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A multi-criteria sustainability and engine performance study of andropogon narudus biodiesel using the PUGH matrix and ML

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The present work provides an experimental, sustainability, and ML-based analysis of Andropogon Nardus biodiesel as a potential second-generation green fuel for compression ignition engines. The biodiesel blends (AN20, AN30, and AN40) were then used on a single-cylinder direct-injection diesel engine over the 25–100% load range and at injection pressures of 190, 210, and 230 bar. Among the three AN30 blends tested, the improvement in engine performance at 230 bar indicates that AN30 provides nearly 15% greater brake thermal efficiency and reduces brake-specific fuel consumption by as much as 31% compared to the neat diesel level. Because of good atomization and the presence of oxygen in biodiesel, significantly lower emission levels of carbon monoxide, hydrocarbons, smoke opacity, and nitrogen oxides were achieved at optimized engine conditions. To evaluate the broader sustainability potential of the fuel, we applied a multi-criteria PUGH matrix analysis of performance (high & low) and emissions (atmospheric & land use)/sustainability (high & low) indicators. Out of all the fuel tested, the most favorable compromise between combustion modes was achieved with AN30 at 230 bar, which represents the best operating condition among the fuels tested. The experimental patterns were also employed to develop machine-learning models for predicting engine responses across an entire cruising range, and the results compared the prediction accuracy with models found ensemble-based algorithms provided the best prediction accuracy of the three models evaluated. These studies demonstrate that biodiesel produced from Andropogon narudus possesses decent potential as a sustainable biofuel for use in diesel engines when mixed at appropriate ratios and injected at appropriate pressures.

Keywords Andropogon narudus biofuel, Energy effiency, Machine learning, Sustainability assessment, PUGH matrix

The ever-rising global energy needs, the increasing depletion of petroleum-based energy resources, and the high environmental hazard of fossil fuel combustion are causing investigators to look for alternate sustainable available resources to find possible fuels for use in the diesel engines[35,36]. Diesel engines will be the primary engines used in the power plant for transportation, agricultural machinery, and stationary power generators

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facilities because of their high thermal efficiency, long service life, and high reliability. However, petroleum-based diesel is overconsumed and also causes serious environmental pollution because it emits harmful substances including nitrogen oxides (NOx), carbon monoxide (CO), hydrocarbons (HC) and particulate matter (PM). Collectively, these emissions are among the most significant drivers of air pollution, climate change and associated disease burden. Therefore, one of the primary research directions for the internal combustion engine is within that a sustainable alternative fuel is obtainable with respect to both. power plant emissions reductions as well as engine performance damage. Among these other potential renewable fuel sources studied for diesel engines, biodiesel has proven to be a very promising alternative to traditional diesel fuel. Biodiesel is an alternative fuel used in diesel engines, which is usually produced from vegetable oils, animal fats, or waste oils, which are essential to carry out transesterification to generate fatty acid methyl esters (FAME). Some of the most notable benefits of biodiesel compared to fossil diesel are its biodegradability, lower sulfur content, higher flash point, and lower toxicity. Biodiesel molecules contain oxygen in their chemical structures that promotes more complete combustion and fewer products of incomplete combustion, such as carbon monoxide and hydrocarbons. Numerous experimental investigations have been undertaken on the combustion characteristics and exhaust emissions characteristics of CI engines on biodiesel produced from non-edible feedstocks like jatropha, pongamia, mahua, and waste cooking oils, and they have shown improvement[1]. Biodiesel contains inherently higher amounts of fuel-bound oxygen, which promotes the oxidation reactions during the diffusion combustion stage, resulting in efficient combustion and lower soot precursor formation[6]. Due to its high viscosity, high density and low calorific value, biodiesel can affect the spray formation, atomization quality, ignition delay and heat release characteristic. All these characteristics are essential in air–fuel mixing inside the combustion chamber and thus can influence overall engine performance and emission characteristics as well. For example, the higher viscosity of biodiesel can lead to a larger droplet size after injection which in turn leads to poor atomization at low injection pressures[2]. Biodiesel can have a lower heating value which could reduce peak combustion temperature, and this might influence the thermal efficiency of the engine similarly to the effect of a shorter injection duration. Based on these findings, the optimization of engine operating parameters is critical when operating biodiesel fuels in compression ignition engines. Fuel injection pressure is one of the most significant engine operational parameters given the significant impact on spray atomization, fuel–air mixing, and combustion characteristics. The injection pressure will directly affect the process of the dousing droplets after the fuel is injected into the combustion chamber. The increase in injection pressure produces finer atomization of the fuel droplets and thereby provides better spray penetration and improved air–fuel mixing, leading to better-explored combustion and reduction of incomplete combustion emissions such as those of HC and CO[3]. It further helps to vaporize the liquid fuel and mix it with air fuel prior to combustion, making the mixture uniform. Simultaneously, while higher injection pressures can also increase combustion chamber temperatures and oxygen concentrations, leading to thermal NO_x pathways, which can in turn increase the formation of nitrogen oxides. Therefore, it is of paramount importance to characterize how biodiesel fuel properties interact with injection pressure variation to assess the optimal conditions that improve engine performance and control emissions[4]. But even considering alternative fuels, an increasing interest in the last few years has taken a sustainability-oriented evaluation framework for alternative fuels; conventional engine calculations comprise typical engine characteristics, including exegetical parameters, brake thermal efficiency, brake specific fuel consumption, NOx, CO, HC, and smoke emissions. While these parameters provide important information regarding engine performance, in the case of alternative fuels specifically, sustainability underlies the ultimate question of long-term viability: availability of resources, economic feasibility, renewability, and environmental effect[4]. Therefore, the need for a simultaneous evaluation of multiple performance indicators in alternative energy systems has led researchers to practice multi-criteria decision-making (MCDM) approaches with an increasing frequency. Such methods allow for systematic comparison of various fuels through technical, environmental, and socio-economic criteria[5]. There has been joint work. within the broader scope of energy system analysis that demonstrates that the integration of experimental energy system analysis with tools focused on areas of sustainability increases the fidelity of fuel analysis and can lead to more informed decision-making from an energy systems engineering perspective[6]. Andropogon Nardus is a perennial grass that can be cultivated in semi-arid regions and marginal lands. It has been considered a promising second-generation biodiesel feedstock among the possible renewable feedstocks to produce biodiesel. It is a fast-growing plant with good biomass productivity that can grow in poorer soils with very low agricultural inputs. Second-generation biofuel crops like Andropogon Nardus can be grown on non-arable lands without competing with oil and thus avoid the food–fuel conflicts associated with conventional biodiesel feedstocks, such as edible oil feedstocks. This combination of traits makes the plant a potentially highly sustainable feedstock for biodiesel production in areas of low crop availability[7,8].Compression ignition engines have been extensively studied with biodiesel from non-edible feedstocks, and a plethora of research has been reported on enhancing the performance aspects of biodiesel from non-edible oils with respect to combustion behavior, emission characteristics, and engine efficiency improvements. Multiple studies have shown the ability of oxygenated biodiesel fuels to improve oxidative reactions during diffusion combustion, resulting in lower levels of unburned hydrocarbons and carbon monoxide at practically acceptable engine performance. Studies on biodiesel–diesel blends also reported better combustion stability and lower particulate emissions than diesel, which was ascribed to the oxygen content of individual molecules of the biodiesel[9]. Furthermore, the extensive literature available on the optimization of fuel injection parameters (such as injection pressure and timing) proves that these parameters have a significant impact on spray atomization, droplet breakup, and air–fuel mixing processes and subsequently on combustion efficiency and pollutant formation. The last few works have also emphasized the need to incorporate sustainability assessment frameworks with the engine tests to evaluate the overall environmental and socio-economic viability of various alternative fuels[10]. The use of multicriteria decision-making approaches such as the PUGH matrix and other ranking methods to rank competing alternatives based on their performance, emission, environmental, and economic criteria has been a common practice in energy system studies[11–13].

Although biodiesel production from non-edible feedstocks has received a great deal of attention in the literature, most previous studies on biodiesel have concentrated on conventional sources for biodiesel production, such as jatropha, pongamia, mahua, and waste cooking oils, while relatively little research has focused on second-generation energy crops, such as Andropogon narudus. Moreover, several prior studies assessed engine performance and emission features separately and did not combine sustainability assessment and predictive modeling approaches. In recent years, machine learning techniques have been increasingly used to predict engine performance and emissions because they can capture more complex nonlinear relations between operating parameters and engine response. However, research related to integrated experimental engine testing along with sustainability assessment frameworks, and machine learning based predictive modelling of biodiesel fuels are limited. Therefore, an integrative analytical framework combining experimental analysis, sustainability assessment, and machine learning prediction is needed to provide a more holistic view of the applicability potential of emerging biodiesel feedstocks for compression ignition engine application.

Hence, the goal of this study is to perform a neutral analysis of the feasibility of Andropogon Nardus biodiesel as a second-generation sustainable combustible for the operation of compression ignition engines. A single-cylinder direct injection diesel engine was tested under different loads using biodiesel–diesel blends (AN20, AN30, and AN40) for three different injection pressures of 190, 210 and 230 bar. The evaluations were done systematically for engine performance, combustion characteristics, and emission behavior. In additions to this experimental assessment, a multi-criteria sustainability assessment (combining technical, environmental and socio-economic indicators) using a PUGH decision matrix method was performed to evaluate the optimum fuel mixture and operating condition. In addition, high-performance machine learning models were developed that predict key engine performance and emission metrics, as a function of operating variables. The analytical framework provides a systematic evaluation of new biodiesel feedstocks and similar evaluation tools may facilitate enhanced biodiesel sustainability strategies for compression ignition engine applications.

Materials and methods

Fuel procurement and blend preparation

The biodiesel from Andropogon narudus, studied here, was obtained from a qualified local biofuel seller who supplies biodiesel derived from non-food raw material. The fuel was generated by a conventional alkali-catalysis transesterification pathway with purification of the delivered fuel. Underwriting the biodiesel quality, full ASTM biodiesel specification sheet submitted by supplier (high quality)[7,12,13].

The fuel nomenclature and break-up is shown in Table 1 The blends were acquired at room temperature from typical laboratory conditions. Prior to the entry of the engine fuel system, all the blends were properly mixed with the help of mechanical stirrer. Both preparation and test processes involved neither chemical additives nor preheating methods. The reference fuel was the commercial diesel fuel propositioned on equivalent automotive diesel fuel specifications. All fuels were stored in sealed, kept dry, and tested in sealed conditions for undisturbed use during a limited time frame, preventing post-synthesis oxidation or degradation effects.

Physicochemical properties of fuel

The physicochemical properties of Andropogon narudus biodiesel and its blends were determined based on ASTM standard test procedures, which are naturally accurate and reliable. Calorific value, kinematic viscosity, density, flash point, latent heat of vaporization, and cetane number were analyzed standard methods by ASTM D5865, D445, D4052, D92, E2071, and D613 respectively. Table 2 test fuel properties measured using a detailed procedure[7].

Thus, the physicochemical properties of AN biodiesel blends directly affect their combustion behavior and emission formation. This is due to the longer ignition delay time of biodiesel due to the higher cetane number, which ultimately leads to superior and smooth combustion. The intrinsic oxygen content in the fuel encourages complete oxidation of intermediate species, which in turn reduces HC, CO, and smoke emissions. The higher viscosity and density of biodiesel can, however, alter spray characteristics—particularly at lower injection pressures. Biodiesel (BD), having a lower calorific value and higher latent heat of vaporization than diesel, reduces the previously mentioned property, therefore resulting in lower peak combustion temperatures responsible for lower NO_X formation. Hence, this intrinsic nature of the fuel is directly connected to the recorded trends in performance and emissions.

Engine operating conditions

Figure 1 shows the schematic arrangement. The performance and emissions of Andropogon narudus biodiesel blends were characterized in a single-cylinder, four-stroke, direct injection (DI) diesel engine at various loads. The engine was run at a constant speed of 1500 rpm, which is typical for stationary and agricultural engines. The

Sl.no	Andropogan Narudus (%)	Diesel (%)	Abbreviation
1.	80	20	AN20 + D80
2.	70	30	**AN30 + D70**
3.	60	40	**AN40 + D60**

Table 1. Fuel Nomenclature and Split Up.

Properties	Units	Diesel	AN	ASTM Standards	AN20 + D80	AN30 + D70	AN40 + D60
Calorific value	MJ/kg	44.52	36.27	ASTM D5865	42.9	42.05	41.2
Kinematic viscosity at 40 °C	CST	3.9	4.18	ASTM D445	3.96	3.984	4.01
Density	Kg/m³	820	910	ASTM D 4052	838	847	856
Flashpoint	°C	76	50	ASTM D92	70.8	68.2	65.6
Latent heat of vaporization	(kJ/kg)	262	305	ASTM E2071	271	274.9	279
Cetane number	–	47	45	ASTM D 613	46.6	46.4	46.2

Table 2. Physicochemical properties of fuel blends used in the experimentation.

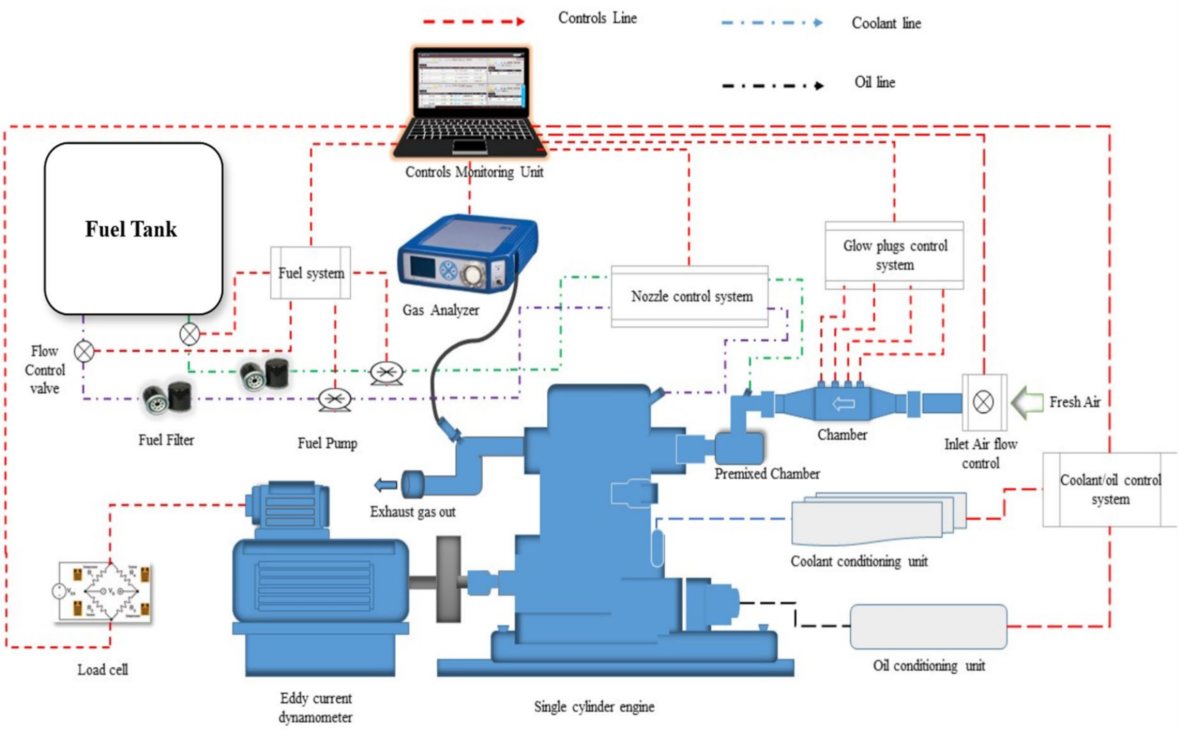

Fig. 1. Schematic Arrangement of the Engine Setup (Microsoft visio 2021)[7].

compression ratio was set at 17.5:1, and 190 bar, 210 bar, and 230 bar injection pressures were employed for the proper atomization of diesel as well as biodiesel blends. The fuel injection timing was maintained at 23° prior to the top dead center (bTDC) to provide constant combustion stability for all the test fuels. An eddy current dynamometer was used to supply a 0% to 100% load in steps of 25% to the engine. The engine was initially thermally stabilized before preparing for each test to avoid cold start effects on the engine, and evaluated three times for each blend (AN20, AN30, and AN40) for data accuracy and reproducibility. The controlled operational conditions allowed for the fair comparison of the combustion, performance, and emission characteristics of Andropogon narudus biodiesel blends and diesel fuel.

Experimental setup

Instruments used for experimentation

Engine specifications

The instruments used for engine specification of the experimental engine are listed in Tables 3 and 4. A single-cylinder, four-stroke, vertical water-cooled direct injection (DI) diesel engine, which is common in pump and basic stationary applications, was selected for the experimental study. This engine was self-started by hand cranking and used a circulation water cooling system which provided thermal stability in long- run period testing. The thermal lubrication is from a forced lubrication system with an oil sump and the engine is fitted with a mechanical centrifugal governor for controlling the engine speed. An eddy current dynamometer was used to impose and measure variable loads on the naturally aspirated intake system and connected engine. Also, a

S. No.	Parameter measured	Instrument used	Measurement error/uncertainty
1	Brake Power/Torque	Eddy Current Dynamometer	± 0.2 Nm
2	Fuel Consumption	Burette and Stopwatch	± 0.5 mL (burette), ± 0.1 s (stopwatch)
3	In-Cylinder Pressure	Piezoelectric Pressure Sensor	± 0.5 bar
4	Crank Angle	Crank Angle Encoder	± 1° CA
5	Exhaust Gas Temperature	K-Type Thermocouple	± 1.5 °C
6	NO_X, CO, HC, and CO_2 Emissions	AVL 444 Five-Gas Analyzer	NO_X ±10 ppm, CO ± 0.02%, HC ± 10 ppm
7	Smoke Opacity	AVL 437 Smoke Meter	± 1 HSU (Hartridge Smoke Unit)

Table 3. Instrument used in the research.

S. No.	Parameter	Specification
1	Engine Type	Single-cylinder, 4-stroke, DI
2	Cooling System	Water-cooled
3	Rated Power	5.2 kW at 1500 rpm
4	Engine Speed	1500 rpm (constant)
5	Compression Ratio	17.5:1
6	Bore	87.5 mm
7	Stroke	110 mm
8	Displacement Volume	661 cc
9	Injection Type	Mechanical direct injection
10	Injection Pressure	190 bar, 210 bar, 230 bar
11	Injection Timing	23° bTDC
12	Dynamometer Type	Eddy current
13	Cooling Type	Water-cooled
14	Starting Method	Manual crank
15	Fuel Used	Diesel and *Andropogon narudus* blends
16	Combustion chamber	Hemispherical

Table 4. Engine specification.

K-type thermocouple to measure the EGT and an optical crank angle encoder (1° crank angle (CA) resolution for combustion analysis) were used. The engine was powered using standard diesel and different compositions of Andropogon narudus biodiesel in a performance, combustion, and emission comparative evaluation[14].

Schematic arrangement

Uncertainty analysis

After the continuous operation system reached steady-state operation (i.e., at constant speed, stabilized exhaust temperature, and stable fuel flow), each experimental condition was repeated three times to ensure the reliability of the results reported. The mean of repeated measurements is reported, and repeatability was confirmed as the difference between repeated readings did not exceed the acceptable value.

For each derived parameter, uncertainty was determined using the uncertainty propagation method by combining the instrumental uncertainties for directly measured quantities such as torque/load, speed, fuel consumption, and temperature with experimental repeatability.

$$R = \sqrt{(U_1{}^2 + U_2{}^2 +} U_3{}^2 + U_4{}^2 + U_5{}^2 + \ldots \ldots .U_n{}^2 \quad (1)$$

Estimations of uncertainties were made according to the instrument accuracies (as shown in the instrumentation table), and repeatability of measurements was ± 1.2% for BTE, ± 1.5% for BSFC, and within acceptable limits for the used sensors for emissions. The total combined uncertainty (expressed at the 95% confidence level) of the experimental measurements was ± 1.93%. The obtained values for BTE and BSFC are substantially larger than the combined uncertainty and are therefore deemed experimentally significant and repeatable[15].

The uncertainties in the measurements that are listed in Table 3 have been obtained directly from the manufacturer specifications of the respective instruments used in the experimental setup. These specifications are the maximum measurement errors allowed by the manufacturers of the instruments used under standard operating conditions. To ascertain the fidelity of the experimental data, each test condition was repeated 3 times and reported. Uncertainty propagation was used to calculate the uncertainty of the dependent variables BTE and BSFC based on the uncertainty of the directly measured parameters, torque, fuel consumption, engine speed and temperature, calculated using the root-sum-square method[10].

Sustainability assessment

Selection of evaluation criteria

Figure 2 shows the procedure for the development of the PUGH matrix. Ten criteria were selected for a complete analysis of the sustainability of the fuel blends. These were performance-based criteria such as BTE and BSFC; emission criteria such as HC, CO, smoke, and NO_X; and sustainability criteria such as fuel availability, cost, renewability, and overall sustainability. These criteria were grouped into three diverse categories: technical (performance and emissions), environmental, and socio-economic considerations.

Development of Pugh matrix

A multi-criteria PUGH matrix approach, a common method for relative ranking of engineering options, was used to conduct the sustainability assessment. The criteria that were chosen can be traced back to major technical, environmental, and practical aspects related to biodiesel from the perspective of compression ignition engine operation, namely, performance and emissions, the renewability of the fuel, and operability. To avoid subjectivity in weighing the criteria, each was weighted equally to ensure representation of the three categories (performance, environmental impact of the life cycle, and sustainability indicators). The metric used is a simple comparative scoring system, with each fuel condition being benchmarked to the diesel baseline and given positive, neutral, or negative scores based on performance degradation or improvement. This way provides a transparent form of procedure to determine the optimal operating condition with the least environmental interference.

The relative merits of the various fuel blends were analyzed using the PUGH decision matrix. The matrix provides a structured way to compare alternatives against many criteria. Each of the criteria was compared against the others on an ordinal five-point scale from −2 (least desirable) to +2 (most desirable) for each combination of fuel-injection pressures. The baseline was the D100 fuel at 190 bar, and scores were awarded based on experimental trends: higher BTE and lower BSFC, HC, CO, NO_X, and smoke values were awarded higher scores. Scores were estimated for non-quantitative parameters such as availability, renewability, and sustainability based on biodiesel production potential, raw material availability, and environmental effect[9].

Scoring and aggregation

Once all the scores had been assigned, they were summed across the ten criteria to generate a total score for each fuel blend. The overall scores provided a single number value that represented the overall performance and sustainability of each blend. The alternatives were then ranked according to this, with the highest-rated fuel blend considered the most suitable for sustainable engine applications.

Machine learning methodology

Figure 3 shows the machine learning method. Development of a machine learning framework for model-based prediction of engine performance and emission parameters at operating conditions.

Dataset description

The experimental dataset used for machine learning was obtained from engine tests conducted at various loads, blend ratios, and injection pressures. The dataset included the performance and emission parameters measured under steady-state conditions[37].

A total of 60 operating points were generated from structured engine experiments conducted by using four fuel conditions, three injection pressures, and five engine load levels to prepare the machine learning dataset.

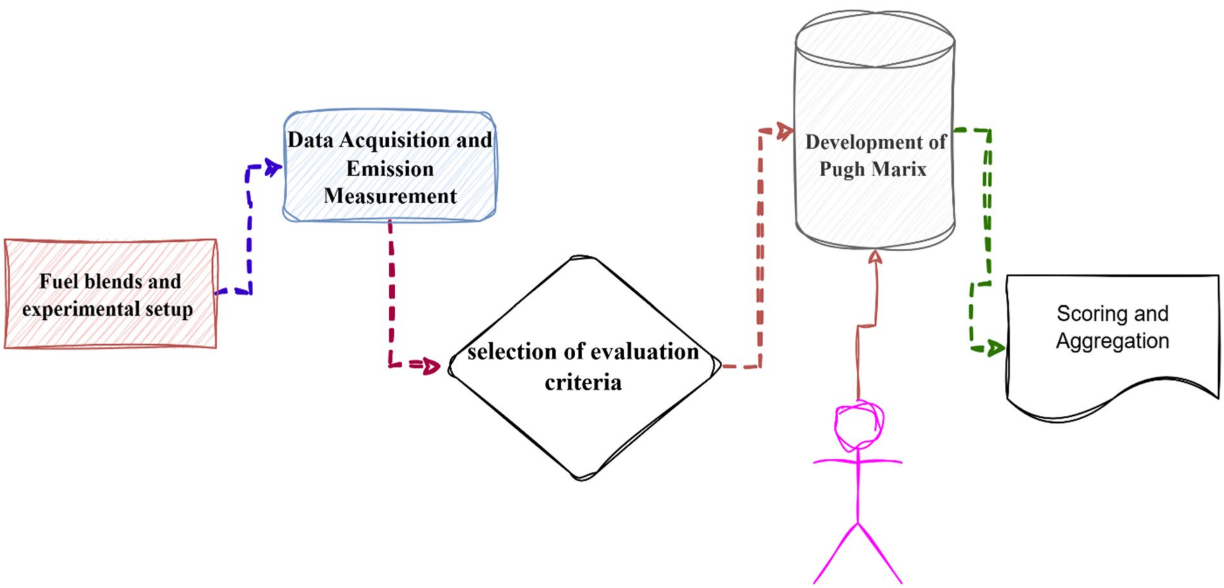

Fig. 2. Development of Pugh matrix.

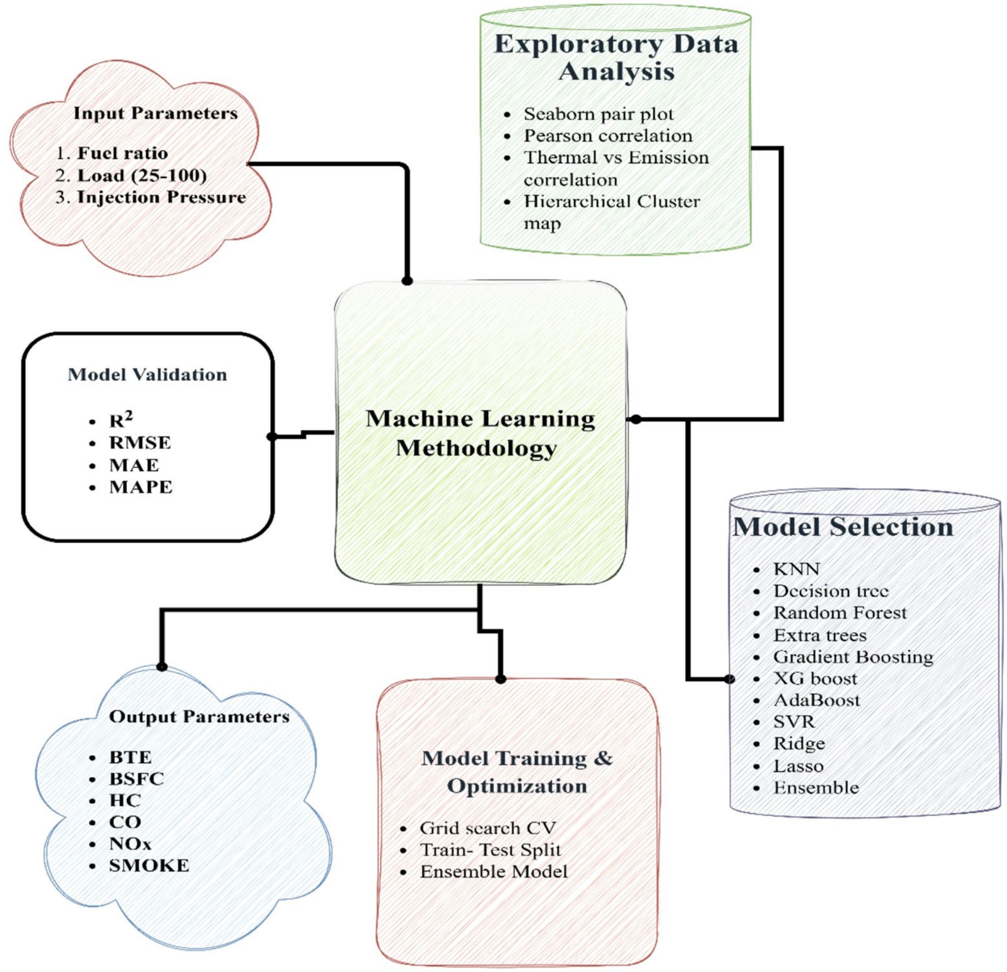

Fig. 3. Machine learning methodology.

There were three replicates per condition, and the mean values of each condition were used for machine learning modeling. Fuel blend ratio, injection pressure, and engine load were used as input parameters, and BTE, BSFC, HC, CO, NO_X, and smoke emission were used as output features.

An 80:20 split of the dataset was performed to separate its training and testing subsets, leading to 48 training samples and 12 testing samples. ring model development, we also applied cross-validation techniques to improve generalization and prevent overfit.

Input and output parameters

The fuel blend ratio, engine load, and injection pressure served as input variables, and the output parameters included the brake thermal efficiency (BTE), brake specific fuel consumption (BSFC), hydrocarbon (HC), carbon monoxide (CO), nitrogen oxides (NOX), and smoke opacity.

Model selection

In order to encapsulate the nonlinearity nature of inputs vs. output on underlying engineering model, various regression-based machine learning algorithms were potentially tested. Among these decision trees, random forests, extra trees, gradient boosting and ensemble-based ones.

Non-linear correlations of engine operating parameters and performance–emission responses were determined based on analysis of data obtained using different machine learning algorithms. The chosen models cover various learning paradigms: single decision trees, ensemble-based methods, and boosting. This gives the opportunity to compare simple and interpretable models to more sophisticated ensemble methods that usually provide better prediction accuracy and robustness. Instead of proceeding with a single algorithm, without any validation step, the comparative approach leads to the detection of the most accurate model for a concrete experimental dataset.

Training and validation procedure

To assess the performance of the model, the experimental dataset was split into two portions: training and testing. Different versions of the multiple regression algorithms, namely, decision tree, random forest, extra trees, gradient boosting, support vector regression, and three different methods based on the ensemble mechanism, were implemented to find and capture the nonlinearities between the input and output parameters.

Multiple validation techniques were used to reduce the likelihood of overfitting. To ensure that model performance was performed on unseen data, the dataset was split—independently—into train and test subsets. Moreover, cross-linearization methods of model splitting were used in model building to check for generalizability between different partitions of the data. Another true statement in our comparison is the favoring of ensemble-based algorithms, which are less linear and more prone to overfitting than single-tree models. The training and testing performance metrics strongly agree with one another, indicating that the predictive characteristics of the built models are stable and applicable.

Performance evaluation metrics

The performance of our model was estimated using conventional statistical metrics such as R-squared (R^2), root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE). Model cross-validation techniques were carried out to increase the robustness of the model and prevent any overfitting on the test data[11].

Results and discussion

Performance and combustion analysis

Brake thermal efficiency (BTE)

Figure 4, shows the Brake Thermal Efficiency (BTE) of Andropogon narudus (AN) biofuel for different injection pressures (190, 210 and 230 bar) and engine load (25%, 50%, 75% and 100%), the trends are quite clear and very consistent with the analysis. Above all, the BTE of the AN biofuel(biodiesel) at each level of injection pressure measures follow a clear trend of improvement while sweeping the engine load from 25% to 100%. This makes

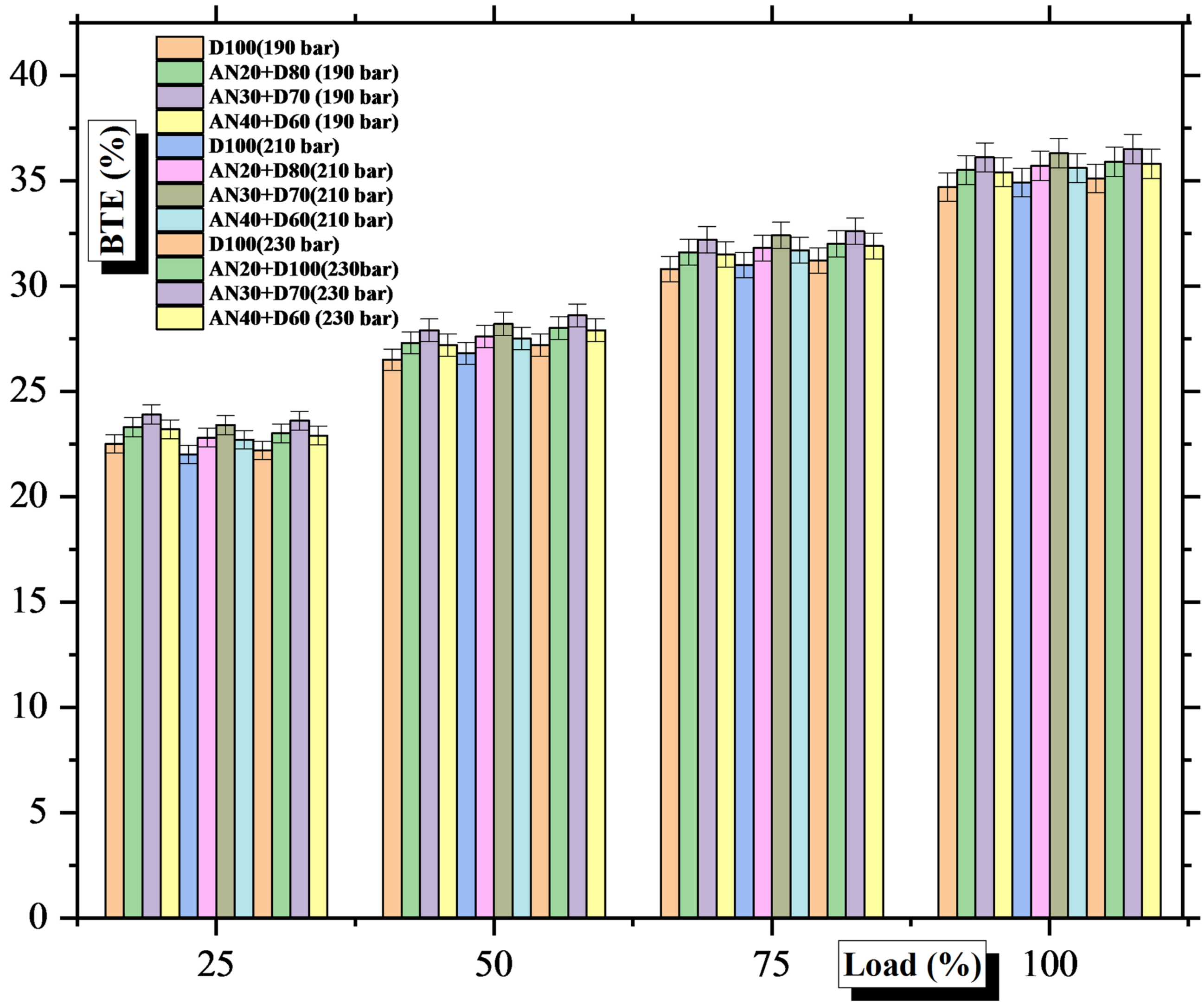

Fig. 4. Load vs. brake thermal efficiency.

sense when compared to internal combustion engines, whereby greater loads to promote better burning and larger ratios with energy not lost, thus usually more efficient. In addition, the increase of brake thermal efficiency positively correlates with the increase of injection pressure. In particular, high injection pressure can contribute high BTE values below 30 bar because compared with 190 bar, most BTE values can be obtained at 230 bar, particularly on the heavier engine loads[15].

This improvement is supported by abundant research, referencing that increased injection pressures lead to finer fuel atomization and improved fuel-air mixture in the combustion chamber. Better atomization and a more uniform mixture led to high-quality and efficient combustion, as told in most studies on biofuel performance. The results show that the best injection pressure can affect combustion efficiency very favorably in the reduction of ignition delay and with more favorable fuel distribution.

Although the performance clearly gains from the highest injection pressure applied, the increase in BTE becomes limited at the determined test pressure. For the AN30 blend, the BTE values at the highest injection pressure of 230 bar were always the highest, confirming that this injection pressure is the best choice to improve combustion. The data suggests that the performance of Andropogon narudus as a biofuel generally supports earlier studies that it can be considered as a competitive substitute fuel that could compete with and, in some cases, exceed the performance of conventional diesel under optimum operating conditions[16]. The increase in BTE best condition (AN30 at 230 bar) was greater than the determined experimental uncertainty (± 1.93%) and reproducible over several runs. As such, the change in BTE can be considered statistically significant given the repeatability of the measurements. The increase in brake thermal efficiency and the decrease in BSFC are correlated to the injection of the biodiesel, which is an oxygenated compound, and the higher injection pressure, which enhances spray atomization as well as air–fuel mixing, thereby providing significantly improved combustion and heat release characteristics.

But at injection pressure beyond an optimum point, the increase in atomization may quickly become less pronounced and over penetration or low premixed combustion fraction can restrict the improvement of thermal efficiency, restricting performance change opportunity with higher pressures.

Brake specific fuel consumption (BSFC) (kg/kWh)

Figure 5 expresses the brake-specific fuel consumption (BSFC) for different fuel blends and engine loads (25%, 50%, 75%, and 100%), where the BSFC measures the fuel mass flow rate (here in g/hr) at a set engine output and hence, critically, provides some measure of engine fuel efficiency. When the engine load changed from 25% to 100%, a distinct decrease of BSFC was recognized. This trend reflects some better use of fuel at higher loads as the fraction of total power output attributed to fixed mechanical and pumping losses is smaller. There is significant percentage benefit in BSFC in the jump from low 25% and medium 50% loads, and additional, but less dramatic, gains as load increases even more. The comparison between BSFC values (possibly of two different types of fuel) on columns illustrates how appropriate fuel properties (calorific value, density, viscosity, combustion characteristics, etc.) have a direct impact on the fuel utilization efficiency of an engine. These last two alignment of components lead to a lower BSFC or means that we have more energy in the fuel to there in a more condensed manner, or just that the overall type of fuel that we like to have of course burns more completely. So, most surprisingly not only did the results confirm the principle of basic engine efficiency w/load — but the role of fuel composition and operating conditions was highlighted for best fuel economy[17]. Likewise, the reduction in BSFC seen for the best condition is substantially greater than the total experimental uncertainty (± 1.93%) and was repeatable over multiple trials, indicating that the reduction is not due to measurement noise/ random variation.

Cumulative heat release rate

Figure 6 indicates the Cumulative Heat Release Rate (CHRR) over time for different biofuel-diesel blends of Andropogon narudus (AN) at various injection pressures (D). A straightforward result can be seen in the visual separation of the CHRR profiles with regard to the injection pressure. As the CHRR profiles indicate, the 230 bar injection pressure yields the highest cumulative heat release of all conditions tested, confirming its status as the correct injection pressure. The lower CHRR at 210 bar, particularly for D100 (210 bar), indicates that this injection pressure might not be as beneficial for total heat release for this engine configuration. In comparison, the CHRR of the 190 bar and 230 bar conditions tend to have a higher heat release and this is even more pronounced at the later stages of combustion for the 230-bar group compared to the 190-bar group. This would indicate that higher injection pressure typically results in enhanced and more complete heat release (due to better fuel atomization and mixing associated with higher pressure injection). In addition, the mean of early start of combustion and high combustion of AN blends fuel due to the higher CV and lower viscosity also indicates that blends contribute positively to desirable combustion characteristics by virtue of its own nature in the form of shorter ignition delay and improved combustion process. D100 always has the highest CHRR among the blends and pure diesel (D100) at each pressure group, and an increasing amount of AN blends (AN30 + D70, AN40 + D60) will provide a lower CHRR than AN20 + D80 but still a higher value than D100 (210 bar). It shows that there is a proper blending ratio which make the release of heat maximal with the existence of injection pressure[16].

Ignition delay and combustion phasing (Cumulative heat release characteristics) The lower the ignition delay, the less fuel will be accumulated in the premixed phase, which may be beneficial for smoothing the heat release profile and pressure rise. In contrast, longer ignition delays increase the fraction of premixed combustion, which leads to a higher heat release peak and higher in-cylinder pressure. Since the AN had more atomization and shorter ignition delays under higher injection pressures based on the results of the present study, the main combustion phase was closer to top dead center. In this way, pressure developed automatically in a stable manner, and thus lead to an improvement in thermal efficiency.

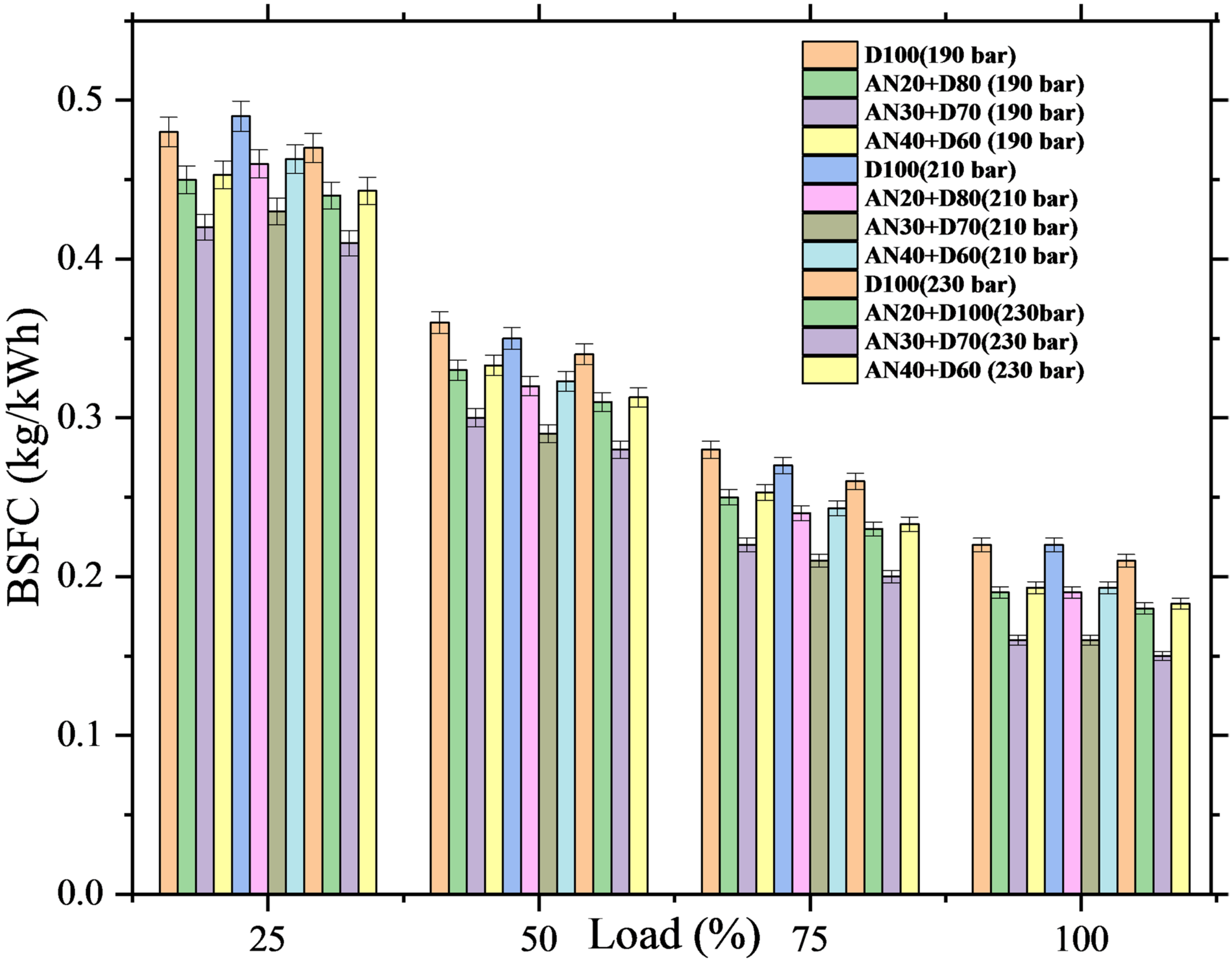

Fig. 5. Load vs. BSFC (kg/kWh).

Overall, the AN30 blend at 230 bar offered the best compromise between performance, emissions and sustainability, providing the most stable operating condition throughout all three analyses.

Emission

Hydrocarbon (HC)

Figure 7. Hydrocarbon (HC) emissions in g/kWh of Andropogon narudus (AN) biofuel blends with diesel (D) for different engine runs (0% D – 50% D –100% D) under varying load and injection pressure conditions. A clear trend observed is the sharp decrease in the HC emissions as the engine load increases from 0% to 75% and a slight increase at 100% load. D100 at 190 bar into interpretation, in which at 0% (0.48 g/kWh) and 25% loads (0.38 g/kWh), HC emission reduced around 20.83% and keeps reducing at 50% load reducing another 18.42% to 0.31 g/kWh. As expected and consistent with internal combustion engine behavior, the lower the load, the less complete combustion due to low cylinder temperature, and thus greater first HC emissions. In general, however, there is a large increase in HC emission for this condition of around 21.43% from 0.28 g/kWh at 75% load to 0.34 g/kWh at 100% load due to localized fuel-rich zones or wall wetting effects as identified for high injection rates[19].

Moreover, the effect of fuel blending period and fuel injection pressure is observed by the investigation. Under 100% load, the HC emissions of blends are lower than that of neat diesel at 190 bar; for instance, the value of AN30 + D70 was 0.32 g/kWh, a 5.88% reduction compared with that of D100 (0.34 g/kWh) under the same operating conditions. The drop could be caused by the biofuel high in oxygen promoting complete combustion. For D100 at 100% load, this injection pressure increase was additionally always accompanied by a reduction in HC emissions, with the HCs then decreasing from 0.34 g/kWh at 190 bar to 0.32 g/kWh at 210 bar (approximately 5.88% decrease) and again down to 0.29 g/kWh at 230 bar (approximately 9.38% reduction compared to 210 bar, or, 14.71% reduction compared to 190 bar). This is a well-known phenomenon where higher injection pressures aids in improved atomization, spray penetration and air-fuel mixing, thus improving combustion and reducing unburnt hydrocarbons. In short, the findings highlight that despite significant contributions from load to HC emissions, the level of effectiveness coming from optimizing fuel blend ratio and injection pressure constitutes

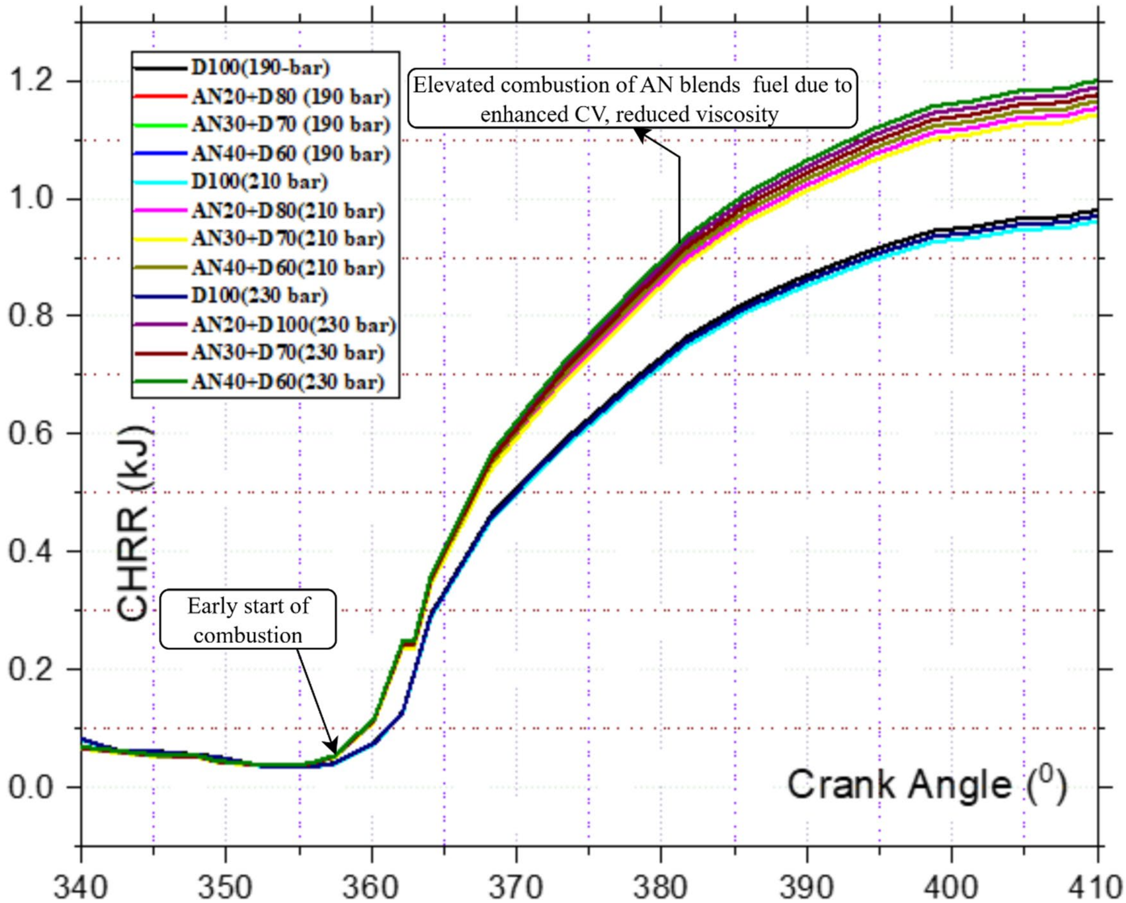

Fig. 6. Crank Angle (0) vs. CHRR (kJ).

a further, critical step towards reducing the products of muss-5 incomplete combustion[18]. The decrease in HC emissions with AN biodiesel blends is mainly due to the oxygen atoms contained in the molecules of the fuel, leading to better oxidation of unburned hydrocarbons in the late stages of combustion. Furthermore, finer fuel droplets resulting from higher injection pressures and resultant improved atomization promotes more effective air–fuel mixing and reduced local rich or quenching zones where HC formation is known to be high. Biodiesel also has a shorter ignition delay which leads to controlled combustion and reduces the production of unburned hydrocarbons.

Carbon monoxide (%)

Figure 8, shown here, shows the Carbon Monoxide (CO) emissions in % for different fuel blends of Andropogan narudus (AN) with diesel (D), at different engine loads and injection pressures (190, 210, and 230 bar). A notable trend seen in most of the fuel blends and injection pressures is a decline in the emission of CO with an increase in engine load from 0% to 50% or 75%, with a rise thereafter at 100% load. For example, taking D100 at 190 bar into account, emissions of CO declined from 0.017% at 0% load to 0.0118% at 50% load, an approximate 30.6% reduction. This early reduction is because, under light loads, combustion is incomplete because of reasons such as reduced cylinder pressures and temperatures and higher heat losses, resulting in increased CO production. With increased load, combustion efficiency improves, and as a result, CO is reduced. But at 100% load, CO emissions for D100 (190 bar) rose to 0.016%, a considerable increase of about 35.6% from 75% load. Such an increase under full load is common, usually because of localized fuel-rich regions, limited availability of oxygen, or flame extinction at high rates of fuel injection, all of which prevent complete oxidation of carbon to CO_2 and thereby result in elevated CO.

In addition, the results also show the effect of fuel blending as well as injection pressure on CO emissions. Overall, compared to pure diesel under comparable circumstances, blends tend to have lower CO emissions especially at higher loads. At 100% load and 230 bar for example, AN40 + D60 offered 0.0124%, around 6.06% lower than D100 (0.0132%) at the same pressure. Normally the decrease is attributed to the natural oxygen content of the biofuels such as the hydrogen level of AN shortens the combustions process by providing additional oxygen for oxidation of carbon to CO_2, even in locally oxygen-deficient environments. As far as injection pressure is concerned, increased injection pressures tend to result in lower CO emissions, especially during higher loads. For example, under 100% load condition, D100 emits CO of 0.016% at 190 bar, which decreases to 0.014% at 210 bar (an average decrease of 12.5%), and again to 0.0132% at 230 bar (an average

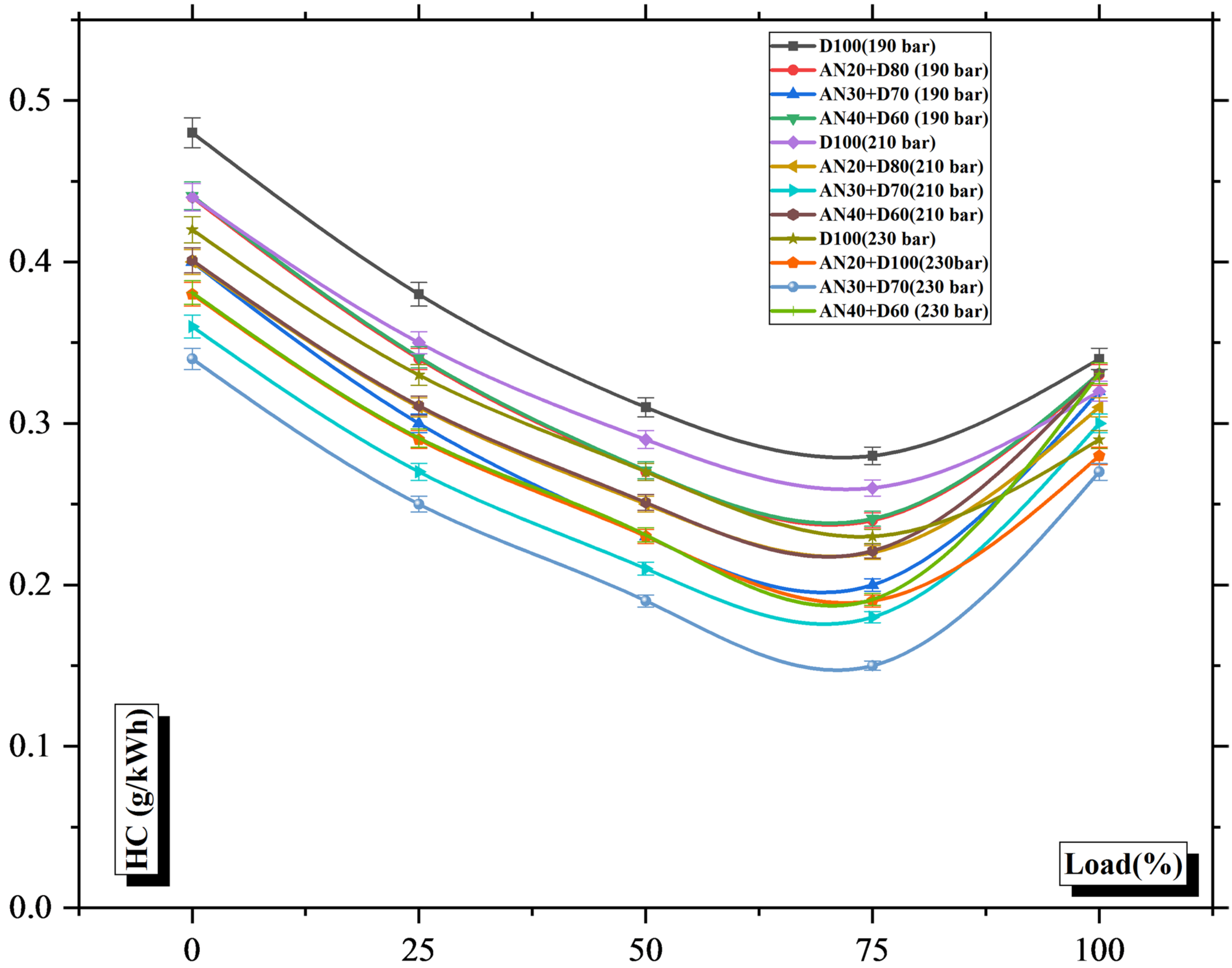

Fig. 7. Load (% vs. hydrocarbon emission (g/kWh).

decrease of 5.7% over 210 bar and a 17.5% decrease over 190 bar). This is consistent with research that shows that raised injection pressure raises fuel atomization and air mixing with the fuel, which increases the completeness of the combustion and decreases the formation of CO. In summary, the results demonstrate that emissions of CO are very sensitive to engine load, fuel blend fraction, and injection pressure, with raised injection pressures and AN blends generally tending to minimize CO, except for raised loads where raised fueling may lead to a slight raise[19].

The decrease of CO for the AN biodiesel blends is attributed to the effect of the bound oxygen contained in the fuels, which can promote the oxidation of CO-to-CO_2 during the expansion stroke. Higher injection pressures also promote further atomization and therefore more homogeneous air–fuel mixtures, which reduces locally rich regions that dominate CO formation. In addition to that, the higher cetane number of biodiesel decreases the ignition delay and further promotes the smoother combustion, which complements the reduction of the incomplete oxidation products like CO.

Smoke (%)

Figure 9 shows the smoke emissions, in terms of opacity percentage or an equivalent measure, for different fuel blends of Andropogon narudus (AN) with diesel (D), measured during different engine loads and injection pressures (190, 210, and 230 bar). Either of those can lead to smoke emissions, which are burnt carbon particles (soot) and a direct measurement of incomplete combustion.

One of the clearest and consistent trends in the data for all fuels and injection pressures is the dramatic spike in smoke emissions as the engine load increases from 0% to 100%. D100 at 190 bar took smoke emissions from 15.00 at no load to 100% load 55.00, an approximate 266.7% increase. Such a steep increase is typical of a diesel engine simply due to the way more fuel is introduced to the combustion chamber in higher loads.

. Without sufficient oxygen or sufficient time for thorough mixing and combustion, particularly in areas that are fuel-rich, the formation of soot becomes highly prominent.

In Diesel Engines, from the result indicates fuel blending and injection pressure impact on smoke emission. Generally, Blends produce less smoke under the same conditions as pure diesel (D100), especially at full loads.

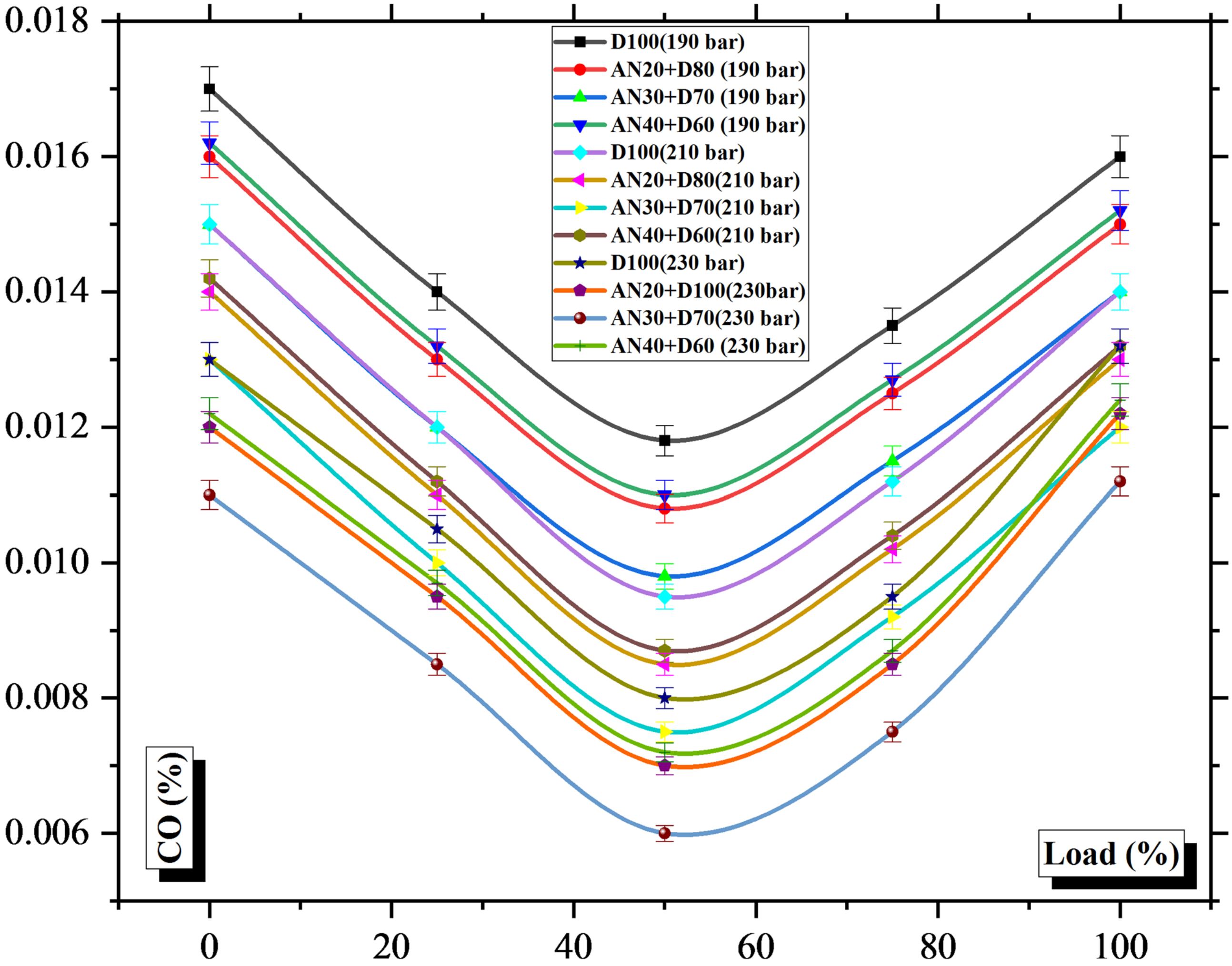

Fig. 8. Load vs. Carbon Monoxide (%).

For example, at 100% load and 230 bar, AN40 + D60 produced 45.50 units of smoke, a 2.0% decrease compared to D100 (46.40 units) at the same pressure. This smoke decrease with biofuel blends has been explained because of the oxygen content integrated into the biofuel molecule, which promotes more efficient combustion and reduces the tendency for soot formation, particularly in the latter part of combustion. As for injection pressure, higher injection pressures tend to make less smoke at any load. For example, at 100% load, D100 presents smoke emissions of 55.00 at 190 bar, decreasing to 50.50 at 210 bar (an approximate 8.9% decrease), and then to 46.40 at 230 bar (an approximate 8.1% decrease from 210 bar, and 15.7% decrease from 190 bar). This is in line with studies showing that increased injection pressure enhances fuel atomization, enhances air-fuel mixing, and provides greater spread of the fuel spray, reducing fuel-rich zones and enabling more complete combustion, which directly reduces smoke formation and particulate matter. The results clearly illustrates that smoke emissions are extremely sensitive to engine load with pronounced increases at high loads, whereas AN blends and high injection pressures are efficient measures to suppress these unwanted emissions[20]. Smoke generation from diesel engines is heavily controlled by local fuel-rich regions along with incomplete combustion of soot precursors. The AN biodiesel blends, in addition with their acid, contain additional oxygen; as a result, the soot particle oxidation is also enhanced during the diffusion combustion period. Furthermore, increases in injection pressure have been shown to promote better spray breakup and air–fuel mixing, which leads to a reduction in the locally rich regions that lead to soot nucleation. By virtue of the above aspect of fuel-bound oxygen and improved atomization, smoke emissions are much lowered compared to neat diesel operation.

Oxides of nitrogen (ppm)
Figure 10 shows the exhaust NOx concentration (ppm) using AVL five-gas analyzer for diesel and various blends of Andropogon narudus biodiesel measured at diesel engine with different loads and injection pressures. A monotonically decreasing relation between engine load and NOx emissions was clearly observed in the case of all fuel combinations tested. This trend follows the typical behavior of compression ignition engines, where higher load conditions equate to increased amounts of fuel injected, leading to higher in-cylinder temperatures,

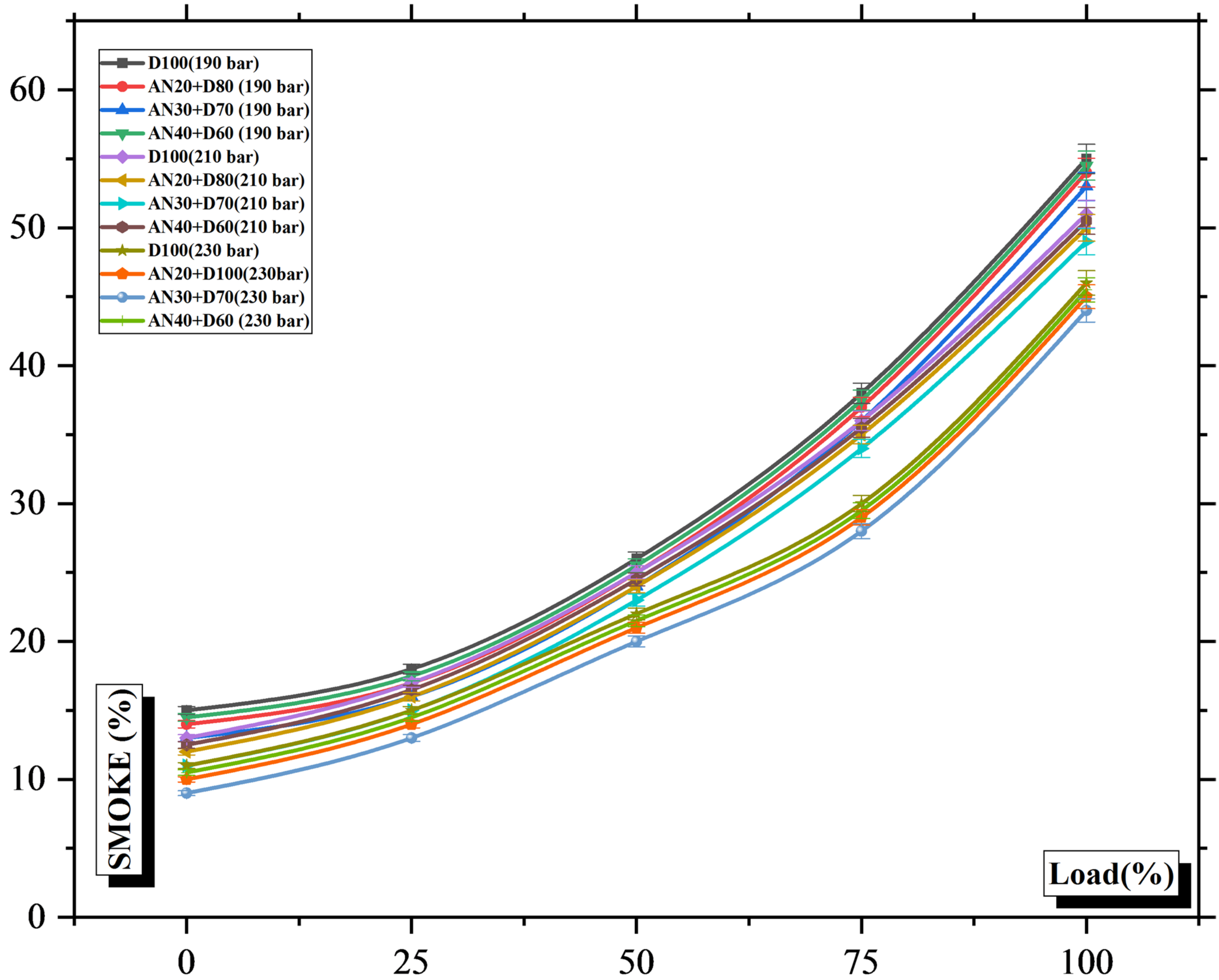

Fig. 9. Load vs. SMOKE (%).

and increased NO generation through the thermal pathway associated with the long form of the Zeldovich mechanism.

The NOx at 190 bar injection pressure for pure diesel (D100) increased from about 451 ppm at no load to around 900 ppm at full load. All the biodiesel blends demonstrated lower NOx amounts compared to the diesel at all loads. At no load, AN20 + D80 reduced the NOx emission to 251 ppm and to 700 ppm at full load, and AN40 + D60 further reduced NOx between 167 ppm and 673 ppm. The decrease is mainly due to the lower peak combustion temperature and the different heat release characteristics of biodiesel blends in spite of the oxygen content of biodiesel[21].

At the higher injection pressures of 210 bar and 230 bar, a similar trend is recorded. At 210 bar, diesel NOx data ranged from 348 ppm to 845 ppm while NOx for AN40 + D60 decreased and fell between 317 ppm–823 ppm. Between 348 ppm and 845 ppm NOx was emitted for diesel at 230 bar, whilst NOx emissions for AN40 + D60 ranged between 298 ppm and 795 ppm which is lower than diesel. Higher injection pressure usually provides for improved atomization and premixed combustion, which generally results in higher temperature at peak and hence more NOx formation. But this effect is mitigated by the presence of biodiesel, which has a lower heating value and a shorter ignition delay.

In conclusion, the findings indicate that while NOx emissions do rise appreciably with the load, the inclusion of Andropogon narudus biodiesel blends successfully minimize the amount of NOx, in comparison to neat diesel, with the entire range of operating conditions. This reveals the promise that can be achieved with biodiesel blends to have an optimum balance between combustion and emission behavior[22].

Sustainability assessment

Allocation of scores for pugh matrix

See Table 5.

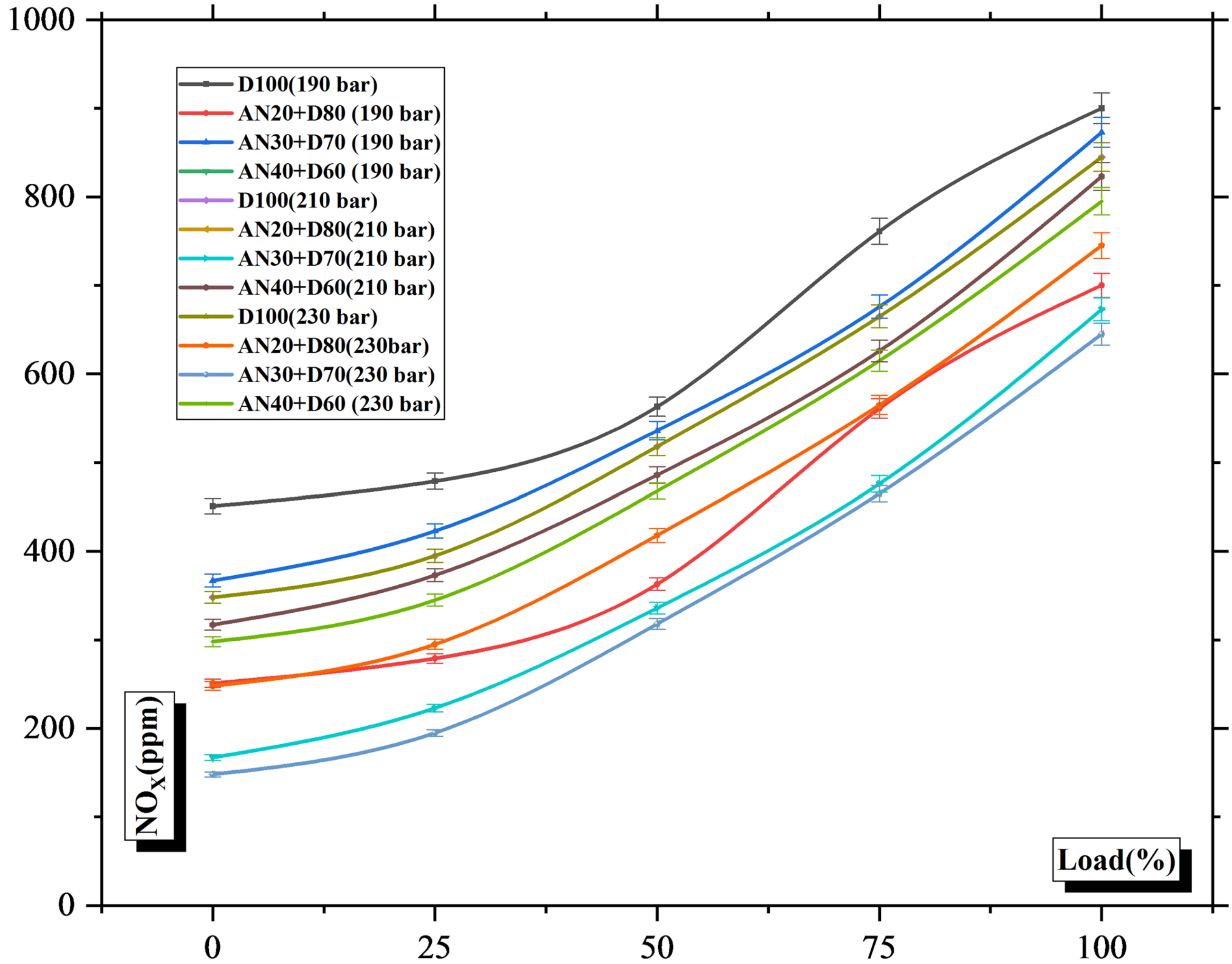

Fig. 10. Load vs. NO_X (ppm).

Fuel Combination	BTE	BSFC	HC	CO	Smoke	NOx	Availability	Cost	Renewability	Sustainability	Total Score
D100 at 190 bar	0	−2	−2	−1	0	−2	2	−2	−2	−2	−11
AN20 + D80 at 190 bar	1	−1	−1	0	−1	−1	1	0	1	0	−1
AN30 + D70 at 190 bar	2	0	0	1	0	0	1	1	2	1	8
AN40 + D60 at 190 bar	1	−1	−1	0	0	−1	1	2	2	2	5
D100 at 210 bar	1	−1	−1	−1	0	−1	2	−2	−2	−2	−7
AN20 + D80 at 210 bar	2	0	0	1	0	0	1	0	1	0	5
AN30 + D70 at 210 bar	2	1	1	2	1	1	1	1	2	1	13
AN40 + D60 @210 bar	2	0	0	1	1	0	1	2	2	2	**11**
D100 @ 230 bar	2	0	0	0	2	1	2	−2	−2	−2	**1**
AN20 + D80 @ 230 bar	2	1	1	1	0	1	1	0	1	0	**8**
AN30 + D70 @ 230 bar	2	2	2	2	2	2	1	1	2	1	**17**
AN40 + D60 @ 230 bar	2	1	1	1	2	1	1	2	2	2	**15**

Table 5. Shows the Pugh matrix table and their scores.

Performance evaluation

The brake thermal efficiency (BTE) and brake specific fuel consumption(BSFC) were the most important parameters to decide engine performance for various fuel blends and injection pressure. Of all the combinations, AN30 + D70 at 230 bar had the best performance parameter score with maximum BTE(+ 2) and minimum BSFC(+ 2), showing maximum conversion of fuel energy into mechanical work. By comparison, the D100 at

190 bar condition registered a worst score because of inferior thermal efficiency and increased fuel consumption leading to negative scores(−2) for both parameters[23].

Emission characteristics
Emission performance was judged based on hydrocarbons (HC), carbon monoxide (CO), smoke opacity, and nitrogen oxides (NO_X). Biodiesel blends performed better in reducing unburnt HC and CO emissions due to improved oxygen availability in the fuel structure. For instance, the AN30 + D70 and AN40 + D60 blends at 230 bar showed consistently high scores (+ 2 or + 1) across all emission categories. Conversely, D100 at 190 bar resulted in the worst emission profile with multiple negative scores, especially in HC (–2) and NOx (–2), emphasizing the advantage of biodiesel in controlling exhaust pollutants[24].

Socioeconomic and sustainability criteria
Those parameters related to sustainability were fuel availability, cost, renewability, and a composite sustainability impact score. Diesel scored low for renewability (–2) and cost (–2) even though the availability scores were higher, as it is a fossil-derived, non-renewable fuel. Whereas Andropogon narudus-based blends had much higher renewability (+ 1 to + 2) and overall sustainability (+ 1 to + 2) scores, these show their potential as substitute fuels. Economically in terms of cost, biodiesel blends were found to be advantageous locally even at increased processing cost, thus rated neutrally (0) or favorably (+ 1 to + 2)[25].

Total sustainability ranking
Figure 11 Shows the kiviat diagram for all the fuels. From the aggregate scoring, the largest aggregate score of + 17 was achieved by the AN30 + D70 blend at 230 bar, followed by AN40 + D60 at 230 bar (+ 15) and AN30 + D70 at 210 bar (+ 13). These results find the improved performance-emission-sustainability compromises offered through the employment of biodiesel blends at higher injection pressures. Pure diesel (D100) at every injection pressure placed the lowest ranking, − 11 at 190 bar, due to poor emission control and non-renewable fuel characteristics[26].

Figure 12 shows the sustainability assessment scores of all the blends in the experimentation. This ranking of sustainability is consistent with the emission trends and experimental performance trends previously

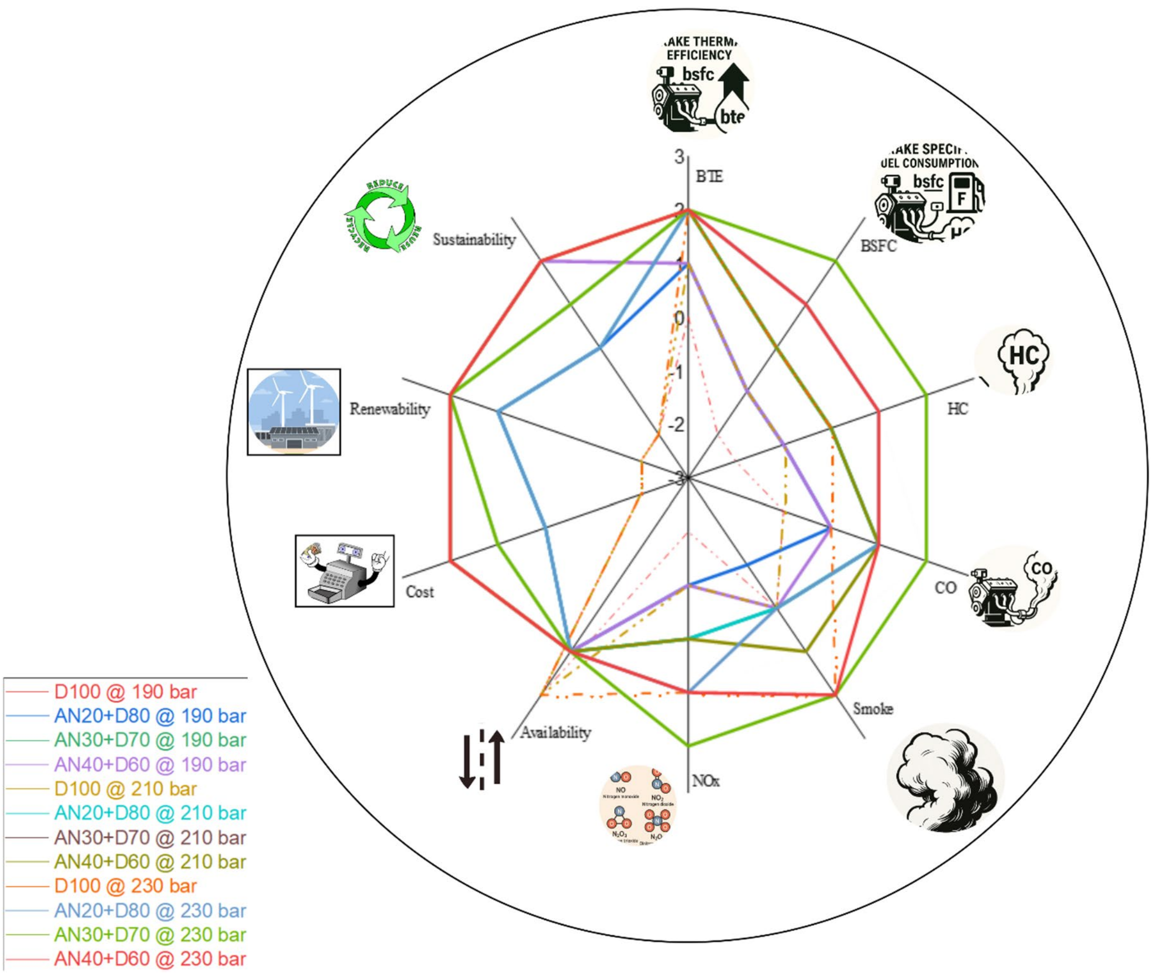

Fig. 11. Represents the kiviat diagram for all the fuels (origin pro- 21 and draw.io).

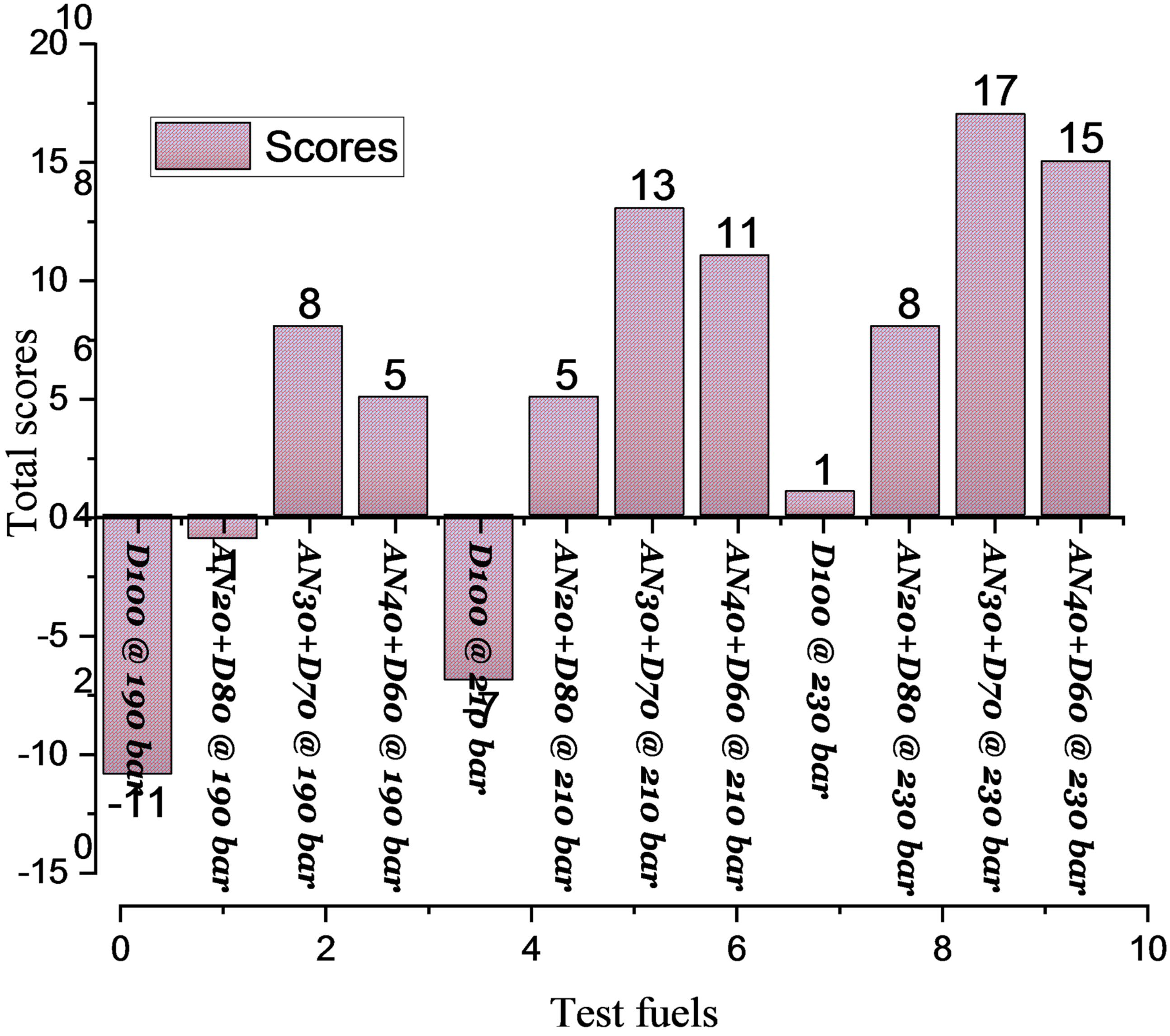

Fig. 12. Total sustainability assessments scores for the test fuels.

discussed. Among the tested combinations, the AN30 blend at 230 bar displayed the maximum brake thermal efficiency, whilst also showing the minimum BSFC, CO, HC, and smoke emissions. This led to enhanced fuel atomization and air–fuel mixing, together with the oxygenated nature of the biodiesel, which all promoted more complete combustion.

Consequently, the same fuel–operating condition combination ranked highest in the PUGH matrix, which corroborates the fact that the sustainability assessment directly mirrors the combustion and emission behavior realized within the experiments[7]. Despite revealing more favorable sustainability scores for higher biodiesel fractions like AN40, performance benefits were slightly constrained by increasing viscosity and decreasing calorific value at higher blend ratios, in accordance with experimental trends both in terms of BSFC and BTE[27].

The results were investigated for robustness by changes in individual performances and emission parameters. The AN30 blend at 230 bar showed the highest brake thermal efficiency and the lowest BSFC, CO, HC, and smoke emissions. Because the overall ranking is based on an aggregated performance across several independent criteria, moderate design changes in individual parameters or scoring weights result in no change in overall ranking trend. It implies that the optimum condition found is stable and relatively insensitive to small perturbations of the evaluation criteria.

Machine learning discussion and interpretation

Figure 13 shows the differences in prediction accuracy for six performance and emission parameters are shown in the comparative model evaluation. The experimental trends of the performance and emission studies are closely mirrored by the machine learning results. Experimental data of parameters like BTE, BSFC, and smoke that resulted smooth progression and variation with load, blend ratio, and injection pressure in experimental

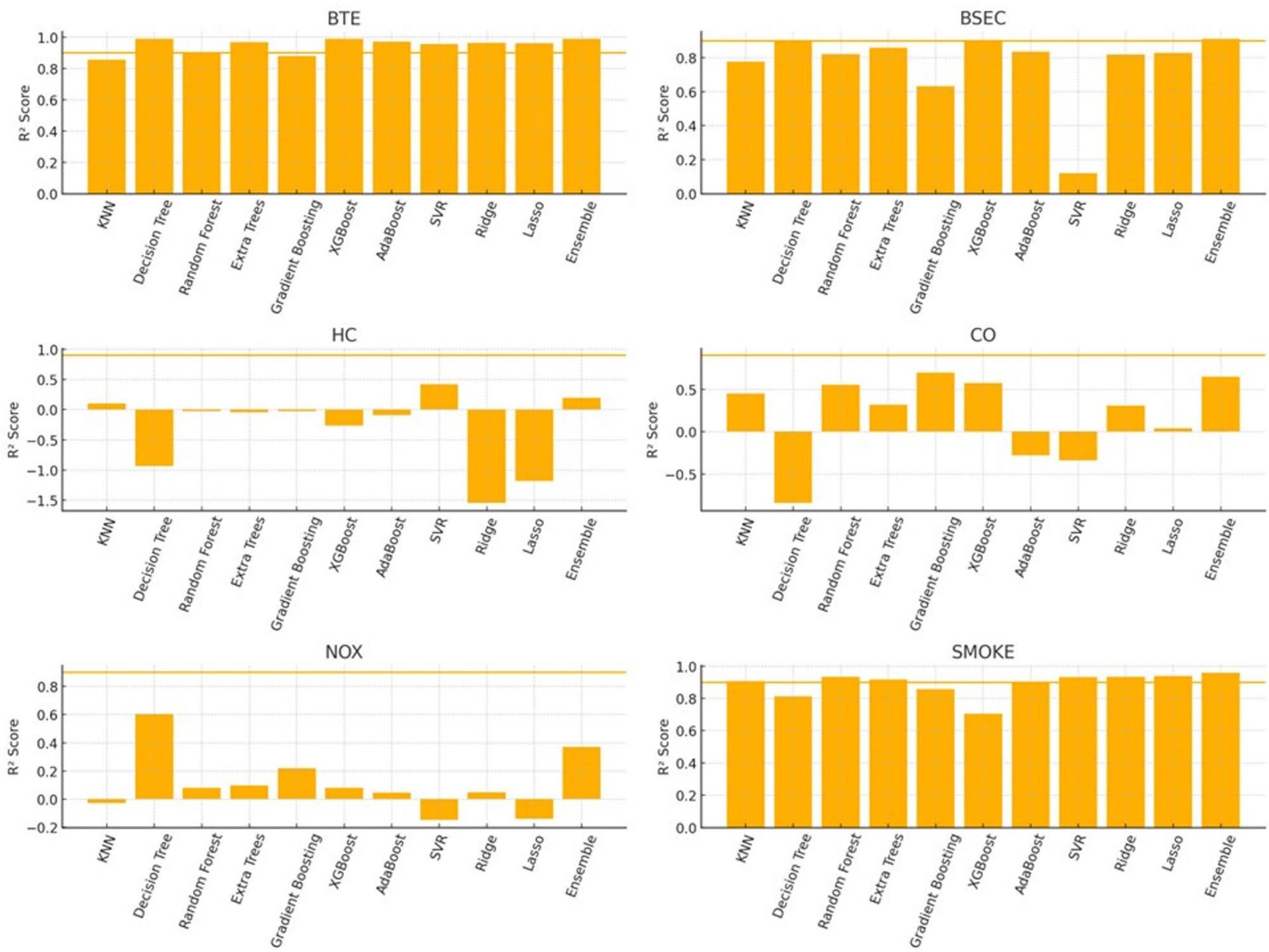

Fig. 13. Shows the differences in prediction accuracy.

Rank	Model	Avg R^2 (High = Good)	Avg RMSE (Low = Good)	Avg MAE (Low = Good)
1	Ensemble	**0.6787**	15.8964	13.2592
2	Gradient Boosting	0.5441	17.9702	13.146
3	Random Forest	0.5438	19.2598	13.6664
4	Extra Trees	0.5201	19.06	15.6045
5	KNN	0.5106	20.3299	16.891
6	XGBoost	0.4976	19.5482	14.4769
7	SVR	0.3238	21.1574	14.708
8	AdaBoost	0.3971	19.5981	15.8099
9	Decision Tree	0.2555	**13.3977**	**12.0955**
10	Ridge	0.2543	19.9124	17.3834
11	Lasso	0.2418	21.5596	17.9845

Table 6. Shows the comparative ranking for all the machine learning models and their ranking based on output parameters.

data also resulted in more correct predictions from the ML models. This confirms the basing parameters are ruled by consistent combustion conditions and depend on fuel calorific value, oxygen content, and atomization quality.

Table 6 shows the ranking of our machine learning models and their ranks eleven machine learning models across three evaluation metrics to obtain average scores over all engine outputs have been achieved. Higher R^2 means better accuracy in prediction, while low RMSE and MAE show lower prediction error as well. the Ensemble model ranked first overall, in that it has the highest average R^2 (0.6787) among all models with reasonably low RMSE and MAE, which once again suggests that combining models is better at generalization. Gradient Boosting and Random Forest are not far behind, suggesting that tree-based methods are powerful for capturing nonlinear behavior in the engine. Extra Trees and KNN Simulation return moderate accuracy and boosting structure of XGBoost makes it perform a little better than those two, but still not gradient Boosting. The models SVR, AdaBoost, Ridge and Lasso had weaker results which suggests that these methods lack the ability to fit complex relationships in our data. Though it is a simple algorithm, Decision Tree produces the lowest RMSE and MAE, but the R^2 is low, showing that it fits individual samples well, but does not generalize well. In summary, the Ensemble learning revealed itself as the best performance and emission outputs predictions balance system[28].

Figure 14 shows the correlations matrix, and it shows that Correlations of the inputs with their outputs in terms of thermal performance and emission characteristics are also contained in the correlation matrix. Load has a remarkably high positive correlation with BTE (0.993) and SMOKE (0.955), while it is strongly negatively correlated with BSEC (−0.959). As discussed previously, the improvement in efficiency and decrease in specific fuel consumption under increasing engine load is logical because combustion stability increases with engine load. Load similarly shows a weak negative correlation with NOX (−0.787), reflecting lower levels of NOX produced at high loads under these experimental conditions.

Injection pressure show weak correlations related to most outputs and the highest influence on CO (−0.611) and HC (−0.302). Therefore, injection pressure is more sensitive than performance parameters about incomplete combustion emissions. BTE and BSEC displayed an extraordinarily strong inverse correlation (−0.982), confirming the fact that an increase in efficiency leads directly to lower fuel consumption.

Out of the emission parameters, the correlation between HC and CO is the highest (0.708) because both are generated through incomplete combustion. CO shows a similar intermediate positive correlation with

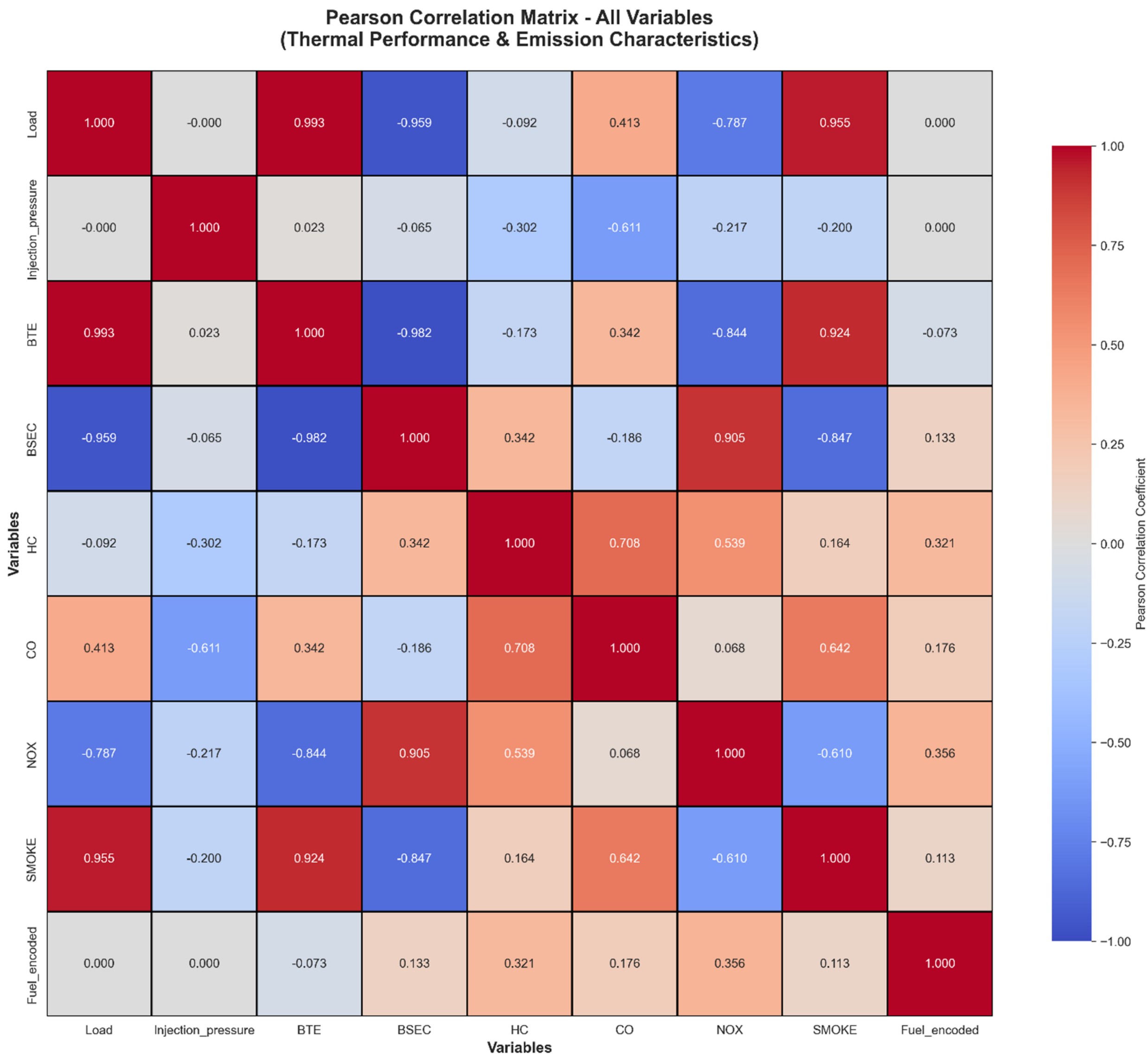

Fig. 14. Indicates the Pearson correlation matrix.

SMOKE, at 0.642, consistent with the premise that poor combustion simultaneously promotes both soot and CO.NOX is strongly correlated with BSEC (0.905) and negatively correlated with BTE (−0.844), such that conditions that serve to promote efficiency in this dataset appear also to tend non-linear thermal NOX formation.

The fuel type (encoded) has just weak correlations with all variables, indicating that fuel category matters less than load or combustion-related parameters on performance and emission within the investigated conditions[29].

Predicted vs. actual

Figure 15 shows the predicted vs. experimental outputs obtained from the best-performing machine learning models are shown below for each output parameter. Highly correct predictions for BTE and BSFC by the ensemble model suggest that these performance outputs are closely and consistently related to the input variables, which include load, blend ratio and injection pressure. This behavior was anticipated, since BTE and BSFC are largely dominated by the global combustion efficiency, fuel calorific value, and air–fuel mixing characteristics, which vary smoothly and predictably as a function of operating conditions[12].

In contrast, prediction accuracy becomes comparatively lower in emission parameters such as HC, CO, and NOx. These emissions are readily affected by local combustion events (flame quenching, temperature distributions and in-cylinder turbulence). These processes are highly nonlinear, sensitive to small variations in mixture formation and combustion phasing and are therefore more difficult to model well over the small experimental datasets available[30].

The much higher accuracy achieved for smoke opacity shows that soot production in the current engine configuration is more directional compared to injection pressure and fuel oxygen concentrations. This higher oxygenation status in Andropogon narudus biodiesel promotes a reduction of soot precursors via a more predictable emission profile through oxidation pathway[31].

In summary, the results reaffirm the suitability of ensemble-based machine learning models for performance predictions as compared to emission characteristics, which require larger datasets or supplementary combustion-related input features such as in-cylinder pressure or heat release parameters, in order to yield more reliable predictions[32].

Figure 16 shows seaborn pair plot, and it shows all the relations and distribution of all the variables present inside those datasets. As seen from the diagonal panels, all the variables have a smooth unimodal distribution, and the performance parameters (BTE&BSFC) sparsely spread in a narrow band. This implies that the variability is

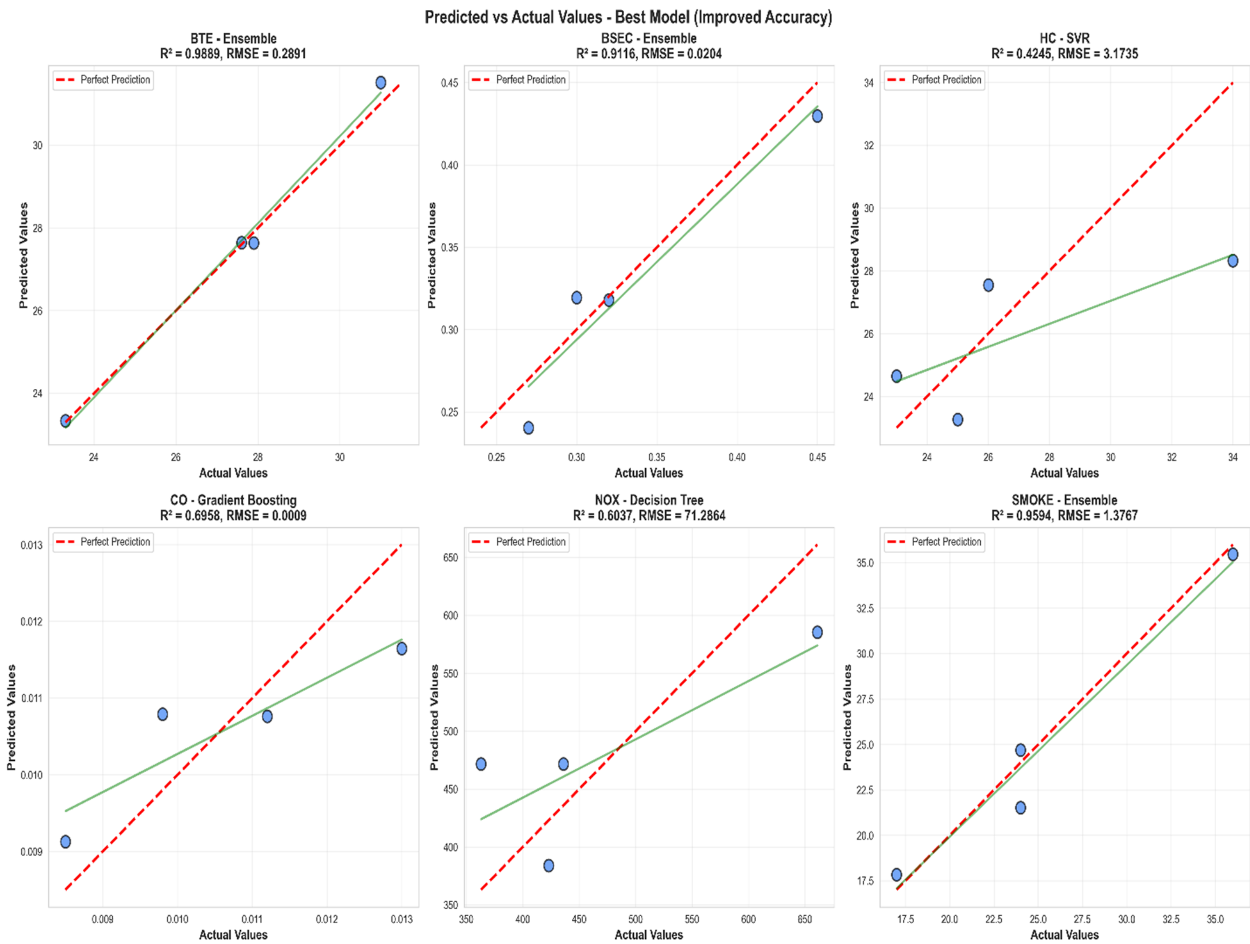

Fig. 15. Indicates the predicted vs. actual values of the best model for each parameter.

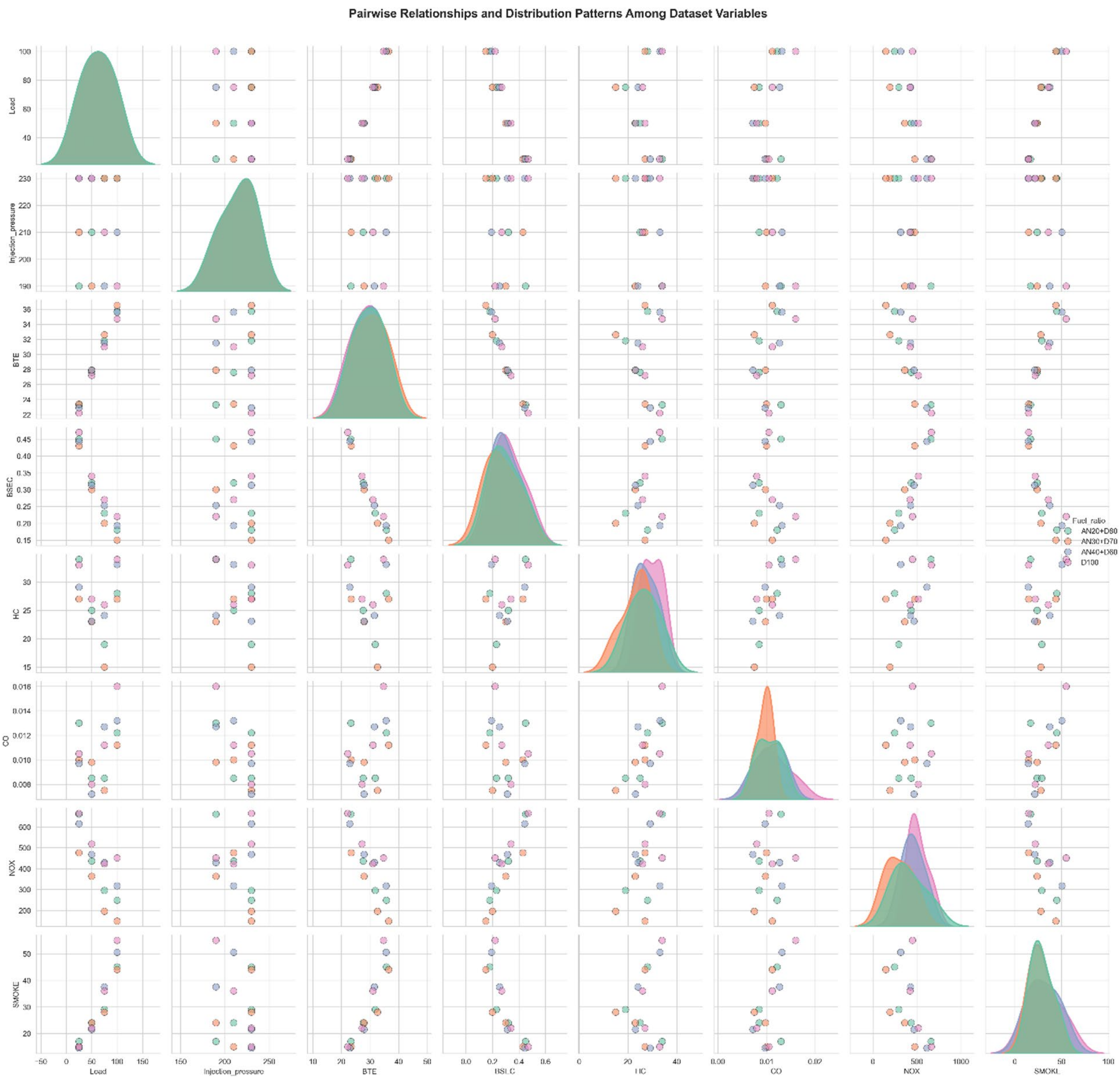

Fig. 16. Seaborn pair plot.

limited and the measurement behavior is stable. In contrast, various emission parameters such as HC, CO and NO_X have more wider and irregular distributions because of their above higher sensitivity to operating conditions and fuel characteristics. The distribution of smoke is relatively symmetrical and concentrated[33].

The scatter plots above the diagonal show the pairwise relationships between variables. Timelines still have an element of noise, but clearer trends can be seen in the case of performance-related parameters, where BTE and BSFC demonstrate their expected inverse relationship, and load, injection pressure and BTE present patterns with a more structured appearance. On the other hand, emission parameters had a more widely scattered pattern, with no indicative linear relationship; hence, they were assumed to be a result of interactions of more than one orifice factor rather than the influence of any single variable. Across most variable pairs the colonel-linear Rule-ratio categories have substantial overlap. Thus, this means that although the outputs change with the fuel composition, it does not contribute to the formation of distinct clusters in the whole dimension feature space[34].

In summary, the pair plot emphasizes that engine performance variables tend to have good, predictable distributions, while emission parameters are complex, non-linear functions. This is consistent with the model evaluation results, where performance metrics were mostly easier to predict unlike emission variables which were more challenging to model.

The trends of the performance and emission parameters under tested operating conditions are well predicted by the machine learning (ML) analysis which supplements the experimentation, in a way confirming that the developed ML models can serve as predictive tools for the optimization of biodiesel engine operation without resorting to uphill experimental trials.

Conclusion

The present work experimentally examined compression ignition engine performance, emission and sustainability suitable to Andropogon narudus biodiesel blended with diesel at different load conditions and injection pressure (190, 210 and 230 bar) operation environments. Multi-criteria decision-making approach in the form of PUGH matrix along with machine learning models was used to determine the best operating condition.

According to the results, the brake thermal efficiency was found to increase with increasing engine load and injection pressure, which is attributed to better atomization of the fuel and air–fuel mixing. The biodiesel blends exhibited similar performance to that of neat diesel but were slightly lower due to their lower calorific value.

The results for emissions analysis substantiated increased combustion efficiency because CO, HC, and smoke emissions reduced with increase of load and rise in injection pressures. In comparison, exhaust NOx concentration (ppm) increased with engine load for all fuel combinations as expected due to higher in-cylinder temperatures and increased thermal NO formation. Nevertheless, all Andropogon narudus biodiesel blends had significantly lower NOx emissions than neat diesel at all the operating conditions, pointing toward its potential emission reduction. Out of all the tested conditions, the AN30 + D70 blend with injection pressure of 230 bar was found to be the best combination providing a balance of performance Vs emissions. This is like the sustainability evaluation based on the PUGH matrix, where this condition was scored higher than all other alternatives.

The machine learning models developed in this study performed well in predicting performance and emission parameters thus helping to reduce experimental effort and paving a path towards their use in optimization studies. In conclusion, the results substantiated that the biodiesel blends derived from Andropogon narudus can be used as a potential alternative fuel in CI engines suitable for acceptable performance along with enhanced emission characteristics. Further reduction of NOx emissions would be attractive, so future work could investigate advanced control strategies, such as injection timing optimization and exhaust gas recirculation, along with long-term durability and cost analysis to establish economic feasibility.

Data availability

The datasets used and/or analysed during the current study are fully available within the manuscript **.**.

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Author contributions

Elumalai P.V. conceived and designed the study, performed data analysis, and wrote the manuscript. C. Ahamed Saleel contributed to methodology design and manuscript review. Mohammad Imtiyaz Gulbarga assisted in data interpretation. Fayaz Hussain and Sher Afghan Khan contributed to literature review and technical discussions. Parvathy Rajendran supported data validation and graphical representations. Chaloemphol Kaewthep and Xu Yong provided Funding, supervision, and guidance throughout the study. All authors read and approved the final manuscript.

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Declarations

Competing interests
The authors declare no competing interests.

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