policy

Introduction

Passenger and light-duty vehicles are a significant portion of urban emissions (Hitchcock et al. 2014; Slovic and Ribeiro 2018). In late years, locals were exposed to contaminant levels of particulate matter above the recommendations in near 80% of urban areas (WHO 2016). Urban air pollution is a critical risk to global health, and the impact of the exposure has been described in the current literature (Currie et al. 2014; Kim et al. 2017). The International Energy Agency (IEA 2018; IEA 2019) reports that CO_2 emissions from fuel combustion decreased by around 12% in the European Union and 16% in the USA. However, the Americas' overall levels showed little change, as growing economies such as Brazil (+43%) and Mexico (+24%) increased emissions. The world's energy demand is increasingly growing nowadays, and fossil fuel depletion is becoming a crucial and worldwide issue, not only concerning the road transport sector. In effect, the extensive economic growth model has led to severe damage to the ecological environment, and severe air pollution problems have occurred frequently in the last decade. More than 25 billion tons of CO_2 from worldwide human activities are released annually into the atmosphere (Iodice et al. 2017a; Iodice et al 2019). Therefore, the development of new technologies (such as battery electric vehicles for sustainable mobility) and the changing from conventional fuel to biofuel should be a rigorous necessity to meet the energy demands for the transportation sector and limit the production of CO_2 and particulate matters in urban contexts (Iodice et al. 2017b).

Non-fossil fuels are considered renewable since they are produced from a natural source. An example is ethanol

The original online version of this article was revised: The correct images of Figures 3 and 5 are presented in this paper.

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(C_2H_5OH), a natural fuel produced from sugarcane that is considered an alternative source to fossil fuels (Schwaderlapp et al. 2012; Schifter et al. 2013; IEA 2018; Roso et al. 2019). Despite the advancement of electric vehicles, transport energy's progress falls on a complex interchange between various actors, besides being distinct in different parts of the world. For instance, in developing countries, transport energy policies rely on the already established fuel distribution network, and significant changes might be implemented to change this scenario (Kalghatgi 2018). Plausible projections indicate that by 2040 around 90% of transport energy will come from combustion engines powered by petroleum (WEC 2011). The mixture of the two fuels, gasoline and ethanol when adequately combined, improves the general energy efficiency of the vehicles, the torque, and the engine power for application in flex-fuel technology (Delgado et al. 2007; Venugopal et al. 2013; Roso et al. 2019) in addition to reducing emissions of greenhouse gases when compared to pure gasoline (Venugopal et al. 2013; IEA 2018; Schifter et al. 2018; Roso et al. 2019). However, the low ambient temperature might increase emissions (Suarez-Bertoa et al. 2015), independent of the ethanol content (EC). Currently, more than 20 countries around the world already adopt a blend of ethanol in commercialized gasoline, such as the USA (E10) and Brazil (E27) (ANP 2015). The use of gasoline-ethanol blend can benefit air quality in the cities compared to gasoline in conventional engines (Rice et al. 1991).

The trend towards using liquid fuels derived from petroleum and the global need to reduce the level of pollutant emissions amply justify ethanol's addition to pure gasoline in the short term (Beer and Grant 2007). A flex-fuel engine emerged to best adapt to this mixture. Ethanol has a higher-octane number that allows the operation with higher compression rates without entering auto-ignition and greater efficiency (Roso et al. 2019). Technically, these engines allow the compression rates to be changed, as the delay in advance the ignition point, the operating temperature (electronic thermostatic valves), and the fuel injection time variation. However, Barakat et al. (2016) noted a low slope linear relationship between fuel consumption and ethanol concentration. Other authors (Guerrieri et al. 1995; Topgul et al. 2006; Cataluna et al. 2008) reported a sharp rise in fuel consumption using the ethanol-gasoline blend. Cahyono and Abu Bakar (2011) found a decrease in engine torque and power when ethanol was used as a fuel compared to gasoline. However, those findings are just related to the use of ethanol blend in conventional gasoline ignition engines. Ethanol is characterized by a higher heat of vaporization than gasoline. This aspect makes the intake manifold's temperature lower because ethanol requires more heat to evaporate, increasing the engine's volumetric efficiency. However, a higher heat of vaporization could cause lower combustion temperature and burning velocity and higher CO and HC emissions. The Reid vapor pressure (RVP) of ethanol is significantly lower than gasoline, and then the resulting lower volatility can cause difficult cold transient of the engine during the warm-up phase. Nevertheless, the ethanol-gasoline blended fuels do not have an RVP value that ranges linearly with the percentage of ethanol in the blends. With the increase of ethanol content at first, the RVP of the blended fuel rises to reach a maximal value at about 15% v/v of ethanol addition (so facilitating the cold-start), while after, at higher ethanol percentages, the RVP declines (Iodice et al. 2017b).

The application of data mining techniques in fuel blends tests can identify information more accurately by applying algorithms. Data mining is the method of discovering information from a defined set of data. The approach uses mathematical analysis to extract patterns and trends that might exist in data. Predictive analytics and machine learning resources can be used for accurate checks on the environmental impact of fossil, and non-fossil fuel blends, considering managing data growth, integrating and analyzing data to obtain useful decision-making insights in the use of fuels (Shah and Trivedi 2012; Jorge et al. 2017). In most cases, these predictive rules are clearly understood when transformed into "If-Then" rules, which can help generate control strategies that might enable policymakers' appropriate decision-making and recommendations in urban transportation to mitigate the pollution output.

Although soft computing has been applied to forecast emissions from SI engines using ethanol blends (Thakur et al. 2020), most studies use traditional artificial neural networks (ANNs) and neuro-fuzzy inference systems (ANFIS) for modeling purposes (Najafi et al. 2016). We suggest that a machine learning algorithm is suitable for predicting the environmental impact when using different gasoline and ethanol blends in a spark-ignition engine. Therefore, the present study's objective was to develop a model to estimate the gasoline and ethanol blends (pure gasoline; 25, 50, 75% ethanol blended with gasoline; and 100% ethanol) environmental impact in a flex-fuel engine using the data mining approach.

Materials and method

Powertrain test platform

The Powertrain (a Renault® flex-fuel engine) used was a mobile platform, consisting of a 1598 cm^3 engine, four cylinders in line, and eight valves, cooling by water pressure circuit, with sequential multipoint electronic fuel injection system and a management module (Injepro brand ®, model EFI-light v2) that allowed to control and access the actuators map. The platform featured all the automotive vehicle systems with a fuel supply system and reservoir, cooling system with radiator and fan, electrical system (alternator and battery), and starter. The engine specifications are presented in Table 1.

Table 1 Technical specifications of the powertrain engine

Volume	1.598 cm^3
Fuel system	Sequential multipoint electronic injection
Cylinder displacement	80.5 mm
Number of cylinders	4
Compression ratio	9.5:1.0
Combustion chamber layout	Roof-shaped pent
Upper piston geometry	Top piston crown on plate
Camshaft	2 - DOHC without VVT
Connecting rod length	137 mm
Diameter × stroke	79.0 × 81.4 mm
Geometric compression ratio	11.0: 1
Inlet valve opening (B-TDC)	10° (ref. 1 mm)
Inlet valve closure (A-BDC)	20° (ref. 1 mm)
Inlet valve diameter × lift	30 × 7.95 mm
Exhaust valve closure (B-BDC)	30° (ref. 1mm)
Exhaust valve closure (A-TDC)	0° (ref. 1mm)
Exhaust valve diameter × elevation	24 × 7.00 mm
Ignition order	1–3–4–2

The engine was instrumented with data acquisition systems (Fig. 1), composed of a system to acquire the test data. A system to control the engine registered the test data (Manager module, model EFI-light v2, InjePro®). An exhaust gas system was used to collect exhaust gas samples and analyze emission concentration (PC - Multi-Gas, Napro®, SP, Brasil).

The engine was warmed up before the tests started. It was brought to a condition of 924.4 mB of the indicated average effective pressure and subjected up to 900 rpm (low speed), 2000 rpm, and 3000 rpm to measure the concentration of gases (carbon monoxide (CO), carbon dioxide (CO_2), oxygen (O_2), hydrocarbon (HC), nitrogen oxide (NOx), corrected carbon monoxide (COc), corrected hydrocarbon (HCc = dilution factor × measured HC)), factor dilution (F-dilution), dilution, λ, and the air-fuel ratio.

Fuel blend testing

The tests were carried out using ethanol (anhydrous alcohol) and gasoline. The properties of ethanol and gasoline are shown in Table 2. The mixtures used in the Powertrain test were pure gasoline (E0), gasoline with 25% ethanol (E25), gasoline with 50% ethanol (E50), gasoline with 75% ethanol (E75), and pure ethanol (E100). Brazilian standard gasoline is sold with 27% ethanol (ANP 2015; ANP 2017). The extraction of this volume of ethanol was carried through decantation and separation for standardization purposes before the test.

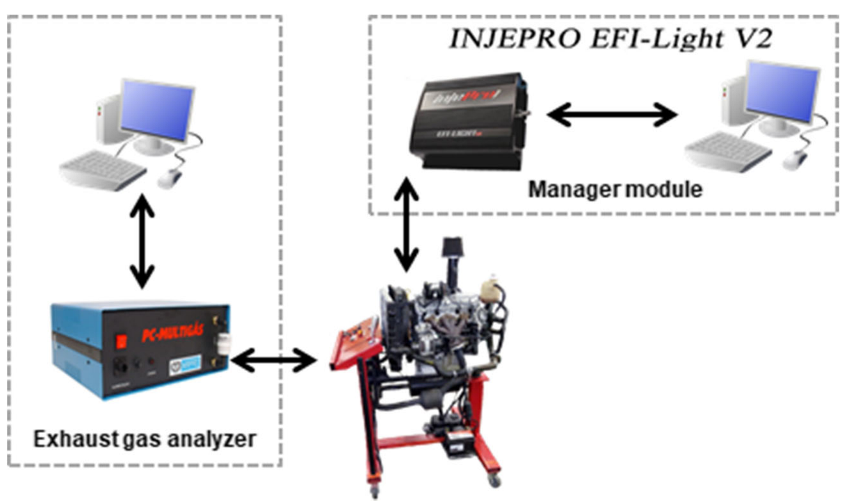

Fig. 1 Schematic diagram of the flex-fuel engine assembly and instrumentation

Table 2 Some properties values of tested ethanol and gasoline

Property	Ethanol	Gasoline
C-fraction (mass %)	52.2	87.4
O-fraction (mass %)	34.7	0
Density (ρ, kg/m^3)	785.1	715–780
Stoichiometric air/fuel ratio (-)	9.0	14.2–15.0
Kinematic viscosity (mm^2/s)	1.3	0.5
Reid vapor pressure (RVP) (kPa)	16.0	48-103
Research octane number (RON) (-)	108–109	84
Lower heating value (MJ/kg)	27.0	44.0
Latent heat vaporization (kJ/kg)	920	380

Values adapted from Park et al. (2010) and Iodice et al. (2017b)

Before starting each data collection, we decontaminate the engine oil. The engine was started and running at idle (900 rpm) until the thermostatic valve opens (observed when the fan is running), when the 30-min count starts running at idle and only then start testing.

The analyzer was maintained for an initial warm-up period, which consisted of two fan activation cycles to ensure the correct measurement of the gases. Within that period, the software reported that the equipment was heating up. Then, the equipment's leak test was verified by closing the gas capture probe and waiting for the screen's instructions to start the tests. Before starting the measurement, the equipment performs a check to detect HC residues' presence in the environment. This procedure aims to confirm that before measurements start, the indicated value is at its minimum. After the engine was already idling (900 rpm), it was expected 60 s, which was the estimated time to stabilize the gas reading and thus obtain a lesser variation in data collection. At the end of the 60-s cycle, a new cycle with a rotation of 2000 rpm and 3000 rpm later was installed and maintained as the previous test, with data being collected using the same procedure as the initial one.

Data analysis

Data on gas concentrations (carbon monoxide (CO), carbon dioxide (CO_2), oxygen (O_2), hydrocarbon (HC), nitrogen oxide (NOx), corrected carbon monoxide (COc = dilution factor × measured CO), corrected hydrocarbon (HCc = dilution factor × measured HC)), dilution factor (F-dilution), dilution (dilution =CO,% + CO_2,%), λ, and the air-fuel ratio were measured and collected in function of engine speed (900, 2000, and 3000 rpm) and fuel mixtures (gasoline and ethanol content: 0, 25, 50, 75, and 100% ethanol content). The test was performed three times for each variable, each time lasting 30 s, where data were continuously registered to calculate the mean values of gas concentrations, F-dilution, dilution, λ, and the air-fuel.

Data pre-processing was performed in Excel spreadsheets for further processing in the data mining software RapidMiner Studio® v9 (Hofmann and Klinkenberg 2014; Rapidminer Studio 2020). RapidMiner® is a data mining platform designed from elementary building blocks, called operators. Each operator performs a specific action on the data: loading and storing data, transforming data, or inferencing a model in the data (Habib and Umar 2015; Ristoski et al. 2015). The data set of the tests in the powertrain was loaded, stored, and transformed. After this data pre-processing, a predictive model was inferred through the operators' processes (split data - 80% training data and 20% to develop the model; Random forest; apply model and performance) interconnecting their input-output ports (Fig. 2).

The attributes used to build the predictive model in data mining using the modeling classification were gasoline-ethanol mixture (0% ethanol, 20, 50, and 75% ethanol and 100% ethanol), the environmental impact (which was discretized in ordinal categorical data "low," "average," and "high" according to the values of CO_2 emission, Table 3), the engine speed (900 rpm, 2000 rpm, and 3000 rpm), and the λ. When λ = 1, the mixture is stoichiometrically correct. When λ < 1, the mixture is rich, and when λ > 1, the mixture is lean.

Discretization reduces and simplifies data, making learning faster and the results more robust. After applying discretization, the data were treated as nominal data during the data mining process (Garcia et al. 2013). The use of classification algorithms based on Random forest (operator: random forest) was applied to generate rules for predicting the effect of the mixture of gasoline and ethanol on the environmental impact due to the air-fuel rotation λ. The model validation was parameterized using the operator split data with a percentage split of 80% for training and 20% for testing.

The percentage of correctly classified samples compared to the number of all examples is accuracy (Eq. (1)). The rate of true positives to all as positive predicted samples is the precision (Eq. (2)). The recall is the ratio of precisely predicted positive observations to all the target classes (Eq. (3)). The confusion matrix was calculated to find the prediction accuracy using the classifying performance. The kappa (κ) is a statistical coefficient of inter-rater reliability applied to evaluate two appraisers' agreement. In this study, we assumed that the classification was appropriate when κ ≥ 0.60.

$$\text{Accuracy} = (\text{TP} + \text{TN})/(\text{TP} + \text{FP} + \text{FN} + \text{TN}) \quad (1)$$

$$\text{Precision} = \text{TP}/(\text{TP} + \text{FP}) \quad (2)$$

$$\text{Recall} = \text{TP}/(\text{TP} + \text{FN}) \quad (3)$$

where *TP* is true positives, TN is true negatives, FP is false positives, and FN is false negatives.

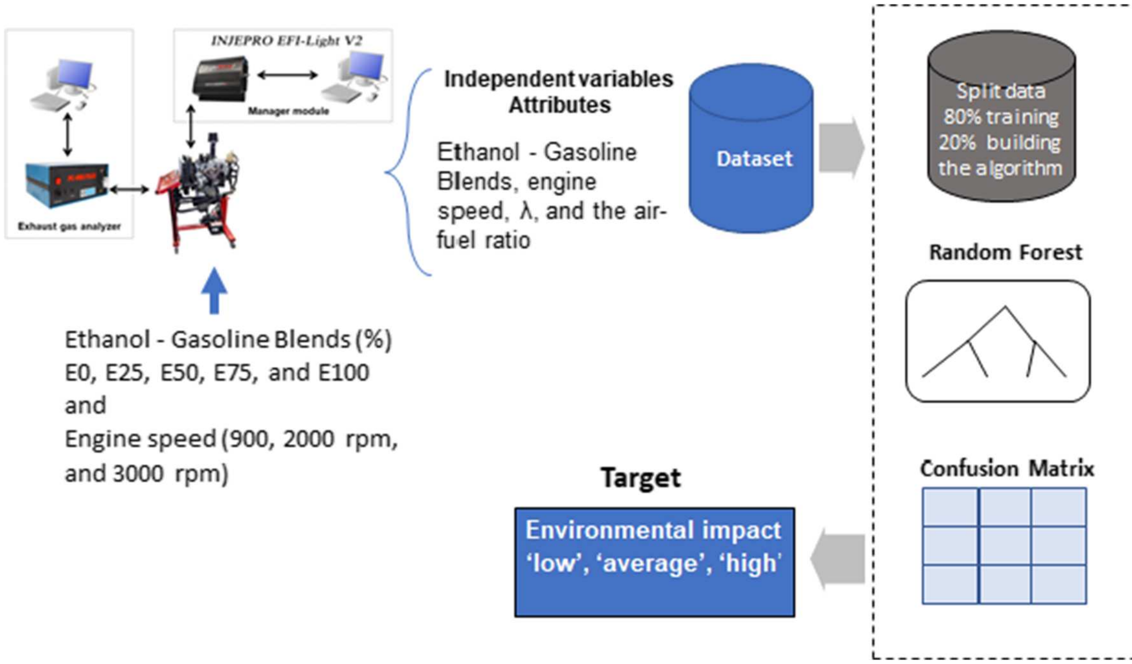

Fig. 2 The flow of the data mining process using the Random forest algorithm, illustrating the data processing steps and classification

Results

Gasses concentration

The results of the concentrations of CO, CO_2, O_2, HC, NOx, COc, and HCc; F-dilution; dilution; λ; the air-fuel ratio as a function of fuel mixtures (E0, E25, E50, E75, and E100); and engine speed (900, 2000, and 3000 rpm) are shown in Table 4.

Fuel tests without ethanol content (E0) showed average concentrations of 3.05 to 9.01% at 3000 rpm for CO concentration. The CO_2 concentrations were 2.43% when at low speed, 10.80% for 2000 rpm, and 4.63% for 3000 rpm. The O_2 concentrations were 15.07% for low speed, 3.10% for 2000 rpm, and 6.97% for 3000 rpm. HC ranged from 201.67 to 351.33 ppm vol. NOx showed values from 3.00 to 21.33 ppm vol. The COc concentration presented values from 3.33 to 10.43 ppm vol. The HCc concentration ranged from 2.99 to 7321.33 ppm vol. The dilution factor varied between 1.10 and 36.20. The λ ranged from 1.06 to 2.00. The dilution was 5.49 to 13.78% vol, and the air-fuel ratio was 14.68 to 27.57 (Table 4).

The fuel tests with a blend of 25% ethanol content (E25) showed an average CO concentration from 2.92 to 13.48% vol. CO_2 concentrations ranged from 2.47 to 13.07% vol, and for O_2 concentration was from 0.00 to 15. 23% vol. Hc results were from 88.33 to 712.00 ppm vol, and NOx results were from 0.00 to 33.67 ppm vol. Results of COc concentrations were from 3.90 to 13.50% vol and from 3.90 at 712.00 ppm vol for HCc, with dilution factor ranging from 0.74 to 2.62, dilution from 5.75 to 20.35, λ from 0.64 to 2.00, and air-fuel ratio ranged from 8.80 to 27.56 (Table 4). The fuel tests with a 50% ethanol (E50) blend showed an average CO concentration from 1.76 to 12.31% vol. Results of CO_2 concentration were from 3.13 to 10.70% vol and for O_2, from 0.27 to 16.03% vol. HC concentration values ranged from 10.67 to 152.33 ppm vol and from 0.00 to 6.33 ppm vol for NOx. COc concentration results were 5.39–12.30% vol, and HCc concentration varied from 31.33 to 152.67 ppm vol, with a dilution factor between 0.81 and 3.09. The dilution varied between 4.88 and 18.43, while the λ was 0.69–2.00. The variation of the air-fuel ratio was 6.25–18.02. Fuel tests with a mixture of 75% ethanol (E75) showed a CO average concentration of 1.97–12.06% vol and CO_2 concentration from 2.97 to 7.97% vol. The results of O_2 were from 3.53 to 16.07% vol, and HC results were from 84.00 to 241.33 ppm vol. Results of NOx concentration were from 0.00 to 3.67 ppm vol and from 5.92 to 12.07% vol for COc. HCc concentrations found concentrations were from 183.33 to 245.00 ppm vol, with a dilution factor between 0.83 and 3.08. The dilution varied from

Table 3 Discretization of the environmental impact based on CO_2 emissions

CO_2 emissions (%, vol)	Environmental impact
≤ 2.6	"Low"
>2.6 and ≤ 8.5	"Average"
>8.5	"High"

Source: Gentner et al. (2017)

Table 4 The concentration of CO, CO_2, O_2, HC, NOx, COc, and HCc; F-dilution; dilution; λ; and the relationship air-fuel for gasoline (E0), 25% ethanol (e25), 50% ethanol (E50), 75% ethanol (E75), and 100% ethanol (E100)

Ethanol blend	Speed (rpm)	CO (% vol)	CO_2 (% vol)	O_2 (% vol)	HC (ppm vol)	NOx (ppm vol)	COc (% vol)	HCc (ppm vol)	F-dilution	Dilution (% vol)	λ	Air-fuel ratio
E0	≤900	3.05	2.43	15.07	297.00	6.00	8.34	771.33	2.81	5.49	2.00	27.56
	2000	2.99	10.80	3.10	201.67	3.00	3.33	2.99	1.10	13.78	1.06	14.68
	3000	9.01	4.63	6.97	351.33	21.33	10.43	7321.33	36.20	13.66	1.10	15.10
E25	≤900	2.92	2.47	15.23	123.67	0.00	7.60	318.67	2.62	5.75	2.00	27.56
	2000	3.90	13.07	0.00	88.33	0.00	3.90	3.90	0.87	16.97	0.89	12.30
	3000	13.48	6.87	0.00	712.00	33.67	13.50	712.00	0.74	20.35	0.64	8.80
E50	≤900	1.76	3.13	16.03	10.67	0.00	5.39	31.33	3.09	4.88	2.00	18.02
	2000	7.74	10.70	0.27	152.33	0.00	7.74	152.67	0.81	18.43	0.77	6.98
	3000	12.31	5.83	3.30	145.00	6.33	12.30	145.00	0.83	18.16	0.69	6.25
E75	≤900	1.97	2.97	16.07	84.00	3.67	5.92	245.00	3.08	4.92	2.00	18.02
	2000	7.62	7.97	4.53	173.33	0.00	8.12	183.33	1.00	15.58	0.95	8.56
	3000	12.06	6.07	3.53	241.33	1.67	12.07	241.33	0.83	18.13	0.71	6.39
E100	≤900	1.32	3.93	15.37	66.67	0.00	3.74	191.00	2.88	5.26	2.00	18.02
	2000	5.54	10.90	2.20	105.33	0.00	5.54	5.54	0.91	16.45	0.91	8.16
	3000	10.65	7.27	2.30	401.67	0.00	10.66	401.67	0.84	17.91	0.72	6.48

rpm rotations per minute, *F-dilution* factor of dilution, *air-fuel ratio* relationship between the air and the fuel

4.92 to 18.13% vol, the λ varied from 0.71 to 2.00, and the air-fuel ratio was 6.39 to 18.02.

Fuel tests with 100% ethanol (E100) showed average CO concentration of 1.32–10.67% vol, from 3.93 to 10.90% vol for CO_2, and from 2.30 to 15.37% vol for O_2. HC's concentration varied from 66.67 to 401.67 ppm vol and for NOx was 0.00 ppm vol. COc concentration was from 3.74 to 10.66% vol and varied from 5.54 to 401.67 ppm vol for HCc, with a dilution factor between 0.84 and 2.88. The dilution varied from 5.26 to 17.91% vol, the λ varied from 0.72 to 2.00, and the air-fuel ratio was 6.48 to 18.02 (Table 4).

Random forest results

This operator generated a Random forest model, an assemblage of a certain number of random trees. These trees are created on bootstrapped subsets of the input data. Each node of a tree signifies a splitting rule for one specific attribute. Only a subset of attributes was considered for the splitting rule selection. For classification, the rule is splitting values belonging to different classes. The building of new nodes is repeated until the stopping criteria are met. Each random tree generates a prediction for each input by following the tree branches following the splitting rules and evaluating the leaf. We used the minimal leaf size = 2. The model classification had an accuracy of 73% and κ =0.61.

We selected three trees for estimating the environmental impact. First is using the percentage of ethanol in the fuel blend and engine rotation (Fig. 3). The second and third trees were selected by adding air-fuel and λ variables to the previous ones (Figs. 4 and 5). Such trees represent the forecast of environmental impact due to the fuel blend. In the confusion matrix (Table 5), the model's accuracy is presented (73%). The prediction for the "average" environmental impact class was 90% (true average = 90%), the "high" environmental impact classification precision was 70% (true high = 70%), and for "low" impact, it was 0% (true low = 0%). However, the model lacked the precision to classify the "low" environmental impact.

The "If-Then" rules are described as follows. If the percentage of the ethanol mixture is ≤ 12.5%, then the impact is "low" (24% of the samples). If the ethanol content percentage > 12.5%, the engine rotation needs to be checked. If the engine rotation is ≤ 1500 rpm, then the environmental impact is "average" (28% of the samples). If the engine rotation is > 1500 rpm, another leaf needs to be checked, the ethanol blend. If the ethanol mixture is > 87.5%, then the environmental impact is "high" (14% of the samples). If the ethanol mixture is ≤ 87.5%, then the environmental impact is "average" (17% of the samples). If the ethanol mixture is ≤ 62.5%, then the environmental impact is "high," and if the ethanol mixture is < 62.5%, then the environmental impact is "average" (Fig. 3).

From the input data, the model predicted that when the ethanol blend is below 12.5%, there is a high chance of the environmental impact will remain "low." Otherwise, it depends on the engine rotation and the ethanol blend, but in all cases, the result will be either "average" or "high" impact.

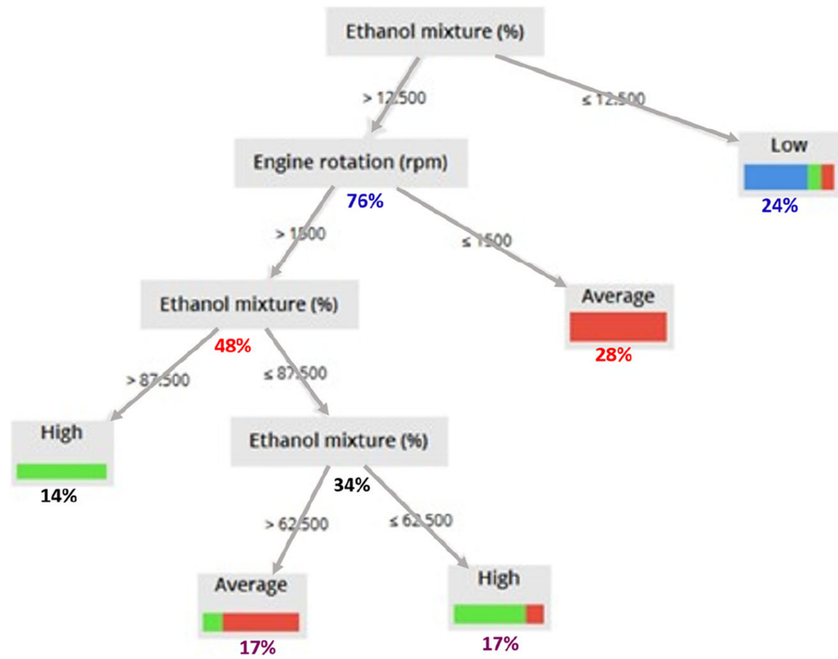

Fig. 3 The random tree for classifying the ethanol and gasoline blend's environmental impact using the variables ethanol blend and engine rotation

This result is a hint towards the limit of ethanol blend to cause low environmental impact.

The results of the decision tree using the λ and the air-fuel ratio are shown in Fig. 4.

If the λ is > 0.857, then one must check the air-fuel ratio. If the air-fuel ratio is > 19.61, then the impact is high (16% of the samples). If the air-fuel ratio is ≤ 19.61, then one needs to recheck the air-fuel ratio. If the air-fuel ratio is > 12.6, then the environmental impact is "average" (20% of the samples). If the air-fuel ratio is ≤ 12.6, then one has to check λ. If λ is > 0.917, then the environmental impact is "low" (ratio of the total = 7% of the samples). If λ is less or equal to 0.917, then the environmental impact is "high" (ratio of the total = 7% of the samples). If λ is ≤ 0.857, then the air-fuel ratio needs to be checked. If the air-fuel ratio is ≤ 6.07, then the environmental impact is "high" (7% of the samples). If the air-fuel ratio is > 6.07, then the air-fuel ratio needs

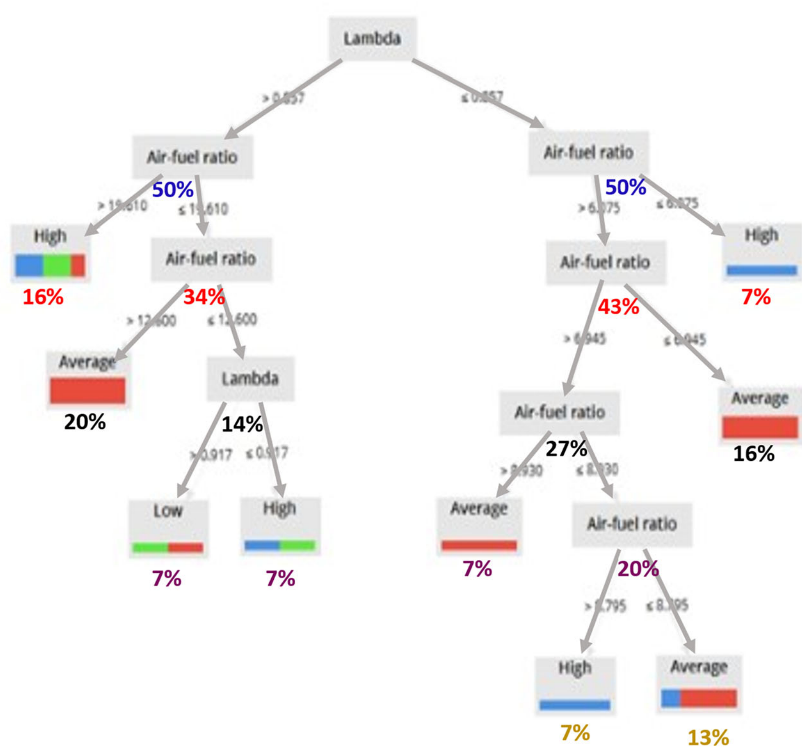

Fig. 4 The random tree for classifying the ethanol and gasoline blend's environmental impact using the variables λ and the air-fuel ratio

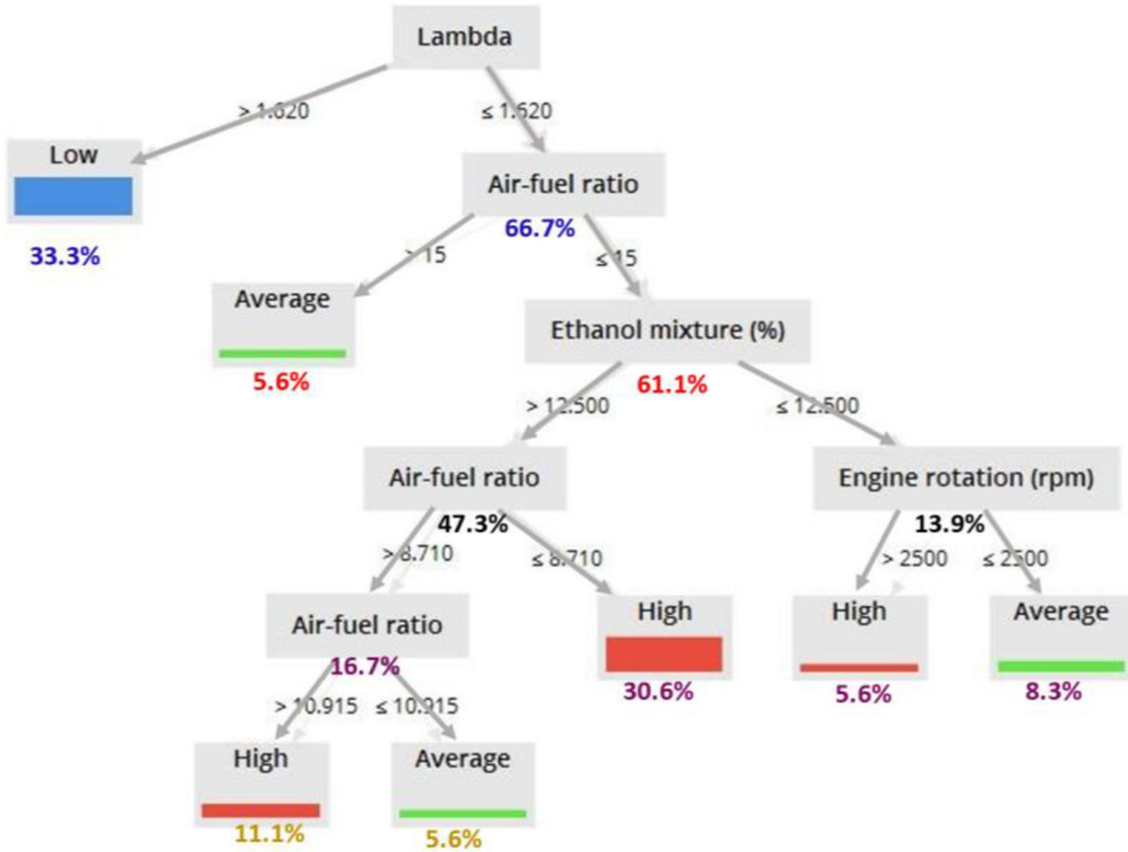

Fig. 5 The random tree for classifying the ethanol and gasoline mixture's environmental impact using λ, ethanol blend, engine rotation, and the air-fuel ratio

to be rechecked. If the air-fuel ratio is > 8.930, then the environmental impact is "average" (7% of the samples). If the air-fuel ratio is > 8.795, then the environmental impact is "high" (7% of the samples). If the air-fuel ratio is ≤ 8.795, then the environmental impact is "average" (13% of the samples) (Fig. 4).

The tree model shows two subtrees equally divided, and the model found out that the split value of λ is 0.857. In both subtrees, we found the air-fuel ration dependence leading to either "average" or "high" environmental impact. The "low" option represents only 7% of the samples, meaning that it might not be a probable result.

Figure 5 presents the random tree for classifying the ethanol and gasoline mixture's environmental impact using the gasoline blend, λ, engine rotation, and the air-fuel ratio.

Table 5 Confusion matrix of the model for the classification of the environmental impact of ethanol and gasoline blends.

Predicted \ True	'high'	'low'	'average'	Class precision (%)
'high'	3	1	1	70
'low'	0	0	0	0
'average'	1	1	8	90
Class Recall (%)	70	0	90	Accuracy = 73%

The number of samples=45.

If λ > 1.620, then the environmental impact is "low" (33.3% of the samples). If λ ≤ 1.620, then the air-fuel ratio needs to be checked. If the air-fuel ratio is >15, then the environmental impact is "average" (5.6% of the samples). If the air-fuel ratio is ≤ 15, then the ethanol blend needs to be checked. If the ethanol blend is ≤ 12.5, then one needs to check the engine rotation. If the engine rotation is > 2500, then the environmental impact of "high" (5.6% of the samples); otherwise, it is "average" (8.3% of the samples). If the ethanol blend is >12.5, the air-fuel ratio needs to be checked. If the air-fuel ratio is ≤ 8.71, the impact is "high" (30.6% of the samples). If the air-fuel ratio is > 10.915, then the environmental impact is "high" (11.1% of the samples); otherwise, it is "average" (Fig. 5).

The tree model foresaw the environmental impact "low" based on λ > 1.620. Otherwise, the other variables need to be checked. A significant result ("high," 30% of the samples) was inferred to air-fuel in the range of 8.71 and 15, and an ethanol blend >12.5%.

Discussion

The use of ethanol, particularly in spark-ignition engines, is appealing due to its reasonably high octane and the fact that it is cleaner than gasoline. The current test results showed that the CO concentrations for all fuel mixtures indicated values above the reference of CONAMA (2019) above 0.5% vol. However, HC at 2000 rpm with a mixture of 25% and 50% EC at low speed presented values within the recommended emission limit (ANP 2015; CONAMA 2019). Considering the HCc results, they were within the acceptable limit (lower emissions) at 2000 rpm for E0, E25, E75, and E100 and at low speed in E50 mixtures and E75. The concentrations for CO_2 also showed values within the limit for all fuel mixtures at 2000 rpm (CONAMA 2019). However, the proposed value is obtained from a vehicle using more complex anti-pollution devices than that tested in the present study, such as direct injection, plasma ignition, and recirculation of exhaust gasses. In developing countries, more than 50% of passenger vehicles are old concept cars (Kalghatgi 2018; Slovic and Ribeiro 2018) like the one studied in the present research. Therefore, estimating the environmental impact proposed here refers to short- or medium-term mitigation before developing countries' population has access to better urban transportation policies.

The Otto cycle engine is generally not ideal since other output gases from incomplete fuel ignition come out of the exhaust system. When the combustion is ideal, all O_2 that enters the engine is used for ignition. The lower the gas concentration in the exhaust system, the closer the combustion is to the ideal (Thakur et al. 2017). The higher the concentration of CO_2 in the exhaust system, the better the combustion. The air-fuel ratio can also affect the CO_2 level. With the lack of a rich mixture (O_2), the carbon combines with the oxygen in the burning generating CO (incomplete combustion). CO is considered a very toxic and reactive gas, so the lower the percentage, the better the combustion. HC also results from incomplete combustion in fractionated parts of long chains of non-oxidized fuel. The lower the HC concentration, the better the mixture's combustion (Roso et al. 2019).

The fuel blends E25, E50, E75, and E100 had a dilution factor of less than 1 for 2000 rpm and 3000 rpm. However, in the test with pure gasoline, the dilution factor went from 36.20 to 3000 rpm. An increase in total hydrocarbon (HC) emissions was detected as ethanol in the fuel increased (Schifter et al. 2018). In the present study, the HCc indicated higher emissions for pure gasoline (E0) and with a mixture of 25% (E25) of ethanol in a rotation of 3000 rpm.

The addition of ethanol to gasoline can reduce pollutant gas emissions in ignition engines (Elfasakhany 2015; Koç et al. 2009). The higher is the EC in the fuel mixture, the lower the environmental impact. However, Beer and Grant (2007) suggest that higher evaporative emissions because of the increase in vapor pressure for EC higher than 30% of ethanol may present environmental and mechanical issues. In the present study, mixtures with a higher percentage of ethanol had a lower environmental impact than mixtures with a lower EC that had a more significant environmental impact ("average" to "high"). According to Schifter et al. (2018), ethanol blended with gasoline in various concentrations is the most used alternative for positive-ignition engines to incorporate non-fossil components and diversify energy input in transportation. However, most current literature studies apply gasoline-ethanol to a designed gasoline engine (Schifter et al. 2013; Schifter et al. 2018; Roso et al. 2019). In flex-fuel engines, the use of ethanol generates higher torque. Engines powered by ethanol need a higher compression ratio (useful volume between the piston head and the head-fixed volume defined in the engine construction).

The complete oxidation of carbon in the fuel might increase CO_2 emissions with ethanol in gasoline design engines as higher latent heat of vaporization might occur (Elfasakhany 2015). However, increasing CO_2 can be reduced by raising the EC for slower engine speeds (Garcıa et al. 2010). Knoll et al. (2009) studied conventional vehicles' performance and emissions (1999 to 2007) with up to 20% by ethanol volume. The authors found that the EC increase resulted in reductions in total hydrocarbons and carbon monoxide and increases in ethanol emissions and aldehydes. Fuels added to ethanol (E0, E10, E20, and E30) reduce CO, CO_2, and NO_X emissions without significant energy loss than gasoline in a four-cylinder spark-ignition engine (Doğan et al. 2017). The authors carried out combustion tests with gasoline and mixed with ethanol (50 and 85% v/v) in an engine with a maximum power of 15 kW, performed at eight different engine speeds, oscillating from 1500 to 5000 rpm, with increments of 500 rpm, and the results showed that the addition of ethanol to gasoline implied a reduction in CO and HC emissions, in the whole engine speed range. The addition of ethanol increased the values of λ and made combustion more complete, reducing gas emissions since the latent heat of vaporization of mixed fuels is higher than that of gasoline, providing greater efficiency to the engine's combustion process (Canakci et al. 2013; Najafi et al. 2015).

In low EC, the CO_2 emissions varied between blends, suggesting a dependence with C and H fuel contents. As the EC rises, the NOx emissions decrease, and the E85 (or highest EC fuel) shows the lowest NOx emissions. Such an effect might be associated with temperature decline at the end of the compression stroke (Schifter et al. 2013). Suarez-Bertoa et al. (2015) found an increase in CO_2 emissions in blends with high EC (E75 and E85) compared to low EC (E5, E10, and E15). In the present study using a flex-fuel engine, the developed model indicated that low EC (<12.5%) associated with low engine rotation (<1450 rpm) leads to low environmental impact. On the other hand, high EC associated with either low or high engine speed tend to lead to average or high environmental impact, agreeing partially with previous studies (Koç et al. 2009; Schifter et al. 2018).

Gas emissions using five λ values and six gasoline/ethanol blends indicate that rich mixtures ($\lambda < 1$) tend to produce higher concentrations of CO and HCs in exhaust gases (Schirmer et al. 2017). As λ increases, the higher quantity of oxygen in the air leads to smaller amounts of produced gases. However, in lean mixtures, HC emissions tend to increase again because combustion may be incomplete. Tests with increasing EC in the fuel-alcohol blend showed that ethanol reduces carbon emissions, possibly because of the oxygen contained in ethanol molecules, resulting in improved combustion and allowing more significant advantage to be taken of the fuel's thermodynamic properties (Schifter et al. 2013).

In a previous study, the addition of 40% ethanol to the unleaded gasoline gave the best results for the reduction of carbon emissions by about 30% at a 9:1 compression ratio (Topgul et al. 2006). The addition of 60% ethanol to the unleaded gasoline caused a decrease in carbon emissions by about 20%. The addition of 60% ethanol to gasoline caused a 30% reduction in HC emissions at a high compression ratio (Guerrieri et al. 1995). Therefore, the emissions reduction is associated with gasoline-ethanol content and relies on other engine-related characteristics, as we found in the current study.

Most traffic divisions on transit departments worldwide build up rules based mostly on security issues, and those rules rely upon previous scientific knowledge. Tree models are built from sequential, hierarchical decisions that finally lead to some final broad concept. We believe that the generated "If-Then" rules would help policymakers make appropriate educational campaigns to reducing urban pollution in the long run. Public policies and proper advice must be used to convince drivers, especially in developing countries, to reduce their carbon footprint in urban areas concerning driving passenger vehicles.

Conclusions

We developed models to estimate the environmental impact from a flex-fuel engine and different gasoline-ethanol blends in a passenger vehicle. The model forecasts that the environmental impact is "low" to "average" when the fuel has a medium to a high percentage of ethanol blended considering rotation below 2000 rpm. On the other hand, for fuel mixtures with a low percentage of ethanol, the environmental impact depends on other characteristics of the engine and the means of driving. The present study results emphasize that using ethanol blend alone might not be an imminent simple solution to lessen urban pollution by passenger cars. Drivers should be educated on the environmental impact they cause by the way in driving a vehicle.

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Author contribution GTD designed and set up the experiment. IAN, GTD, and NDSL analyzed the data and the application of the data mining approach. NDSL was a major contributor in writing the manuscript. All authors read and approved the final manuscript.

Availability of data and materials Data are available upon request.

Declarations

Ethical statement The authors state that the article's research and its presentation were achieved by following the rules of good scientific practice.

Ethics approval and consent to participate Not applicable

Consent for publication Not applicable.

Conflict of interest The authors declare no competing interests.

Disclaimer The opinions expressed in this manuscript are those of the authors.

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