Proceedings of the 2nd International Civil Engineering Conference on Innovation Technology in Civil Engineering: A Tool for Global Economy Recovery tagged NICE OSUN – CVE UNIOSUN 2025, Osun State University, Osogbo, Nigeria, 26th - 28th August 2025

COMPUTER MODELLING OF THE PERFORMANCE OF BIOETHANOL PRODUCED FROM MAIZE AND GUINEA CORN STALKS IN AN ELECTRIC POWER GENERATING SET

[1]AWOTUNDE, O. W, [2]OPADOJA, D., [3]APAMPA, O. R., & [4]ESO, F. A

[1,4] Department of Mechanical Engineering, Osun State Polytechnic, Iree

[2]Department of Mechatronics Engineering, Osun State Polytechnic, Iree

[3]Department of Agricultural & Bio-Environmental Engineering, Osun State Polytechnic, Iree

Corresponding Author: awotundewaliyi@gmail.com

ABSTRACT

The rising cost of petroleum products and the need to protect the environment from climate change have led to the search for alternative energy sources for internal combustion (IC) engines. Bioethanol, biogas, and biodiesel have been produced to replace gasoline in IC engines. However, for optimal performance, the production process and physico-chemical properties of these biofuels must be improved. This study aimed to produce bioethanol from maize and guinea corn stalks using aluminium oxide nanoparticles as a catalyst. Conventional gasoline was measured by proportion, and the quantity of maize and guinea corn stalk bioethanol was determined by volume proportion. Blends of bioethanol and gasoline were experimented in an electric power generating set at different percentage compositions. The power, voltage, and current outputs of the different blends were measured using a Digital Multimeter. Experimental tests on the Sinwei electric power generating set revealed that E5, a 50-50 blend of maize and guinea corn bioethanol, had the best power output. E1 and E4 lasted longer than others, with running times of 268 and 260 seconds, respectively. Maize stalk bioethanol had better performance compared to the 50-50 blend and guinea corn bioethanol overall. A computer model was developed using Python programming to extrapolate and predict performance values of other mixtures of bioethanol and gasoline in the electric power generating set. The computer model returned identical results as the in experiment, thus confirming the reliability of the model.

Keywords: *Aluminium oxide, Bioethanol, computer modelling, maize, guinea corn, performance, power output*

1. INTRODUCTION

The global demand for energy is increasing, particularly for petroleum fuels. Biofuels like ethanol have been investigated to reduce fuel consumption and engine emissions. Studies have focused on ethanol application techniques, fuel properties of ethanol-gasoline blends, and effects on combustion and exhaust characteristics. Bioethanol mixtures are considered one of the most promising renewable alternative fuels, as they can be fermented and distilled from sugarcane, grain, wood, agricultural solid wastes, coal, sweet sorghum, and more. Bioethanol has several advantages over gasoline, including higher octane number, flame speed, and higher latent heat of vaporization, leading to greater volumetric efficiency. It also includes 35% oxygen, aiding in complete fuel combustion and decreasing dangerous exhaust emissions. However, bioethanol is not widely used due to technological limitations, economic, and regional factors. The exhaustion of oil reservoirs for current fuels like petrol is a significant issue, and reducing harmful gas emissions is crucial for humanity's self-reliance, economy, and global warming. This project aims to analyze the bioethanol performance using aluminum oxide nanoparticles, focusing on the effect of aluminum oxide nanoparticles on bioethanol's fuel properties from dried maize and guinea corn stalks.

The specific objectives of this research include enhancing the physiochemical properties of the produced bioethanol using aluminum oxide nanoparticles, examining the performance behaviors of blend maize and guinea corn stalks bioethanol on electric power generators, optimizing the performance of bioethanol produced from maize and Guinea corn nanoparticles, and developing computer modeling (python) for power output and performance produced by the electric generator. Awotunde *et al.* (2025) reported that the incorporation of Aluminium oxide (Al_2O_3) nanoparticles at a 0.2% concentration as a catalyst significantly enhanced the physicochemical properties of bioethanol compared to non-catalyzed samples. Key properties, including oxygen content, higher calorific value (HCV), lower calorific value (LCV), volatile matter, octane number, auto-ignition temperature, and cloud point, exhibited optimal values at this nanoparticle concentration.

Ambrose *et al.* (2015) proposed the use of wet ethanol, a type of ethanol fuel with high water fractions, as an alternative to traditional ethanol. They developed a mathematical model and experimental data to predict the effect of wet ethanol on internal combustion engine performance. The model successfully simulated pressure and temperature gradients in the cylinder and showed good ability to predict engine performance based on variations of power, torque, conversion efficiency, and specific fuel consumption. The experiments were conducted using an Agrale-M90 single-cylinder engine, modified to operate under spark ignition mode. Wet ethanol blends were prepared from hydrous ethanol collected from a small distillery in the university and distilled water, while commercial fuel was used for tests with hydrous ethanol fuel (HEF). The characterization of all samples was performed in an Anton Paar densimeter, model DMA 4500M, and the new spark ignition, throttle, and port fuel injection systems were controlled by a commercial electronic control unit (ECU). A Bosch LSU 4.2 broadband lambda probe was installed to measure oxygen concentration in the exhaust gas and control the air fuel ratio at which the engine was operating.

Singh *et al.* (2016) conducted several experiments, installing an engine transient dynamometer test bench in a climate-controlled test cell with a four-cylinder MPFI gasoline engine, 120 kW asynchronous dynamometer, fluid conditioning systems, and gas emission measuring equipment. The AVL Puma Open 5.0 test bed automation system was set up to control the dynamometer, fluid controlling systems, and emission measuring equipment. The test cycles were programmed in the Puma for automatic operation of the test run. A combustion air system was installed adjacent to the test cell, equipped with a coolant and oil temperature control system. Fuel metering was performed by the AVL735S, which utilizes the Coriolis principle to measure mass flow of fuel consumed by the engine. The AVL 753C fuel temperature conditioning system can control the fuel temperature between 10 and 80°C. The Horiba 7100 DEGR integrated gas analyzer combined various emission detectors together for gaseous emission measurement.

The global increase in crude oil prices has led to a growing interest in developing alternative fuel sources for electric generators, particularly gasoline. Electric generators play a crucial role in developing countries as an alternate source of power for both domestic and industrial purposes. Engineers and scientists have been exploring the possibility of blending ratios of gasoline and ethanol in the right proportion to power electric generators, with the aim of reducing improving voltage outputs and carbon emissions at the lowest possible costs. Rawal (2020) reported that a spark-ignition engine using ethanol–gasoline blends can be serviceable after making simple modifications on the carburetor system, without causing complications in the operation of the carburetor system. A high compression ratio is often desirable for better engine performance, as it allows the engine to extract more mechanical energy from a given mass of air-fuel mixture due to its higher thermal efficiency. However, a higher compression ratio using gasoline with low octane rated fuel is prone to engine knock due to pressure build up in the engine cylinders. According to available literature, a high compression ratio gives better engine performance if a bio-fuel-gasoline blended fuel with a high octane number, or Research Octane Number (RON), is used. This octane rating measures the self-ignition capability of a gasoline or liquid petroleum fuel. The higher the number, the less likely an engine is to pre-ignite and suffer damage. Each fuel has a different octane number (RON) value, with methanol having the lowest octane number (123) and butanol having the lowest octane number (94). The different blending ratio values directly affect the engine performance. The characteristic output power when the throttle-valve-ratio (TVR) is increased up to 100% with 20% incremental value using gasoline-ethanol blend. The output power increases proportionately up to 60% TVR value. For the TVR value from 80% and 95%, the output power values are almost constant. Similar output power characteristics are observed when operated with different load resistance values. The optimal performance of the engine is achieved for a TVR of 80%.

Ahmed *et al.* (2017) used a Yamaha power generating set with a 171cc, single cylinder, 4-stroke, air-cooled, SI engine directly coupled to an electrical generator of rated output capacity of 2 kW, 220V, 50Hz electricity. Four different fuel samples were experimentally examined, including base gasoline (92 octane) and ethanol (99.9% purity). The rate of fuel consumption in each test was measured using a calibrated fuel burette with the valve, and the exhaust gas temperature was measured using a K-type thermocouple connected to a PID temperature controller. The engine was started by hand cranking with a recoil starter, then the choke valve was turned into full open position.

2. METHODOLOGY

2.1 Production of Aluminum Oxide Nanoparticle

Guava leaves were collected from a guava tree and washed with distilled water and it was dried under room temperature of 25℃ to 27℃. The dried guava leaves were grinded in to powder and stored in a dried container. The extraction of the phytochemicals from the grinded guava leaves was done using soxhlet extractor and ethanol as the solvent. The extraction was done under reflux condition at a temperature of about 70℃ using a temperature-controlled heating mantle. The extracted phytochemical was collected into a beaker. 200g of aluminium oxide was mixed with 600g of the extracted phytochemical to synthensize the aluminium oxide nanoparticle at 60℃. Then Nano fluid is formed. Awotunde et al. (2024) used Aluminium oxide nanoparticles to improve the physicochemical properties of bioethanol produced form maize and guinea corn stalks. In an earlier study, Awotunde et al. (2022) reported that the bioethanol produced from maize stalks had better physicochemical properties in comparison with bioethanol produced from guinea corn stalks.

2.2 Collection of Maize Stalk and Guinea Corn Stalk

Fresh maize stalk and guinea corn stalk were collected from Owode farm, which is located in Ifon-Osun, Orolu local government area of Osun State, Nigeria. The stalk and leaf part were chopped, and sun dried to reduce the moisture. The dried sample were grounded by using a grinding machine. Grinding of sample into powder form was done to increase the surface area of the sample, which will enhance the contact between hemicelluloses and cellulose with dilute acid to reduce cellulose crystalline and remove lignin. This is shown in Figure 1.

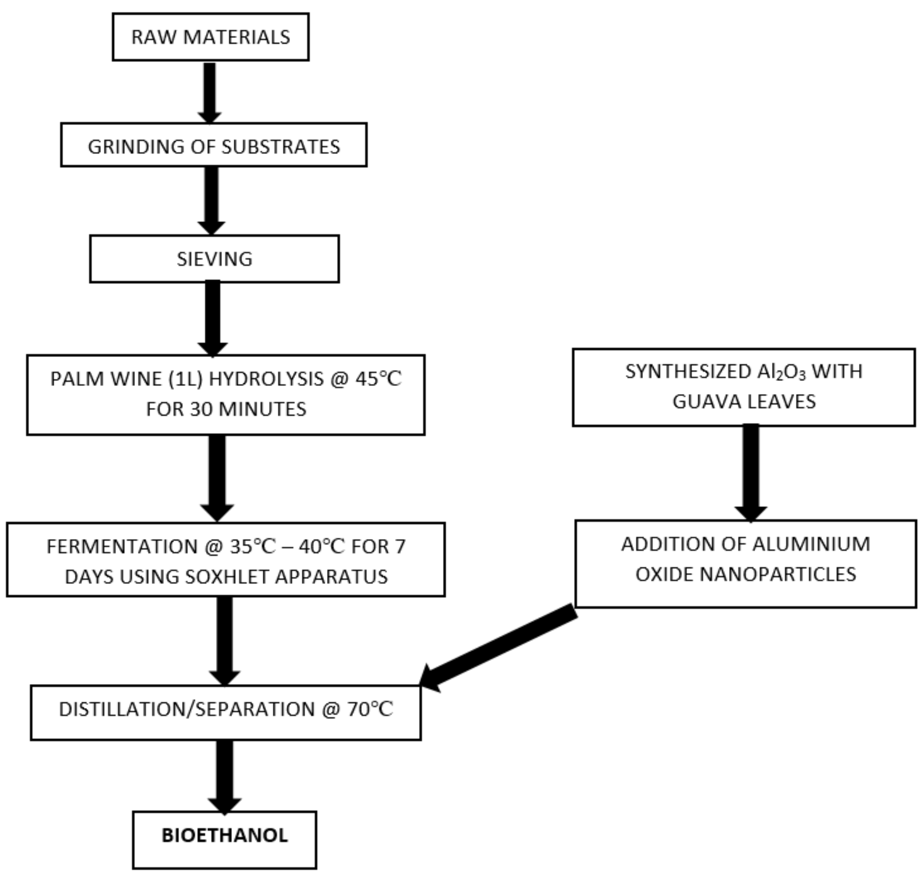

Figure 1: Framework of the lignocellulose of production of bioethanol

2.3 Experimental Set-up

The experiment was designed to determine the power output of the gasoline bioethanol mixtures in the electric power generating set (as specified in Table 1). Also, to determine the performance of each mixture of gasoline and bioethanol in the power generating through the time taken to burn out the gasoline-bioethanol mixture.

Table 1: Technical specification for the electric power generating set

Technical Specification	
Maximum Power	4.8 kW
Rated Power Output	4.5 kW
Voltage	230V
Manufacturer	Senwei LTD. China
Model	

2.4 Multimeter Specifications

The specification for the Multimeter that was used to measure the potential difference (Volts) and current produced by the electric power generating set is a Digital Multimeter, model: DT9205A. The circuit diagram is shown in Figure 2.

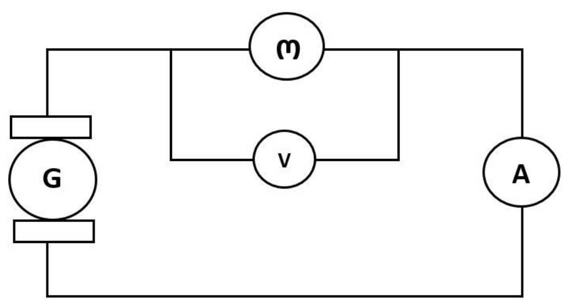

Figure 2: Circuit diagram for the experimental set up

Before the experiment proper was conducted, first the conventional gasoline (petrol fuel) was measured by proportion (40ml is equivalent to 100%). Same goes for the bioethanol produced from maize and guinea corn stalks respectively. Using standard laboratory burette, a 40ml sample of conventional gasoline was taken as 100% gasoline for the test. Based on the 40ml adopted standard, the corresponding quantity of maize and guinea corns stalk bioethanol were determined by volume proportion as follows (Table 2).

2.5 Computer modelling

Modelling and simulation of engineering systems are crucial for providing engineers with insights into system performance under various conditions, saving costs in research and development, and boosting confidence in models. In recent years, researchers have developed digital twins that can model complex systems like traffic in a city, vehicle numbers, security, buildings, people, and behaviours. An artificial neural network (ANN) was developed by Thakur *et al.* (2017) to investigate the correlation between performance parameters and emission components using different gasoline-ethanol blends and engine loads. The ANN model generated the best correlation coefficient (R) ranging from 0.999923 to 0.999977 for all performance parameters and exhaust emissions. The mean relative error values were in the domain of 0.12–5.56%, while root mean square errors were very low. A network with one hidden layer and 20 neurons was selected as the most favorable ANN.

In a study, Thakur *et al.* (2021) applied the adaptive neuro fuzzy inference method (ANFIS) to model the performance and emission characteristics of various blends of ethanol and gasoline. The ANFIS model provided an association between all parameters using specific gasoline-ethanol blends and different engine loads. The results obtained from the model were then contrasted with experimental values to determine the accuracy of the ANFIS predictions. The ANFIS model generated a maximum correlation coefficient (R) of 0.9900–0.9999 and 95.3594% accuracy for both performance and exhaust emissions values. In addition to ANN and ANFIS models, other models such as MATLAB Simulink, Design Expert (Start-Ease), Minitab, Mathematica, and Statistica offer useful modules for modelling and simulation systems based on data. Programming languages like R and Python also offer excellent modules for modeling and simulation of engineering systems.

Table 2: Proportion by volume of conventional gasoline, Maize stalk bioethanol and Guinea corn stalk bioethanol respectively

S/N	Conventional Gasoline		Bioethanol		
	(%)	By volume (ml)	(%)	By volume (ml)	Designation
1	100	40.0	0	0	E0
2	99	39.6	1	0.4	E1
3	98	39.2	2	0.8	E2
4	97	38.8	3	1.2	E3
5	96	38.4	4	1.6	E4
6	95	38.0	5	2.0	E5
7	94	37.6	6	2.4	E6
8	93	37.2	7	2.8	E7
9	92	36.8	8	3.2	E8
10	91	36.4	9	3.6	E9
11	90	36.0	10	4.0	E10
12	89	35.6	11	4.4	E11
13	88	35.2	12	4.8	E12
14	87	34.8	13	5.2	E13
15	86	34.4	14	5.6	E14
16	85	34	15	6.0	E15
17	84	33.6	16	6.4	E16

2.6 Development of Computer models for Power Output and Performance of the produced Bioethanol in an electric power generating set

Computer models in graphical format were developed for the power output derived from the experiment conducted on the bioethanol produced from maize stalk, guinea corn stalk and also for the 50-50 blend of maize and guinea corn. The Python codes used in developing the graphical models for power output and performance of the produced bioethanol in an electric power generating set over time were presented in Appendix 1. Python is a multipurpose high-level object-oriented programming language that was developed in the early 1990s by the Dutch scientist Guido van Rossom. Python has since find good use in the field of information systems, data science, and engineering; especially with respect to the modelling and simulation of systems and phenomena.

Program in Python Language for computer modelling of power output and performance of bioethanol-gasoline mixtures in power generating set

```
# -*- coding: utf-8 -*-
"""
Created on Fri Mar 14 11:07:38 2025

@author: apamps
"""

##############AWOTUNDE MODELS
```

```
###Importing dependent libraries into python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn; seaborn.set()
import seaborn as sns

#########MODEL FPR 50-50 MAIZE/GUINEA CORN POWER OUTPUT
E = np.array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10,])
V = np.array([226, 230, 228, 227, 228, 229, 227, 227, 227, 226, 226])
I = np.array([0.22, 0.21, 0.22, 0.22, 0.22, 0.22, 0.22, 0.22, 0.22, 0.21, 0.21])
P = V*I
t = np.array([212, 268, 171, 216, 260, 222, 239, 213, 201, 144, 95])
sns.lineplot(E, P, label = "Power Output for 50-50 Blend Bioethanol")
plt.xlabel('E: Bioethanol mixed with Gasoline (%)')
plt.ylabel('Power (Watt)')
plt.title('Power output for the different ratios of Bioethanol and gasoline mixture')
plt.legend()

## where V = voltage, I = curent, P = power

#########MODEL FPR 50-50 MAIZE/GUINEA CORN PERFORMANCE IN ELECTRIC POWER
GENERATING SET
E = np.array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10,])
V = np.array([226, 230, 228, 227, 228, 229, 227, 227, 227, 226, 226])
I = np.array([0.22, 0.21, 0.22, 0.22, 0.22, 0.22, 0.22, 0.22, 0.22, 0.21, 0.21])
P = V*I
t = np.array([212, 268, 171, 216, 260, 222, 239, 213, 201, 144, 95])
sns.lineplot(E, t, label = "Performance of 50-50 blend of Bioethanol in Generating set")
plt.xlabel('E: Bioethanol mixed with Gasoline (%)')
plt.ylabel('Time (seconds)')
plt.title('Performance of the different ratios of Bioethanol and gasoline mixture with time')
plt.legend()

#########MODEL FPR MAIZE POWER OUTPUT
E = np.array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12])
V = np.array([226, 227, 227, 227, 225, 225, 227, 225, 226, 226, 226, 226, 225])
I = np.array([0.22, 0.17, 0.18, 0.17, 0.18, 0.17, 0.18, 0.18, 0.18, 0.18, 0.18, 0.18, 0.18])
P = V*I
t = np.array([212, 230, 235, 243, 215, 256, 235, 202, 224, 170, 212, 192, 175])
sns.lineplot(E, P, label = "Power Output for Maize Bioethanol")
plt.xlabel('E: Bioethanol mixed with Gasoline (%)')
plt.ylabel('Power (Watt)')
plt.title('Power output for the different ratios of Bioethanol and gasoline mixture')
plt.legend()

#########MODEL OF MAIZE PERFORMANCE IN ELECTRIC POWER GENERATING SET
E = np.array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12])
V = np.array([226, 227, 227, 227, 225, 225, 227, 225, 226, 226, 226, 226, 225])
I = np.array([0.22, 0.17, 0.18, 0.17, 0.18, 0.17, 0.18, 0.18, 0.18, 0.18, 0.18, 0.18, 0.18])
P = V*I
t = np.array([212, 230, 235, 243, 215, 256, 235, 202, 224, 170, 212, 192, 175])
sns.lineplot(E, t, label = "Performance of Maize Bioethanol in Generating set")
plt.xlabel('E: Bioethanol mixed with Gasoline (%)')
plt.ylabel('Time (seconds)')
```

```
plt.title('Performance of the different ratios of Bioethanol and gasoline mixture with time')
plt.legend()

#########GUINEA CORN MODEL FOR POWER OUTPUT
E = np.array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12])
V = np.array([226, 225, 225, 225, 225, 229, 230, 227, 227, 227, 227, 225, 224])
I = np.array([0.22, 0.16, 0.17, 0.17, 0.17, 0.18, 0.17, 0.16, 0.17, 0.16, 0.17, 0.16, 0.16])
P = V*I
t = np.array([212, 172, 222, 227, 194, 180, 192, 220, 240, 180, 151, 144, 162])
sns.lineplot(E, P, label = "Power Output for Guinea corn Bioethanol")
plt.xlabel('E: Bioethanol mixed with Gasoline (%)')
plt.ylabel('Power (Watt)')
plt.title('Power output for the different ratios of Bioethanol and gasoline mixture')
plt.legend()

#########GUINEA CORN MODEL FOR PERFORMANCE WITH TIME
E = np.array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12])
V = np.array([226, 225, 225, 225, 225, 229, 230, 227, 227, 227, 227, 225, 224])
I = np.array([0.22, 0.16, 0.17, 0.17, 0.17, 0.18, 0.17, 0.16, 0.17, 0.16, 0.17, 0.16, 0.16])
P = V*I
t = np.array([212, 172, 222, 227, 194, 180, 192, 220, 240, 180, 151, 144, 162])
sns.lineplot(E, t, label = "Performance of Guinea corn Bioethanol in Generating set")
plt.xlabel('E: Bioethanol mixed with Gasoline (%)')
plt.ylabel('Time (seconds)')
plt.title('Performance of the different ratios of Bioethanol and gasoline mixture with time')
plt.legend()
```

The graphical representations of the model are represented in Figures 3 – 8.

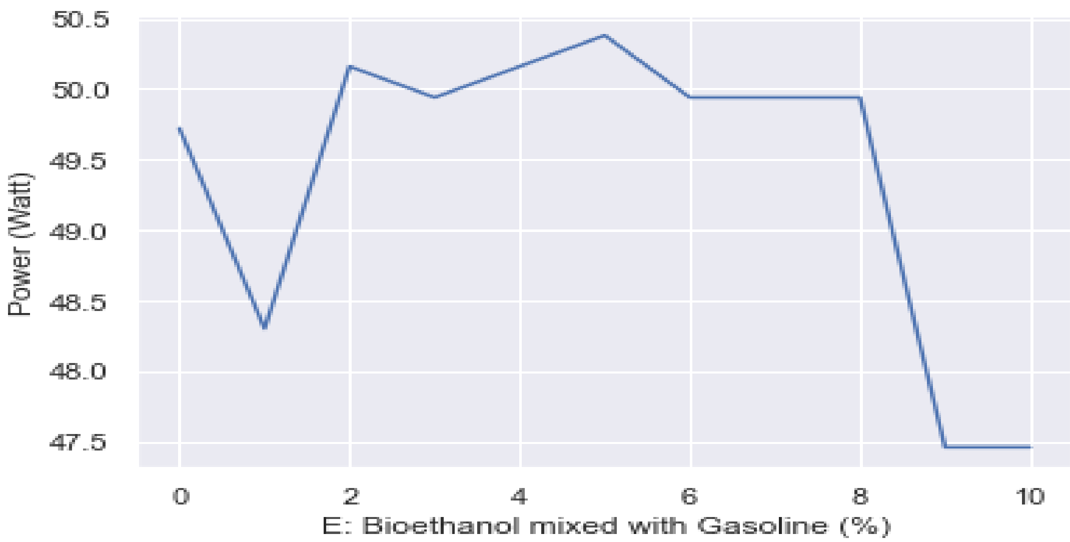

Figure 3: Computer (graphical) model in Python of the power output of the bioethanol produced from 50-50 blend of Maize and Guinea corn stalks.

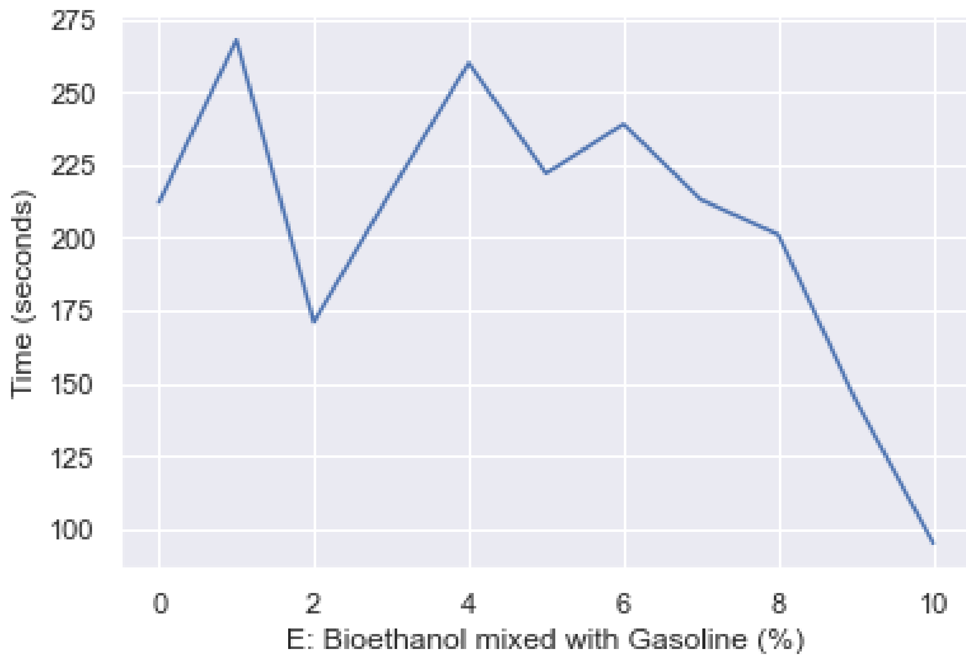

Figure 4: Computer (graphical) model in Python of the performance of the 505-50 blend of bioethanol from Maize and Guinea corns stalks mixed with petrol over time.

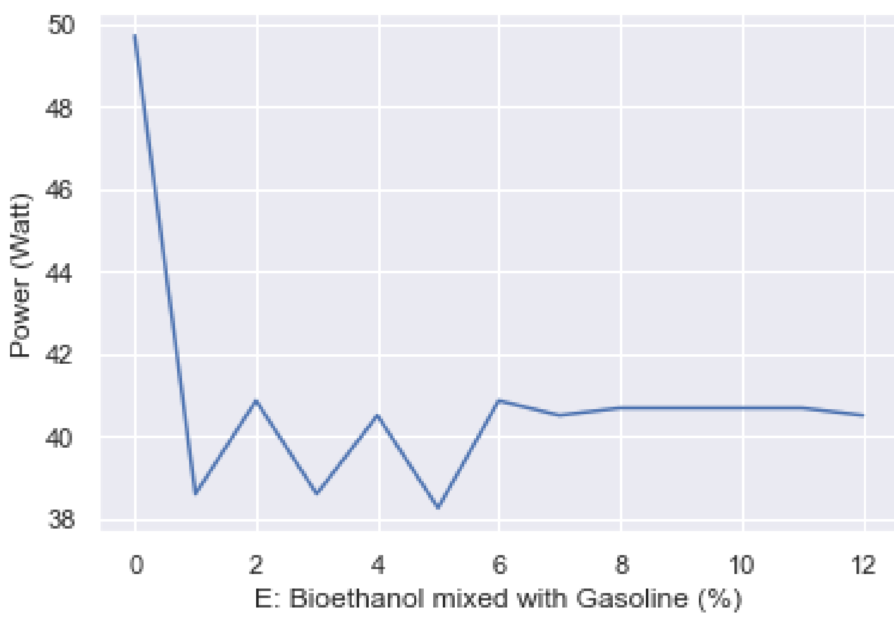

Figure 5: Computer (graphical) model in Python of the power output of the bioethanol produced from maize stalk.

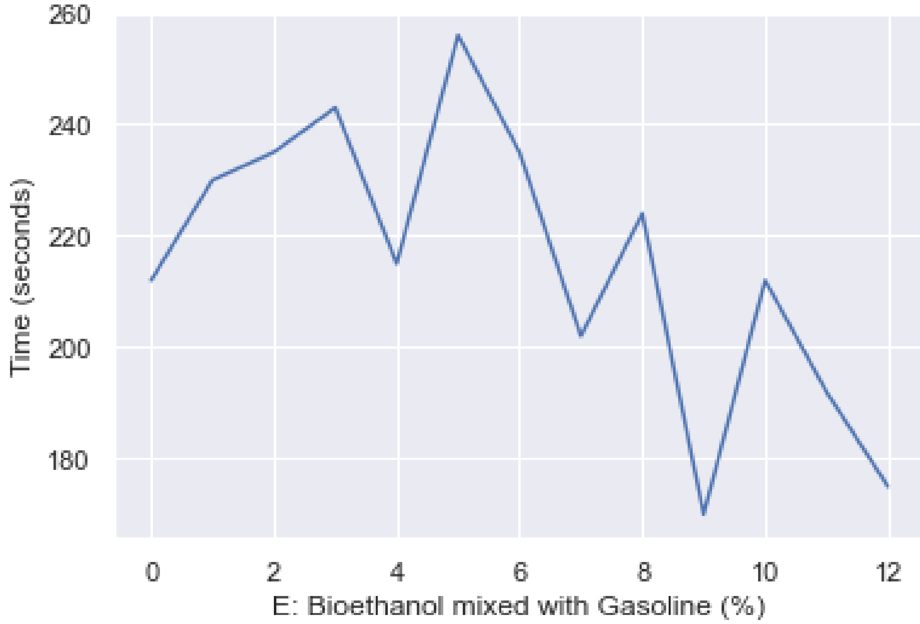

Figure 6: Computer (graphical) model in Python of the performance of the bioethanol produced from maize stalk mixed with petrol over time.

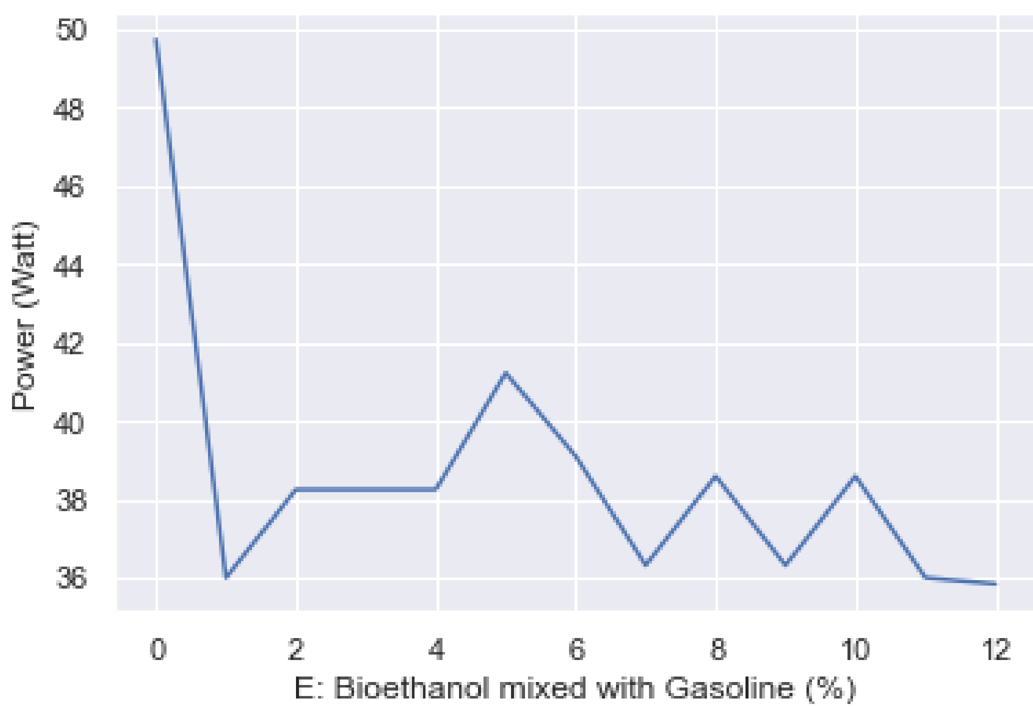

Figure 7: Computer (graphical) model in Python of the power output of the bioethanol produced from guinea corn stalk.

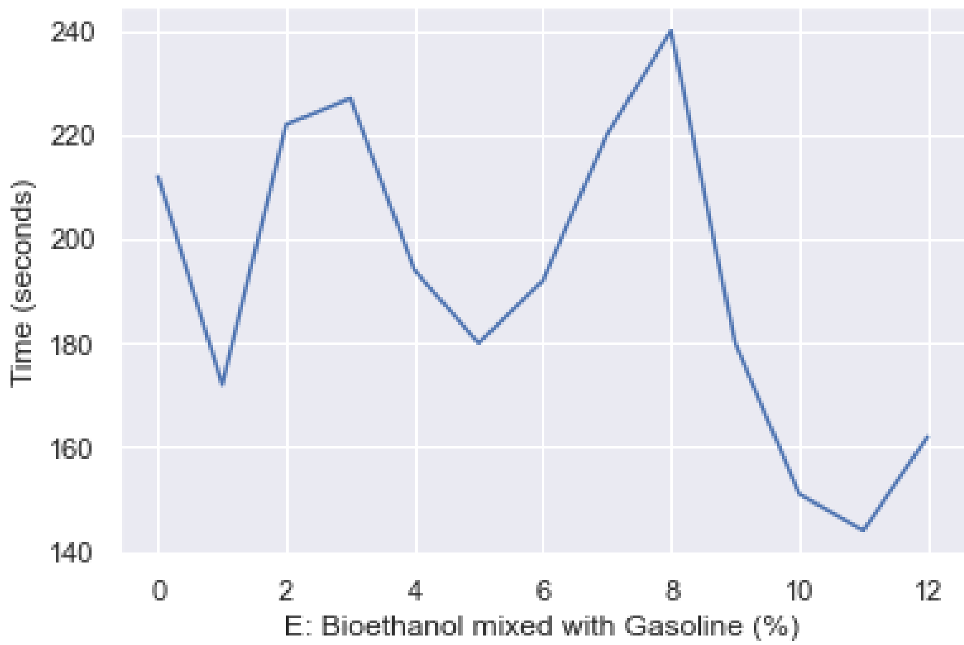

Figure 8: Computer (graphical) model in Python of the performance of the bioethanol produced from guinea corn stalk mixed with petrol over time.

3. CONCLUSION

The results obtained from the experimental tests that were conducted using the Sinwei electric power generating set showed that for the 50-50 blend of maize and guinea corn bioethanol that was mixed with conventional gasoline, E5 had the best power output of all the ratios experimented with. E5 has 95% conventional gasoline mixed with 5% blend of maize-guinea corn in equal proportion by volume (50-50). The results of the performance analysis showed that for the 50-50 Maize-Guinea corn blend, the E1 and E4 lasted longer than others in the electric power generating set with a running time of 268 and 260 seconds respectively. E6 and E5 had a running time of 239 and 222 seconds respectively. Results of the power output of the bioethanol produced from maize stalk that was mixed with conventional gasoline showed that E6 (94% gasoline mixed with 6% bioethanol) had the highest power output (40.86W) from the electric power generating set as measured by the digital multimeter. The performance analysis showed that the E5 (95% conventional gasoline mixed with 5% Bioethanol produced from maize stalk) had the highest running time of 260 seconds in the electric power generating set. E5 (95% conventional gasoline mixed with 5% bioethanol produced from guinea corn stalk had the highest power output (41.22W) of all the ratios of guinea corn produced bioethanol that was tested. Results for the bioethanol that was produced from guinea corn also revealed that E8 (92% conventional gasoline mixed 8% bioethanol) had the highest running time of 240 seconds in the Sinwei electric power generating set. Other samples returned a shorter time for the same experiment. Overall, the bioethanol that was produced from maize stalk had the better performance when compared with the 50-50 blend and the bioethanol that was produced from guinea corn stalk. The guinea corn bioethanol had the least desirable physicochemical properties, power output and overall performance in the Sinwei electric power generating set.

All of the results obtained from the experiments were validated by the developed computer (graphical) models. The models have the capacity to predict and estimate the performance of hypothetical or real life blended mixtures of quantities of conventional gasoline and bioethanol produced from maize and guinea corn stalks respectively. In addition, models that were developed for the 50-50 blend of maize and guinea corn bioethanol also have the capacity to predict and estimate values for the performance of bioethanol based on the proportion of conventional gasoline and bioethanol mixtures in an electric power generating set. The electric power generating set used in the study was based on an internal combustion engine designed primarily for domestic use.

REFERENCES

Ambrós, W. M., Lanzanova, T. D. M., Fagundez, J. L. S., Sari, R. L. Pinheiro, D. K, Martins, M. E. S., and Salau, N. P. G. (2015). Experimental analysis and modeling of internal combustion engine operating with wet ethanol. Fuel 158 (2015) 270–278

Awotunde, O. W., Faluyi, M. O., Opadoja, D., Oyelaran, A. O., Bolaji, B. O., & Opadoja, C. O. (2024). Investigation of the Effect of Aluminum Oxide on the Fuel Properties of Bioethanol Derived from Dried Maize Stalks. *Adeleke University Journal of Engineering and Technology*, *7*(2), 112-121.

Awotunde, O. W., Oyelaran, A. O., Bolaji, B. O. & Opadoja, D. (2025). Comparative analysis of the physico-chemical properties of bioethanol produced from guinea corns and maize maize stalks. Adeleke University Journal of Engineering & Technology (AUJET), 8 (1), 286 – 294 (2025).

Rawal, J. (2020). Performance Improvement of a Portable Electric Generator by Bio-Fuel and Gasoline. IRE Journals, 3 (8). ISSN: 2456-8880

Singh, P., Ramadhas, A., Mathai, R., and Sehgal, A., (2016). "Investigation on Combustion, Performance and Emissions of Automotive Engine Fueled with Ethanol Blended Gasoline," *SAE Int. J. Fuels Lubr.* 9 (1): 2016, doi:10.4271/2016-01-0886.

Thakura, A.K., Merb, K. K. S. and Kavitic, A. (2017). An artificial neural network approach to predict the performance and exhaust emissions of a gasoline engine using ethanol– gasoline blended fuels. *Biofuels*. ISSN: 1759-7269 (Print) 1759-7277 (Online) Journal homepage: http://www.tandfonline.com/loi/tbfu20.

Thakura, A.M., Kavitib, A.K., Singhc, R. and Gehlotc, A. (2021). Modelling the performance and emissions of ethanol–gasoline blend on a gasoline engine using ANFIS. *International Journal of Ambient Energy*. ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/taen20.