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Prediction of engine performance and emissions with *Manihot glaziovii* bioethanol − Gasoline blended using extreme learning machine

A.H. Sebayang[a,b], H.H. Masjuki[a], Hwai Chyuan Ong[a,*], S. Dharma[a,b], A.S. Silitonga[b,c,d], F. Kusumo[a], Jassinnee Milano[a]

[a] *Department of Mechanical Engineering, Faculty of Engineering, University of Malaya, 50603 Kuala Lumpur, Malaysia*
[b] *Department of Mechanical Engineering, Politeknik Negeri Medan, 20155 Medan, Indonesia*
[c] *Department of Mechanical Engineering, Syiah Kuala University, 23111 Banda Aceh, Indonesia*
[d] *Department of Mechanical Engineering, Faculty of Engineering, Universiti Tenaga Nasional, 43000 Kajang, Selangor, Malaysia*

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ABSTRACT

Bioethanol can potentially replace gasoline because of its lower exhaust emissions. The purpose of this study was to investigate the engine performance and exhaust emissions of *Manihot glaziovii* bioethanol–gasoline blends at different blend ratios (5%, 10%, 15%, and 20%). Tests were performed on a single-cylinder, four-stroke spark-ignition engine with engine speed was varied from 1600 to 3400 rpm, and the properties of the *Manihot glaziovii* bioethanol–gasoline blends were measured and analysed. The vapour pressure increased for fuel blends with low concentrations of bioethanol due to the oxygen within the bioethanol molecules and the contribution of the flame speed which can enhance the combustion and improved the engine efficiency. In addition, the engine torque, brake power, and brake-specific fuel consumption (BSFC) were measured, as well as the carbon monoxide (CO), hydrocarbon (HC), and nitrogen oxide emissions. For a fuel blend containing 20% bioethanol at an engine speed of 3200 rpm, the BSFC decreased, with maximum values of 270.7 g/kWh. The CO and HC emissions were lower for the *Manihot glaziovii* bioethanol–gasoline blends. In addition, an extreme learning machine (ELM) model was developed for application in the automotive and industrial sectors. This tool reduces the cost, time, and effort associated with experimental data. The blend ratio of the bioethanol–gasoline blends and the engine speed were used as the input data of the model, and the engine performance and exhaust emissions parameters were used as the output data. The coefficient of determination (R^2) was within a range of 0.980–1.000, and the mean absolute percentage error was within a range of 0.411% − 2.782% for all the parameters. The results indicate that the ELM model is capable of predicting the engine performance and exhaust emissions of bioethanol–gasoline fuel blends.

1. Introduction

Bioethanol is a promising source of energy for replacing gasoline in the future [1,2]. Gasohol is an alternative fuel produced by blending gasoline with bioethanol. Bioethanol has the following advantages over gasoline: a higher octane number, a broader flammability limit, a higher flame speed, and a higher heat of vapourisation [3,4]. The favourable properties of bioethanol result in a higher compression ratio, a shorter burn time, and a leaner burning engine. Generally, bioethanol leads to complete combustion in spark-ignition engines, in contrast to gasoline.

New alternative fuels have been developed for use in spark-ignition engines with a higher thermal efficiency to satisfy the stringent emission regulations in recent years [5,6]. Considerable research has been conducted to investigate the effects of bioethanol on the performance and exhaust emissions of spark-ignition engines [7,8]. Najafi et al. [9] investigated the performance of a four-stroke spark-ignition engine fuelled with gasoline–ethanol blends, finding that the combustion efficiency was improved by 35% for a fuel blend containing 20% ethanol. However, the results showed that the fuel consumption in case of the gasoline–ethanol blend was lower than that when using gasoline as the fuel. Koç et al. [10] investigated the performance of a single-cylinder spark-ignition engine fuelled with gasoline–ethanol fuel blends containing a high percentage of ethanol (50% and 85%), reporting that the brake-specific fuel consumption (BSFC) decreased by 20.3% and 45.6% for blends containing 50% and 85% ethanol, respectively. Ghazikhani et al. [11] analysed the engine performance and emissions for gasoline–ethanol fuel blends. Their results showed that the carbon monoxide

* Corresponding author.
E-mail addresses: ong1983@yahoo.com, onghc@um.edu.my (H.C. Ong).

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(CO) and nitrogen oxide (NO_x) emission parameters were 32% and 38%, respectively, when gasoline was blended with 15% ethanol.

Literature shows that bioethanol–gasoline fuel blends improve the engine performance and reduce exhaust emissions without the need for major design modifications in spark-ignition engines. However, many technical issues must be resolved for using bioethanol in spark-ignition engines, owing to the lower heating value and higher latent heat of evaporation of bioethanol compared to gasoline [12,13]. Bioethanol has disadvantages such as energy content of bioethanol is 34% lower than gasoline [14]. Pure bioethanol is difficult to vaporise which can make starting a car in cold weather difficult [15]. In addition, according to Cheolwoong et al. [16] bioethanol has negatively affect electric fuel pumps by increasing internal wear and undesirable spark generation. Furthermore, bioethanol has issue food versus fuel which concern to increase prices of bioethanol from farmers as well as increase food prices around the world [17].

Thus, a reliable model that is capable of predicting results accurately and can be retrained to solve complex nonlinear problems should be developed [18,19]. Even though numerous studies have been performed to investigate the potential applications of bioethanol in spark-ignition engines, technical issues involving the low viscosity and density of bioethanol must be addressed [8,9]. Therefore, an extreme learning machine (ELM) model was developed in this study to predict the engine performance and exhaust emission parameters of a spark-ignition engine fuelled with *Manihot glaziovii* bioethanol–gasoline blends. ELMs have been used to solve problems in various technical areas [20,21]. Huang et al. [22] developed an ELM model that reduced the time required to train single-layer feedforward neural networks. In general, an ELM is a powerful problem-solving tool because of its higher learning rate compared to traditional algorithms, such as back-propagation. The main aim of an ELM model is to obtain the smallest training error and norm of weights.

To our knowledge, no studies thus far have focused on the performance and exhaust emissions of a spark-ignition engine fuelled with *Manihot glaziovii* bioethanol–gasoline blends at different blending ratios. Hence, the objective of this study was to identify a suitable bioethanol–gasoline blend that yields the best engine performance and lowest exhaust emissions for spark-ignition engines. In addition, an ELM model was developed to predict the engine performance parameters (engine torque, brake power, and BSFC) and the exhaust emission parameters (CO, hydrocarbon (HC), and NO_x) with respect to the engine speed and the bioethanol–gasoline blending ratio. The model developed in this study is particularly useful because it is capable of predicting the engine performance and exhaust emissions of spark-ignition engines fuelled with bioethanol–gasoline blends.

2. Experimental method

2.1. Testing procedure and experimental design

Engine testing was performed using a Subaru EX17 single-cylinder, four-stroke spark-ignition engine. An eddy-current dynamometer was connected to the engine and the auto-controller system. The technical specifications of the engine and dynamometer are given in Table 1. The engine emission parameters for CO, HC, and NO_x were recorded using a BOSCH gas analyser. The measurement range and accuracy of the instruments used in this study are presented in Table 2.

Manihot glaziovii-gasoline bioethanol blends were tested at various engine speeds. The spark-ignition engine was operated using gasoline, and the engine was left to reach steady-state conditions for at least 15 min prior to the measurements of the parameters. Both the engine speed and the fuel consumption were measured once the engine had stabilised and reached steady-state conditions. The engine power and volumetric efficiency were recorded in subsequent stages. Once the spark-ignition engine had reached a stable working condition, the exhaust emission parameters were measured using the BOSCH BEA 350 exhaust gas analyser. All of the tests were conducted under full load conditions. Before the data on the engine performance and exhaust emissions for the fuel blends were collected, the engine was operated entirely on gasoline for a certain period to remove traces of the other fuel blends. The test was performed in triplicate, and the mean value of each parameter was determined for all the tested fuels.

Table 1
Technical specifications of the eddy-current dynamometer and auto-controller unit.

Technical specifications of the dynamometer	
Type	Dynomite#20 eddy current (air-cooled)
Manufacturer	Land & Sea
Absorber load capacity	Maximum torque 88.13 Nm @ 3000 rpm (cold)
	Maximum torque 40.67 Nm @ 3000 rpm (warm)
	Maximum torque 18.98 Nm @ 3000 rpm (hot)
Technical specifications of the dynamometer controller unit	
Model	Auto-ETS1 OM12 C
Accuracy	0.10%
Precision	0.005% ± 1 digit
Weight measurement	Linear (load cell)
Speed measurement	Sensor
Screen type	7-segment, 5 LEDs, character height: 10 mm
Power	VDC ± 10% @ 50 mA max
Operation temperature	0–70 °C
Operation voltage	230 VAC ± 10%, 50–60 Hz
Output	PC interface with Dyno2000 × software

Table 2
Technical specifications of the exhaust-gas analyser.

Exhaust component	Measurement range	Resolution
Carbon monoxide	0–10 vol%	± 0.001 vol%
Hydrocarbon	0–9999 ppm vol	± 1 ppm vol
Nitrogen oxide	0–5000 ppm vol	± 1 ppm vol

2.2. Uncertainty analysis

Experimental errors or uncertainties in the measured parameters may arise from various sources, such as uncertainties in the calibrated instruments, the experimental conditions, and the experimental procedure. Hence, uncertainty analysis was necessary to determine the accuracy of the parameters measured in this study. The percentage uncertainties of the measuring instruments are presented in Table 3.

2.3. Fuel preparation and properties

Manihot glaziovii was used as the feedstock for bioethanol production through enzymatic hydrolysis using α-amylase from *Bacillus licheniformis* Type XII-A and amiloglukosidase from *Aspergillus niger*. The enzymatic hydrolysis process produces sugar which was then used in the fermentation process. *Saccharomyces cerevisiae* yeast was used to ferment the substrate and distillation was then carried out in order to attain high bioethanol yield. Lastly, dehydration process was conducted to produce fuel-grade bioethanol.

The properties of the *Manihot glaziovii* bioethanol were measured according to the standard ASTM D4806. The bioethanol was blended with gasoline at different percentage volumes: 5% (E5), 10% (E10), 15% (E15), and 20% (E20). The properties of the bioethanol–gasoline fuel blends were measured and compared with those of gasoline fuel. Commercial gasoline fuel (Primax 95) was purchased from Petronas, Malaysia and was used as the baseline fuel. This fuel has an octane number of 95. The properties of the *Manihot glaziovii* bioethanol–gasoline blends is presented in Table 4. The *Manihot glaziovii* bioethanol–gasoline blends were mixed well before the engine tests to form a homogeneous blend and prevent the bioethanol from reacting with

Table 3
Accuracies of the measurements and uncertainties of the calculation results.

Measurement	Measurement range	Accuracy	Measurement techniques	%Uncertainty
Load	± 600 Nm	± 0.1 Nm	Strain gauge type load cell	± 1.04
Speed	0–10,000 rpm	± 1 rpm	Magnetic pick up type	± 0.1
Time	–	± 0.1 s	–	± 0.2
Fuel flow measurement	0.5–36 L/h	± 0.01 L/h	Positive displacement gear wheel flow meter	± 1.04
Air flow measurement	0.25–7.83 kg/min	± 0.07 kg/min	Hot wire air mass meter	± 2.0
CO	0–10 vol%	± 0.001 vol%	Non-dispersive infrared	± 0.95
HC	0–9999 ppm	± 1 ppm	Heated flame ionization detector	± 1.8
NOx	0–5000 ppm	± 1 ppm	Electrochemical	± 1.5
EGT sensor	0–1200 °C	± 0.3 °C	Type K thermocouple	± 0.15
Pressure Sensor	0–25,000 kPa	± 10 kPa	Piezoelectric crystal type	± 0.5
Computed				
Brake power	–	± 0.03 kW	–	± 1.29
BSFC	–	± 5 g/kWh	–	± 1.5

water.

2.4. ELM model

The ELM was originally developed for single hidden-layer feedforward networks. Because the input weight and hidden-layer biases of the ELM parameters are selected at random, the ELM has a high learning speed and good generalisation performance. In this study, the engine performance and exhaust emission parameters were used as the input and output data for the ELM prediction model, respectively. It was expected that the blending ratio of the *Manihot glaziovii*-gasoline blends and engine speed had a significant effect on engine performance and exhaust emissions. Therefore, the blending ratio of the fuel blends and engine speed were chosen as the inputs for the ELM model, whereas the engine torque, brake power, BSFC, CO, HC, and NO_x were chosen as the outputs. To develop the ELM model, the network was subjected to two processes: training and testing. In the training process, the network was trained to estimate the output values relative to the input data. In the testing process, the network was tested to either stop training or save the training data, which were used to estimate the output. The reliability of the ELM model was assessed according to the coefficient of determination (R^2) and the mean absolute percentage error (MAPE) which are given by Eqs. (1)– (2), respectively:

$$R^2 = 1-\sum_{i=1}^{n}\left(\frac{(y_{ei}-y_{pi})^2}{(y_m-y_{pi})^2}\right) \tag{1}$$

$$\text{MAPE} = \sum_{i=1}^{n}\left|\frac{y_{ei}-y_{pi}}{y_{ei}}\right| \times 100\% \tag{2}$$

Here, n is the number of experimental data points, y_{ei} is the value of the parameter obtained from the experiments, y_{pi} is the value of the parameter predicted by the ELM model, and y_m is the average value of the parameter obtained from the experiments. The accuracy of the model was assessed according to the following criterion: a larger R^2 and smaller MAPE yields better accuracy and hence, reliability [23].

The R^2 and MAPE values were used to assess the engine performance and exhaust emission parameters predicted by the ELM model [24]. This was important for assessing the prediction capability of the proposed ELM model, considering the scale independence, and preventing ambiguous interpretations arising from infinite, undefined, or zero values due to erroneous measurements [20,25].

3. Results and discussion

3.1. Engine performance parameters

3.1.1. Engine torque

Fig. 1 shows the engine torque for gasoline and *Manihot glaziovii* bioethanol–gasoline at various engine speeds. For both fuels, the engine torque increased with the engine speed. At 3200 rpm, the engine torque was lower for gasoline (11.04 Nm) than that for all the *Manihot glaziovii* bioethanol–gasoline blends: 11.12 Nm (E5), 11.27 Nm (E10), 11.37 Nm (E15), and 11.51 Nm (E20). This was expected because the *Manihot glaziovii* bioethanol–gasoline blends contained approximately $5\% - 10\%$ enriched oxygen and had a higher octane number than gasoline, which improved the combustion. In addition, the heat loss at high engine speeds increased the pressure and temperature inside the cylinder. Increasing the concentration of bioethanol in the fuel blends increased the engine torque because of the decrease in the viscosity and density. This agrees with the results of Najafi et al. [9], who reported that excess oxygen in the ethanol increased the air–fuel ratio and the fuel density. The higher percentage of bioethanol improved the stoichiometric combustion. In addition, the *Manihot glaziovii* bioethanol–gasoline blends had a high latent heat of vapourisation which increased the engine torque. The higher engine torque was due to the high octane number of the fuel, which improved the anti-knock behaviour and increased the ignition delay [26].

3.1.2. Brake power

Fig. 2 shows the brake power for gasoline and the *Manihot glaziovii* bioethanol–gasoline blends with respect to the engine speed. In general, the brake power was slightly higher for the *Manihot glaziovii* bioethanol–gasoline blends, with values of 3.73 kW (E5), 3.78 kW (E10), 3.81 kW (E15), and 3.86 kW (E20). In contrast, the brake power for gasoline was 3.70 kW. The higher brake power was due to the high mean effective pressure for the blends containing high concentrations of bioethanol. Furthermore, the *Manihot glaziovii* bioethanol–gasoline

Table 4
Properties of the *Manihot glaziovii* bioethanol–gasoline blends and gasoline.

Property	Unit	Gasoline	*Manihot glaziovii* bioethanol	E5	E10	E15	E20	E20 [19]	E20 [6]	Standard test method
Oxygen content	wt%	–	34.22	3.69	4.67	5.55	6.35	–	7.36	ASTM D 4814
Density (at 20 °C)	kg/m^3	750.8	794.3	753.7	756.3	760.3	764.6	771.5	759.7	ASTM D 4052
Dynamic viscosity (at 20 °C)	mPa.s	0.4019	1.57	0.42	0.46	0.51	0.56	–	–	ASTM D 4052
Lower heating value	MJ/kg	43.56	27.29	42.82	42.32	41.79	41.28	40.43	39.47	ASTM D 240
Octane number	–	95	109	95.69	96.38	97.07	97.76	89.81	93	ASTM D 2699

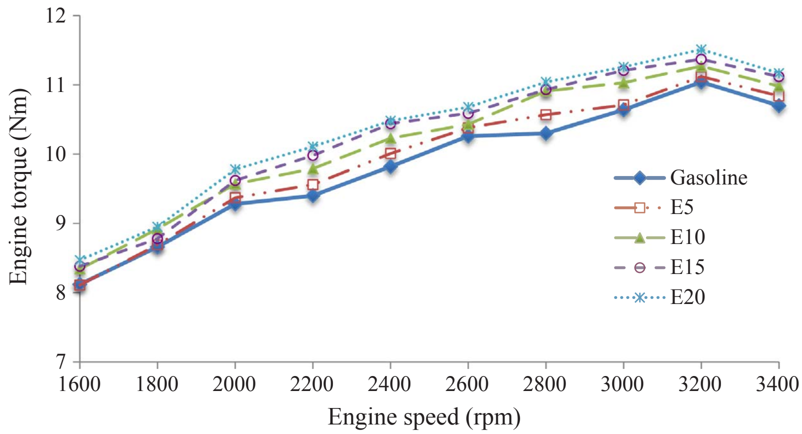

Fig. 1. Effect of gasoline and the E5 – E20 fuels on the engine torque under full-throttle conditions.

blends had higher oxygen content than gasoline, which enhanced the reaction between the oxygen and fuel, thereby releasing more energy [12,27]. Alternatively, the higher brake power may have been due to the improved heating value. The heating value is the energy content of the fuel per unit weight. Compared to gasoline, the higher energy content of the *Manihot glaziovii* bioethanol–gasoline blends resulted in more complete combustion [12,28]. Moreover, the latent heat of evaporation was higher for the *Manihot glaziovii* bioethanol–gasoline blends, which decreased the intake manifold temperature and increased the volumetric efficiency, thus increasing the brake power.

3.1.3. BSFC

Fig. 3 shows the BSFC for gasoline and the *Manihot glaziovii* bioethanol–gasoline blends at various speeds. The BSFC was the lowest at 3200 rpm, with values of 287.80 g/kWh (E5), 278.42 g/kWh (E10), 274.60 g/kWh (E15), and 270.74 g/kWh (E20). When the engine was operated with gasoline fuel at 3200 rpm, the BSFC was 288.8 g/kWh, which is higher than the BSFC for the fuel blends investigated in this study. This is because of the higher oxygen content of the *Manihot glaziovii* bioethanol. When the engine was operated using any of the *Manihot glaziovii* bioethanol–gasoline blends, the BSFC was lower than that for gasoline. Because no modifications were made to the spark-ignition engine used in this study, the desired engine performance is attributed to the high octane number of bioethanol, which resulted in a more complete combustion than that observed when using gasoline. Najafi et al. [9] reported that the BSFC was lower for the E5, E10, E15, and E20 *Manihot glaziovii* bioethanol–gasoline blends because of their lower flash point compared to gasoline, which improved the ignition delay.

3.2. Exhaust emission parameters

3.2.1. CO emission

Fig. 4 shows the CO emissions for the *Manihot glaziovii* bioethanol–gasoline blends and gasoline at various engine speeds**.** The CO emission was lower for the *Manihot glaziovii* bioethanol–gasoline blends than that for the gasoline. The CO emission was 1.49 vol% (E5), 1.35 vol% (E10), 1.18 vol% (E15), and 1.05 vol% (E20) at 3000 rpm. In contrast, the CO emission for gasoline was 1.64 vol% at 3000 rpm. The CO emission decreased as the concentration of bioethanol in the fuel blend increased. The CO emission also decreased when the engine load was increased owing to the increased air–fuel ratio, resulting in more complete combustion [29,30]. According to Costa et al. [15], bioethanol has high oxygen content, which contributes oxygen for the combustion of the air–fuel mixture. The high heat of evaporation of bioethanol increases the engine power during the combustion process at the peak in-cylinder temperature. This reduces the temperature in the combustion cylinder [29]. The high cylinder gas temperature combined with the oxygen concentration of the *Manihot glaziovii* bioethanol–gasoline blends improves the oxidation process of CO, which reduces CO emissions [31].

3.2.2. HC emission

Fig. 5 shows the HC emissions for the *Manihot glaziovii* bioethanol–gasoline blends and gasoline at various engine speeds. The HC emission was lower for the *Manihot glaziovii* bioethanol–gasoline blends than that for the gasoline. The HC emission was 37.35 ppm (E5), 35.21 ppm (E10), 32.14 ppm (E15), and 31.45 ppm (E20) at 3000 rpm. In contrast, the HC emission for gasoline was 40.31 ppm at 3000 rpm. The HC emission decreased as the concentration of bioethanol in the

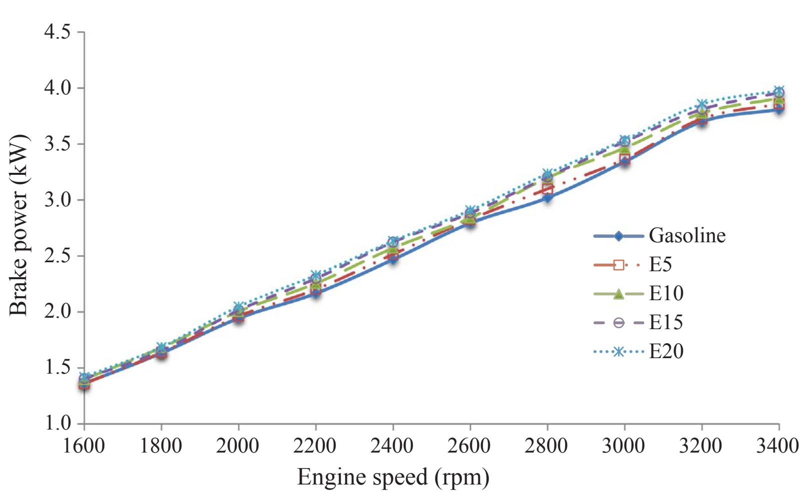

Fig. 2. Effect of gasoline and the E5 – E20 fuels on the brake power under full-throttle conditions.

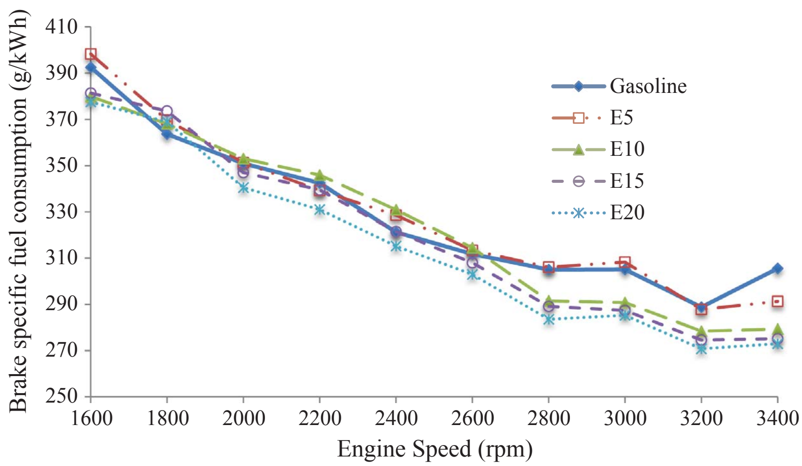

Fig. 3. Effect of gasoline and the E5 – E20 fuels on the BSFC under full-throttle conditions.

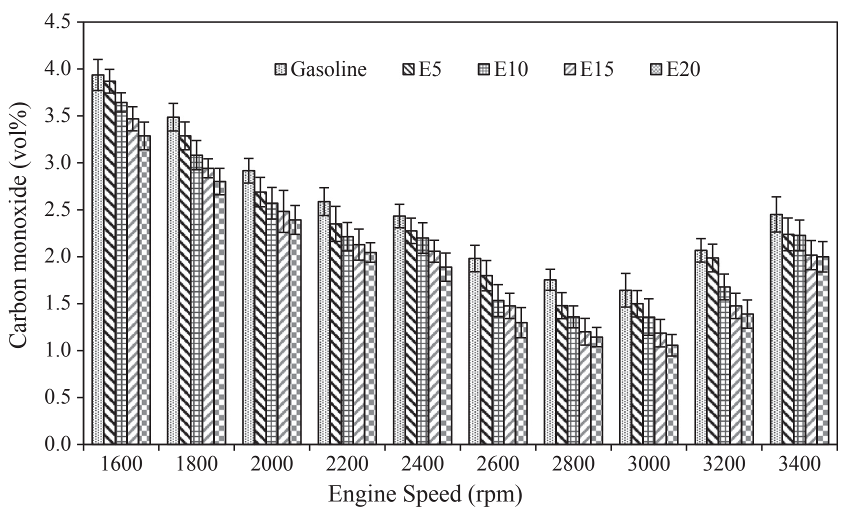

Fig. 4. Effect of gasoline and the E5 – E20 fuels on the CO emissions under full-throttle conditions.

fuel blend increased. The HC emission was higher at lower engine speeds because of the higher heat of vapourisation of bioethanol, which resulted in slow evaporation and poor air–fuel mixing. The flame can be quenched by these effects in the presence of a flow with high turbulent intensities. The shorter ignition delay and more rapid combustion can reduce the HC emissions. At 3000 rpm, the HC emission was 31.45 ppm for the E20 blend, which is lower than that for the others: E5 (37.35 ppm), E10 (35.21 ppm), and E15 (32.14 ppm). The fuel spray characteristics are strongly influenced by the nature of the flow inside the fuel spray and the air in the combustion chamber, which play a role in reducing unburned HC emissions [31]. The higher bioethanol content decreases the cylinder temperature, which increases the HC emissions. Moreover, the HC emissions increase because of wall wetting, insufficient oxygen, and residual fuel in the cylinder [11].

3.2.3. NO_x emission

Fig. 6 shows the production of NO_x emissions from the *Manihot glaziovii* bioethanol–gasoline blends and gasoline with respect to the

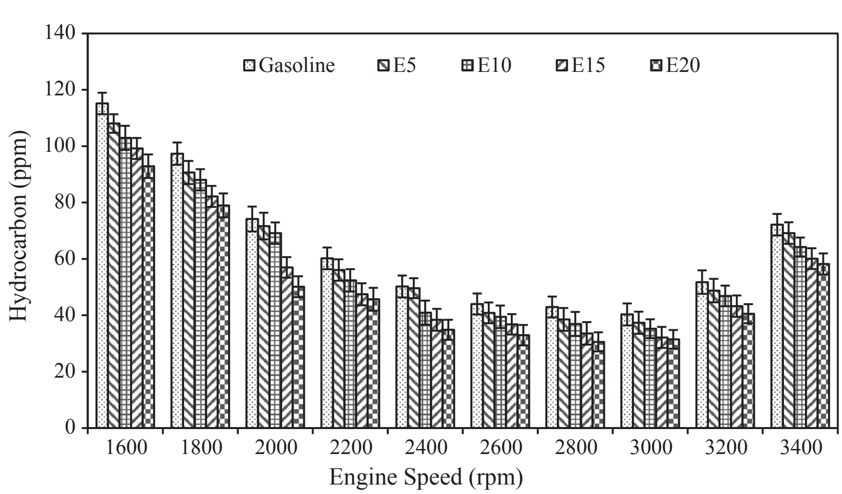

Fig. 5. Effect of gasoline and the E5 – E20 fuels on the HC emissions under full-throttle conditions.

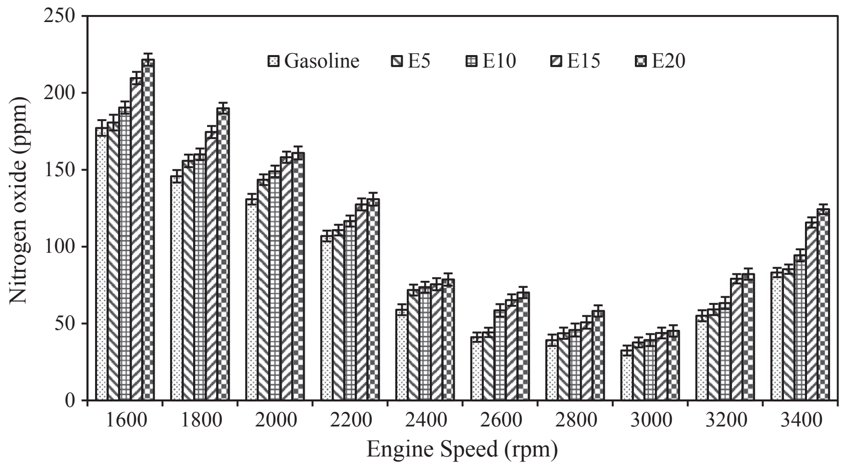

Fig. 6. Effect of gasoline and the E5 – E20 fuels on the NO_x emissions under full-throttle conditions.

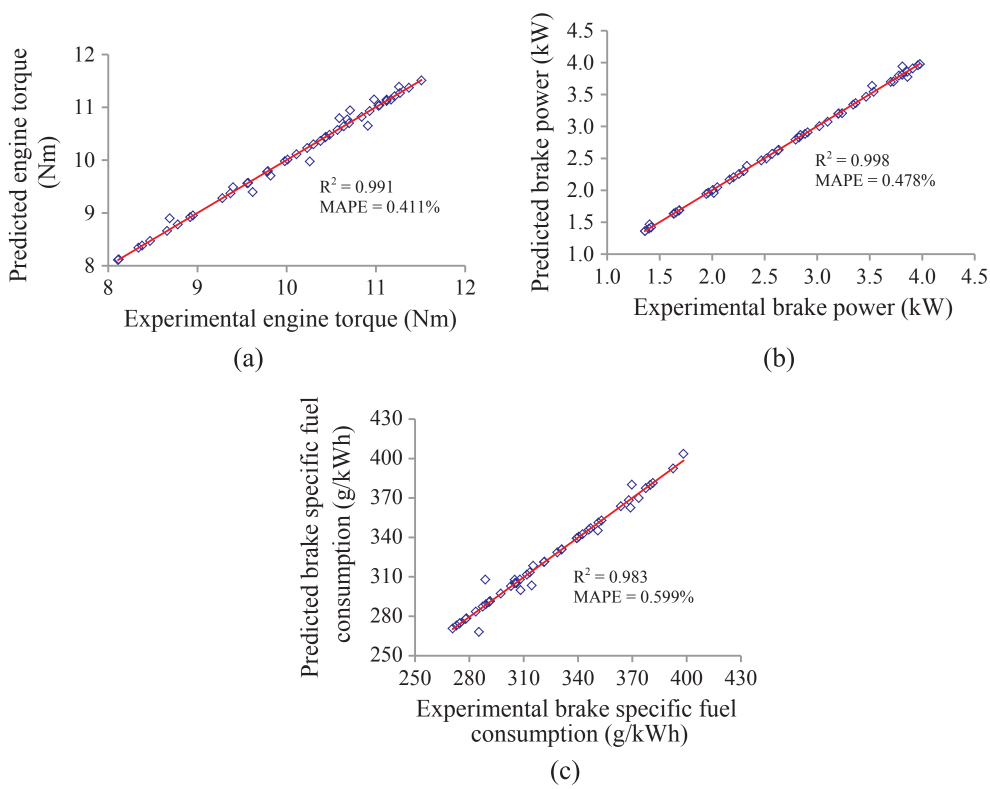

Fig. 7. Predicted versus experimental results for the (a) engine torque, (b) engine brake power, and (c) BSFC.

engine speed. The NO_x emission was generally higher for the *Manihot glaziovii* bioethanol–gasoline blends than for the gasoline, with values of 37.74 ppm (E5), 39.27 ppm (E10), 43.87 ppm (E15), and 45.23 ppm (E20). In contrast, the value for gasoline was 32.46 ppm. Among all the tested fuels (E5, E10, E15, and gasoline), the NO_x emission was the highest for the E20 blend. In general, NO_x emissions depend on the air–fuel ratio and the temperature. A high temperature during combustion and the high oxygen content of the bioethanol yield high NO_x emissions [32] (Celik, 2008). The maximum temperature rise decreases when bioethanol is added into the gasoline fuel because of the higher latent heat of vapourisation and lower heating value of bioethanol compared to gasoline [10]. This agrees well with Canakci et al. [29], who reported that the lower heating value of the fuel blend results in the accumulation of air and fuel in the premixed mode, which leads to a higher cylinder temperature and increased formation of NO_x.

3.3. Prediction evaluation for engine performance and exhaust emission parameters using ELM model

3.3.1. Engine performance parameters

An ELM model was developed in this study based on the data obtained from experiments. The results show that the training algorithm is sufficient to predict the engine performance and exhaust emissions for gasoline-*Manihot glaziovii* bioethanol blends with different ratios of gasoline and bioethanol at various engine speeds. Fig. 7. showed the predicted versus experimental values for the engine performance parameters investigated in this study. The coefficient of determination (R^2) for the engine torque, brake power and brake specific fuel consumption predicted by the ELM model is 0.991, 0.998 and 0.983, respectively. The MAPE is found to be 0.411%, 0.478% and 0.599% for the engine torque, brake power and brake specific fuel consumption, respectively.

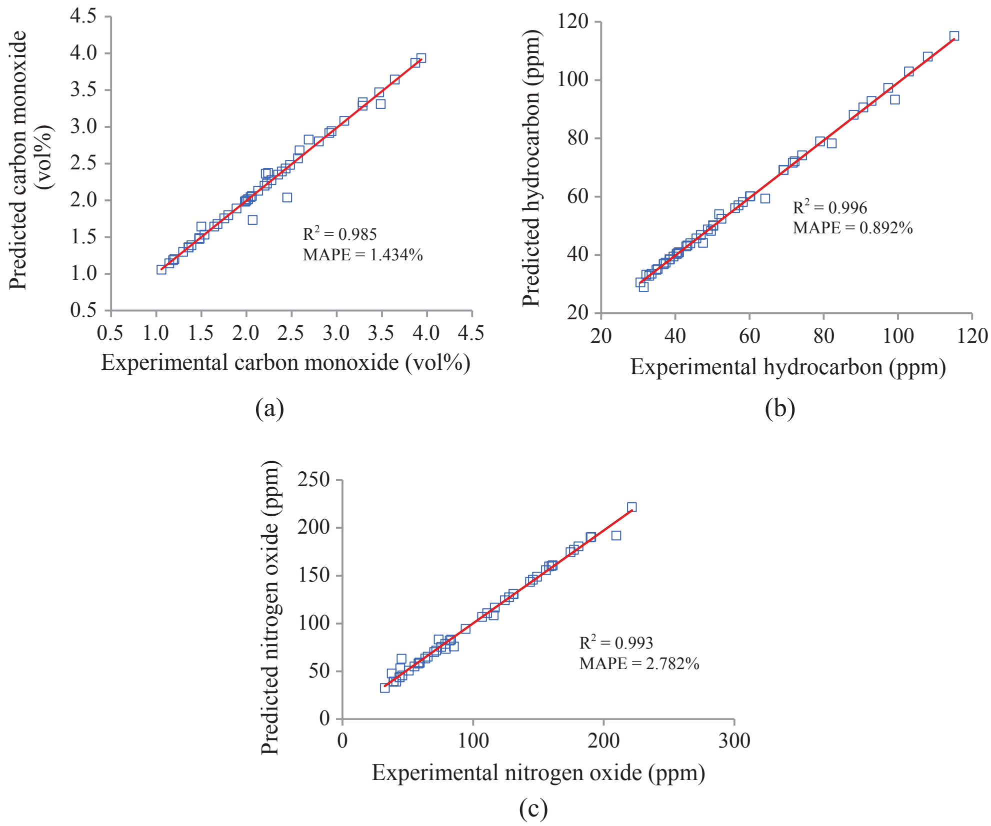

Fig. 8. Predicted versus experimental results for the (a) CO, (b) HC, and (c) NO_x emissions.

3.3.2. *Exhaust emission parameters*

The experimental results confirm that there is a reduction in the carbon monoxide and hydrocarbon emissions decrease due to the higher oxygen content of gasoline-*Manihot glaziovii* bioethanol blends. The excess oxygen helps increase the air-fuel ratio, which in turn, improves combustion. The nitrogen oxide emissions are dependent on the cylinder temperature and air-fuel ratio. Hence, increasing the cylinder temperature during combustion as well as the oxygen present in bioethanol can lead to higher nitrogen oxide emissions Fig. 8(a–c) show that the MAPE is low for all of the exhaust emission parameters investigated in this study, with a value of 1.434%, 0.892%, and 2.782% for the carbon monoxide, hydrocarbon, and nitrogen oxide emission, respectively. The R^2 is found to be 0.985, 0.996, and 0.993 for the carbon monoxide, hydrocarbon, and nitrogen oxide emission, respectively. In general, the R^2 values are very close to 1, indicating that there is a strong correlation between the experimental values and those predicted by the ELM model.

4. Conclusions

Alternative fuels are becoming increasing important in the automotive sector because the depletion of fossil fuel reserves, as well as the environmental issues resulting from the burning of fossil fuels. Bioethanol is considered an eco-friendly, clean, and renewable alternative fuel for spark-ignition engines. Its high-octane number, oxygen content, and volatility are highly desirable properties for spark-ignition engines. In this study, the engine performance and exhaust emission parameters of a spark-ignition engine fuelled with *Manihot glaziovii* bioethanol–gasoline blends were studied. The use of the *Manihot glaziovii* bioethanol–gasoline fuel blends marginally increased the engine torque, brake power, and decreased the BSFC. On the other hand, the CO and HC emissions decreased because of the leaning effect of the bioethanol–gasoline blends and the lower molar H/C ratio of the bioethanol compared to gasoline. The NO_x emissions increased for these blends because of the high latent heat of vapourisation and oxygen content of the fuels, along with the high combustion temperature. In general, there was a remarkable improvement in the engine performance and a reduction in the exhaust emissions for the E20 blend, which contains 20% bioethanol blended with gasoline. Thus, the E20 blend appears to be a good substitute for petroleum-derived fuels for improving the engine performance.

ELM is a modelling technique that has been used in recent years to predict process parameters, which minimizes the time and money spent on experimental studies. ELM has been proven to provide reliable predictions, with values close to those obtained from experiments. In this study, R^2 values were very close to 1.000, and the MAPE values were very low for all the parameters investigated. This indicates a strong correlation between the data predicted by the ELM model and the experimental data. Hence, the ELM model is a feasible and beneficial tool that can be used to predict and evaluate the engine performance and exhaust emission parameters of spark-ignition engines fuelled with bioethanol–gasoline blends.

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