AN modeling for forecasting of VCR engine performance and emission parameters fuelled with green diesel extracted from waste biomass resources

Rajayokkiam Manimaran1 · Thangavelu Mohanraj1 · Moorthy Venkatesan1

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Abstract
In this research work, the experimental tests were conducted on a single-cylinder, constant speed, variable compression ratio (VCR) engine fuelled with green diesel. Initially, bio-oil was extracted from waste Trichosanthes cucumerina fruit seeds using the Soxhlet apparatus. The acquired bio-oil is used to make green diesel through the trans-esterification process. The fuel blends were prepared with different proportions of Trichosanthes cucumerina biodiesel (TCB) in diesel fuel (30%, 50%, and 70%) for the experimental test, and their thermo-physical properties were evaluated according to ASTM standards. At full load condition, the TCB30 blend with CR 18:1 gives closer engine performance of brake thermal efficiency (33.52%), brake specific fuel consumption (0.27 kg/kWh), and exhaust gas temperature (389.56 °C) and reduced emission levels of unburned hydrocarbon by 13.51%, carbon monoxide by 10.82%, smoke opacity by 16.87%, and the penalty of nitric oxide by 17.56% equated with neat diesel fuel. The engine performance and emission parameters are predicted using multiple regression artificial neural network (ANN) models. A database generated from the experimental results is used to train the ANN model. The average correlation coefficient ($R$) of the trained ANN model is 0.99673, which is closer to 1. It indicates that the proposed ANN model can generate the exact correlation between input factors and output responses. As a result, the application of ANN is a better forecasting tool for predicting VCR engine performance and emission characteristics.

Keywords Green diesel · VCR engine · ANN · Prediction · Performance · Emissions

Introduction
Diesel engines create more torque with less fuel consumption than gasoline engines, making them ideal for power machinery, automotive applications, and agriculture (Mohan et al. 2014). However, the engine suffers from smoke, carbon dioxide ($CO_2$), and nitric oxide (NO) emissions which contribute to environmental pollution, global warming, and ozone layer depletion (Elsanusi et al. 2017). The use of fossil fuels is the primary cause of increased emissions in diesel engines. Nowadays, researchers are currently focusing on biodiesel production from waste biomass as an alternative energy source. Biodiesel is the best alternative to fossil fuels, with fuel qualities comparable to straight diesel (Balasubramanian et al. 2018; Ashok et al. 2019). As an appealing technology, it may be extracted from waste biomass resources. The physicochemical qualities of the derived biodiesel are similar to diesel fuel, allowing the engine to run without modification. It reduces $CO_2$, unburned hydrocarbon (HC), smoke, and sulfur emissions during engine operation (Subramani et al. 2020). In recent years, a significant amount of study has been done on different biodiesels in diesel engines, as well as their performance and emission characteristics were investigated (Vigneswaran et al. 2018). For evaluating diesel engine operating parameters, computer-based learning techniques are more useful. Researchers have turned to methodologies that can achieve the same function as engine parameter experiments since they are time-consuming and costly (Mehra et al. 2018; Işcan 2020). The ANN model is commonly utilized in the automobile industry to reduce the number of live experiments. It has a high precision for solving non-linear problems, which is ideal for predicting engine process parameters (Yang et al. 2018). Some studies used the

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*Rajayokkiam Manimaran
manimaran@mech.sastra.edu

1 School of Mechanical Engineering, SASTRA Deemed University, Thanjavur, Tamilnadu, India
ANN model to investigate the impact of engine operating variables on the expected output responses.

Aydın et al. (2020) varied the input factors of engine load and injection pressure by using different biodiesel-diesel blends. The experimental data were used to forecast engine performance and emission characteristics. According to the trained ANN model, the regression coefficient ($R^2$) value for accurate prediction of exhaust emission and performance parameters varies from 0.8663 to 0.9858. When compared to the experimental findings, it can be seen that the highest mean relative error (MRE) is less than 10%. The authors concluded that ANN model results are more useful for forecasting engine process parameters. Krishnamoorthi et al. (2019) investigated the combustion, performance, and emission characteristics of several ternary fuel combinations in a VCR engine. They selected the input factors of compression ratio (CR), engine speed (N), and power output (L) which are taken for optimization. The results showed that the ANN predicted data accurately correlated with the experimental data, with $R^2$ values ranging from 0.910 to 0.999. Overall, the use of the ANN model plays a vital role in improving engine performance and lowering tailpipe emissions. Hoseini et al. (2020) investigated engine process parameters using B5 and B10 blends with alumina nano-catalyst at 30, 60, and 90 ppm s of 30, 60, and 90 ppm. They created the ANN model using the conventional back propagation learning algorithm. For a non-linear mapping between the input and output parameters, a multi-layer perception network (MLP) was used. The ANN model’s $R$ values for training, validation, and testing are 0.9999, 0.9994, and 0.9995, respectively. The fact that the above values are closer to 1 implies that the proposed ANN model is accurate when compared to experimental results. The ANN model appears to be a useful tool for predicting CI engine performance and emission parameters based on the findings.

Babu et al. (2020) developed an ANN model for forecasting CRDi-assisted diesel engine process parameters. The engine experiments were conducted for fixed pre-injection at 30°C before TDC, varying the primary injection timing from 15 to 21°C before TDC, and post-injection which happens at 6°C before TDC to 6°C after TDC. The above operating circumstances illustrate that at advanced injection timing, the minimal emission levels and maximum engine performance are achieved. The RMSE and $R$ values of trained ANN models were 0.01 to 0.02 and 0.980 to 0.998, respectively. Because of its superior accuracy in predicting output responses, the ANN model was found to be preferable among theoretical and empirical models. Sevinc and Hazar (2020) created the ANN model to predict the emission characteristics of a 2-ethylhexyl nitrate (EHN)-diesel fuel-powered thermal barrier-coated engine. The EHN was mixed with diesel at 3%, 6%, and 9% volume fractions in the experimental study, resulting in a considerable reduction in NO and smoke emissions. In the ANN modeling, the engine speed ($n$) was used as an input factor, and the associated output responses were HC, CO, NO, and smoke density. According to the ANN outcomes, the $R$ values for HC, CO, NO, and smoke density are 0.9913, 0.9939, 0.9976, and 0.9974, respectively. Also, all predicted results had a maximum error rate of 10.01% and a minimum error rate of 0.001%. The average of all parameter maximum and minimum error rates was found to be 4.95% and 0.18%, respectively. The above results were confirmed to be within acceptable limits, indicating that developed ANN prediction has a high accuracy rate. Raghuvaran et al. (2020) used an ANN model to forecast palm oil biodiesel-operated CI engine process parameters. They have chosen engine load and palm oil biodiesel blends as input parameters, and the output responses are BTE, BSFC, HC, CO, and NO, respectively. The $R^2$ values for BTE, BSFC, HC, CO, and NO were 0.9994, 0.999, 0.9883, 0.9989, and 0.999, respectively. It was discovered that the trained ANN model could accurately forecast engine performance and exhaust emissions with a regression coefficient close to 1. Overall, the ANN model’s accuracy is ensured by a defined mean square error (MSE) of roughly 0.0004, which is quite low. As a result, the exploratory data demonstrated a substantial relationship between the ANN’s outputs and the exploratory data. Table 1 presents the literature on researchers using the ANN model to forecast engine performance and emission parameters when utilizing various biodiesel blends.

**Motivation and novelty of the present study**

The use of agricultural and other organic wastes as a source of energy has the potential to reduce dependence on conventional fuels. Utilization of energy from biodegradable waste has gained more popularity among municipal solid waste. In this connection, the bio-oil which was obtained from mature/waste Trichosanthes cucumerina fruit seeds can be considered as a reliable option. Numerous research studies have been reported on different biodiesel blends in the VCR engine applications. However, only a minimum level of work has been published in the literature using Trichosanthes cucumerina biodiesel as green diesel. Furthermore, the effect of compression ratio was not proposed on the selected green diesel. So, the current study concentrated on the variation of compression ratios (16:1 to 18:1) and the impact of engine load (0 to 5.2 kW) and TCB blends (30 to 100%) to analyze the VCR engine performance and emission characteristics. At compression ratio 18:1, the TCB30 blend showed higher engine performance and emission characteristics under all loading conditions. When the TCB30 blend findings are interpolated with neat diesel fuel, the engine
| Engine design                                      | Fuel used                                      | Model used | Input parameters                                      | Output parameters                   | $R$ value                                             | Reference                  |
|---------------------------------------------------|-----------------------------------------------|------------|------------------------------------------------------|-------------------------------------|--------------------------------------------------------|----------------------------|
| Single-cylinder, four-stroke, water-cooled, Kirloskar AV-1 model diesel engine | Diesel, Mahua oil and Mahua oil-hydrogen blend (H₂) | ANN        | Engine load, high octane fuel flow rate, fuel injection pressure, and timing | BTE, EGT, HC, CO, NO, and smoke | BTE (0.9981), EGT (0.9994), HC (0.9957), CO (0.9989), NO (0.9993), and smoke (0.9920) | Karthic and Masimalai (2020) |
| Single-cylinder, four-stroke, air-cooled direct-injection diesel engine | Pure diesel and diesel-DEE (diethyl ether) fuel mixtures | ANN        | Engine load, engine speed, and fuel blending ratio | BSFC, BTE, EGT, HC, CO, NO, and smoke | BSFC (0.985), BTE (0.9829), EGT (0.9788), HC (0.964), CO (0.9825), NO (0.9831), and smoke (0.9796) | Uslu and Celik (2018)     |
| Single-cylinder, four-stroke, VCR, water-cooled, vertical DI diesel engine | Diesel-palm biodiesel-ethanol blends | ANN        | Engine load, percentage of diesel fuel, palm biodiesel and ethanol | BSEC, UHC, NO, and CO₂ | BSEC (0.9986), UHC (0.9932), NO (0.9987), and CO₂ (0.9975) | Dey et al. (2020)          |
| Single-cylinder, water-cooled, TF 120 M Yanmar diesel engine | Jatropha curcas- Ceiba pentandra biodiesel-diesel blends | ANN        | Engine speed and biodiesel blends | BSFC, torque, BP, EGT, BTE, CO, CO₂, NO, and smoke | BSFC (0.997), torque (0.997), BP (0.991), EGT (0.995), BTE (0.991), CO (0.997), CO₂ (0.997), NO (0.997), and smoke (0.996) | Dharma et al. (2017)      |
| Single-cylinder, four-stroke, water-cooled, direct injection diesel engine | Citronella and Cymbopogon fleuxous biofuel-diesel blends | ANN        | Brake power and fuel blends | BTE, BSEC, CO, CO₂, HC, NO, and smoke | BTE (0.9965), BSEC (0.989), CO (0.9784), CO₂ (0.955), HC (0.9076), NO (0.9849), and smoke (0.993) | Ramalingam et al. (2020a) |
| Single-cylinder, four-stroke, water-cooled, Kirloskar TV 1 model, CI engine | Orange oil methyl ester (OME)-diesel blends | ANN        | Engine load, fuel blend, and CR | BTE, BSFC, CO, NO, and HC | BTE (0.998), BSFC (0.9999), CO (0.993), NO (0.997), and HC (0.9682) | Karthickeyan et al. (2017) |
| Single-cylinder, four-stroke, forced air- and oil-cooled, Bajaj RE diesel engine | Rice bran methyl ester (RBME) with isopropanol additive blends | ANN        | Engine load and fuel blends | BTE, BSFC, EGT, HC, CO, O₂, CO₂, NO, and smoke | BTE (0.999), BSFC (0.980), EGT (0.995), HC (0.985), CO (0.980), O₂ (0.999), CO₁ (0.999), NO (0.999), and smoke (0.999) | Prasada Rao et al. (2017)  |
| Single-cylinder, 4-stroke, water-cooled, Kirloskar AV1 model, Direct injection diesel engine | Jatropha methyl ester biodiesel blends with hydrogen blends | ANN        | Engine load, biodiesel blends, and hydrogen (H₂) share | BTE, BSFC, EGT, HC, CO, O₂, CO₂, and NO | BTE (0.99398), BSFC (0.99745), EGT (0.99754), HC (0.94012), CO (0.96832), O₂ (0.99847), CO₂ (0.9988), and NO (0.99929) | Javed et al. (2015)        |
performance is closer, and emissions are lower. Based on the above findings, the TCB30 blend can be considered a viable alternative to diesel fuel that can be operated without engine modifications. Another novel feature of this research is the use of an ANN model to forecast VCR engine performance and emission parameters. The ANN model was developed based on the feed-forward back propagation (FFBP) algorithm and trained with experimental data. Subsequently, the performance of the ANN model was analyzed.

Materials and methods

TCO extraction process

TCO is derived from the seeds of *Trichosanthes cucumerina* mature/waste fruits. The fruits are acquired as biomass waste at green markets and horticultural farms. Following that, the seeds are segregated from the fruits and dried in a hot air oven at 65 °C for 1 h to eliminate moisture content. Before being folded into a satin cloth, the 200 g of dried seeds is finely crushed, powdered, and then placed into the Soxhlet’s thimble. A round-bottom flask filled with 280 ml of hexane is placed over the electric heater. Similarly, a reflux condenser is attached to the top surface of the Soxhlet’s thimble for cooling water circulation. Once the extraction process is started, the hexane vapors are distilled over the finely powdered seed and cooled by a reflux condenser. The cold vapors are returned to the chamber and deflated by the syphoning operation. At this end of the operation, a mixture of TCO and hexane is formed. This mixture is heated up to the boiling point of hexane (68 °C) to evaporate them and obtain the pure TCO with the yield of 28.4 ± 0.4% (Manimaran et al. 2020). The complete TCO extraction flow process is presented in Fig. 1.

Fig. 1 TCO extraction flow process

GC–MS analysis for TCO

GC–MS (gas chromatography-mass spectroscopy) analysis was carried out to investigate the various chemical compounds found in TCO. The experiment was carried out using a PerkinElmer Clarus 500 model and a mass spectrometer. GC conditions: The capillary Column Elite-5MS was used to separate TCO components within a 30-m column length, the helium (carrier gas) flow rate was about 1 ml/min, and it operated at 58.3 min, and the column temperature was varied at a rate of 10 °C/min from 150 to 280 °C. The TCO sample was injected in split mode with a split ratio of 1:10. MS conditions: The mass range (40 to 450 amu) with full mode electron ionization at 70 eV, Turbomass ver 5.2.0 software, and the NIST 2005 mass spectral library identified the components present in the TCO sample. The extracted TCO has greater percentages of oleic acid (C\(_{18}\)H\(_{34}\)O\(_2\)), dodecanoic acid (C\(_{12}\)H\(_{24}\)O\(_2\)), n-hexadecanoic acid (C\(_{16}\)H\(_{32}\)O\(_2\)), and octadecanoic acid (C\(_{18}\)H\(_{36}\)O\(_2\)), as seen in Fig. 2. The peak area of oleic acid (C\(_{18}\)H\(_{34}\)O\(_2\)) was found to be the highest in total free fatty acids of TCO, having a peak area of 43.27%. The list of free fatty acids found in the TCO is shown in Table 2. It was also discovered that TCO has the chemical formula C\(_{16}\)H\(_{30}\)O\(_2\), a molecular weight of 252.5 g/mol, and a dark brownish color. As a result, the extracted TCO is synthesized into green diesel using a trans-esterification technique. The GC–MS analytical test was conducted at the SASTRA Deemed University’s Centre for Advanced Research in Indian System of Medicine (CARISM).

Green diesel (TCB) production

In this process, the extracted TCO was converted into TCB as named as green diesel through acid and alkali catalyst, and the overall TCB production process is represented in Fig. 3. Initially, the part of FFA content available in the TCO is removed using acid catalyst 1 wt% of H\(_2\)SO\(_4\) and added...
with the mixture of TCO + CH₃OH heated at the reaction temperature of 60 °C for 45 min to produce the ester. Now, the acid value of esterified TCO is 0.74 mg KOH/mg.

Next, the esterified TCO can be converted into TCB with an alkali catalyst in the trans-esterification process. The sodium methoxide solution was prepared by mixing 250 ml of CH₃OH and 3.5 g of sodium hydroxide in a conical flask. Correspondingly, 1 l of esterified TCO was taken into a beaker and heated up to 60 °C temperature for 30 min. The heated TCO is poured into a separate container added with sodium methoxide solution to form a mixture. It is allowed to settle for 2 h, and the two distinct layers are formed. The ester is formed along with glycerin, deposited at the bottom. It can be eliminated from the ester by a separation process.

Finally, the trace amount of methanol (CH₃OH) and water (H₂O) present in the green diesel was removed while heating beyond 75 °C temperature. In this purification process, pure TCB is produced, and the yield is about 92.7 ± 0.4%. It is blended with neat diesel fuel on a volume basis of 30%, 50%, and 70% respectively and used for experimental analysis. The thermo-physical properties of neat diesel fuel and green diesel (TCB) blends were analyzed using ASTM standards and are mentioned in Table 3.

| Fatty acid          | Molecular Formula | Molecular Weight | % Peak area | Structure |
|---------------------|-------------------|------------------|-------------|-----------|
| Hexanoic acid       | C₆H₁₂O₂            | 116              | 0.2581      | ![Structure](image1) |
| Nonanoic acid       | C₉H₁₈O₂            | 158              | 0.0418      | ![Structure](image2) |
| Undecanoic acid, ethyl ester | C₁₃H₂₆O₂ | 214              | 0.0806      | ![Structure](image3) |
| Octanoic Acid       | C₈H₁₆O₂            | 144              | 2.7896      | ![Structure](image4) |
The neat TCB with diesel fuel blends were prepared on a volume basis for the experimental analysis in the current investigation. Following that, TCB30, TCB50, and TCB70 blends were prepared by combining 30%, 50%, and 70% volume of pure green diesel with 70%, 50%, and 30% amount of diesel fuel, respectively. The design matrix for the test fuels, as well as the TCB and diesel proportions, is shown in Table 4. Once the TCB blends are prepared to the proper proportions, they are mixed for 20 min in a magnetic stirrer with a heated plate set at 1250 rpm to form a homogeneous mixture. To assess the stability of the prepared TCB blends, the fuel samples were kept in a closed container at room temperature for 1 week. Surprisingly, no phase separation was found in any of the fuel samples, and they were all relatively stable at ambient conditions.

**TGA for TCB**

Thermogravimetric analysis (TGA) ensures the thermal stability, volatilization, and decomposition of TCB fuel mass were characterized by the TG and DTG curves (Thiruvenkatachari et al. 2021). Figure 4 indicates the measure of
the TGA index for the decrease in weight percentage with increasing temperature. The weight loss is observed in the green diesel (TCB), ranging from 200 to 300 °C. It is due to the oxidation of organic phases and dehydration of TCB fuel. The DTG curve shows that the TCB peaks occur at the temperature of 264.67 °C. From the DTG peaks, the TCB fuel stability was observed in the temperature ranges between 250 and 300 °C.

**Cost analysis on TCB production**

An economic analysis is an effective approach for choosing raw materials and process technologies for fuel production. Biofuels made from waste feedstocks are a novel technique to encourage the use of alternative energy sources in the future. This study uses waste-to-energy to produce biodiesel from mature or waste *Trichosanthes cucumerina* seeds. The trans-esterification process produced the TCB. Many factors, such as the cost of raw materials, TCO extraction, alcohol, catalyst, and electricity usage, were assumed to estimate the total production rate of TCB. The percentage contribution of each parameter in total input costs for TCB production is shown in Fig. 5. Notably, TCO extraction accounts for 76.42% of expenditures, whereas alcohol (CH₃OH) accounts for 18.35%, catalyst (H₂SO₄ and NaOH) accounts for 3.14%, and electricity accounts for 2.09%. The overall production
rate for 1 l of TCB was calculated to be Rs. 86.75/l. With the mass production of TCB, the fuel price may be further reduced, and the by-product of glycerine credit can be increased.

**Engine experimental setup**

The effect of neat diesel and TCB blends on engine operating variables is tested in a single-cylinder, constant speed, water-cooled, and four-stroke Kirloskar TV1 model CI engine. The experimental tests were conducted at five different engine loading conditions (0 kW, 1.3 kW, 2.6 kW, 3.9 kW, and 5.2 kW) applied through an eddy current dynamometer tested with six fuel blends (neat diesel, TCB30, TCB50, TCB70, and TCB100). A fixed variable compression ratio engine was selected for this experimental analysis. All the test readings are taken for different compression ratios varied from 16:1 to 18:1 by tilting the cylinder head using Allen bolts. The position of the cylinder head was adjusted by the CR adjuster to vary the clearance volume. The CR indicator indicates the variation of compression ratio. A crank angle encoder and pressure transducer are fitted in the test engine to capture the engine combustion data using the data acquisition system (DAS). However, the EGT is measured using a K-type thermocouple.
fixed in the engine tailpipe. Exhaust emissions of HC, CO, CO₂, and NO are measured using AVL DI gas 444 N five gas analyzer. Correspondingly, the smoke emission is measured by an AVL 437C type smoke meter. During the experimental investigation, the test readings are repeated three times for each fuel blend to achieve a measurement accuracy, and their mean values are taken for further studies. The experimental test was
conducted at SASTRA Deemed University’s Thermal Laboratory. The technical engine specifications are mentioned in Table 5, and the experimental setup is presented in Fig. 6(a) and (b), respectively. These results serve as a source file for the ANN tool.

Uncertainty analysis

The analytical methods are used to estimate the uncertainties of random or fixed errors. It may occur during the experimental investigation mainly due to instrument selection and calibration, human data observation, working environment, and analysis method (Gülüm et al. 2019). The random error can be reduced by repetition and averaging. So, the engine tests were conducted three times, and the average values were considered to reduce the random error of the measuring results. The above procedure confirms the accuracy of all measuring instruments used for this research work. Percentage uncertainties of different operating parameters like brake power (BP), engine speed (n), BSFC, BTE, EGT, HC, CO, NO, smoke opacity, and \( \text{CO}_2 \) were measured, and their values are tabulated in Table 6. The square root approach estimates the uncertainty of the different computed parameters from known measured values using Eq. (1) as specified by Holman (2000).

\[
\text{Combined Uncertainty (\%) = } \sqrt{\left(\frac{BP}{\text{unit}}\right)^2 + \left(\frac{n}{\text{unit}}\right)^2 + \left(\frac{BSFC}{\text{unit}}\right)^2 + \left(\frac{BTE}{\text{unit}}\right)^2 + \left(\frac{EGT}{\text{unit}}\right)^2 + \left(\frac{HC}{\text{unit}}\right)^2 + \left(\frac{CO}{\text{unit}}\right)^2 + \left(\frac{NO}{\text{unit}}\right)^2 + \left(\frac{\text{Smoke}}{\text{unit}}\right)^2 + \left(\frac{\text{CO}_2}{\text{unit}}\right)^2}
\]

\[
\text{Combined Uncertainty (\%) = } \sqrt{\left(\frac{0.1}{\text{unit}}\right)^2 + \left(\frac{0.5}{\text{unit}}\right)^2 + \left(\frac{0.8}{\text{unit}}\right)^2 + \left(\frac{1.3}{\text{unit}}\right)^2 + \left(\frac{0.2}{\text{unit}}\right)^2 + \left(\frac{1.5}{\text{unit}}\right)^2 + \left(\frac{0.7}{\text{unit}}\right)^2 + \left(\frac{1.1}{\text{unit}}\right)^2 + \left(\frac{0.2}{\text{unit}}\right)^2}
\]

The combined uncertainty of the experimental test is ±2.731%.

### Results and discussion

#### Brake thermal efficiency (BTE)

Figure 7 exemplifies the variation of BTE with BP for CR 16:1, CR 17:1, and CR 18:1. The effective burning of test fuels inside the combustion chamber and conversion of useful BP output is named the BTE (Dhinesh et al. 2016). The figure shows that the increase in engine load (L) and CR increases the BTE gradually for all test fuels. However, the neat TCB and its blends follow the decrease in trend for all loading conditions. The TCB blends with lower heating value and higher kinematic viscosity and density promote inferior atomization and vaporization, leading to lesser BTE (Ashok et al. 2018). Among the different TCB blends, the TCB30 blend shows improved BTE for all CR and engine load variations because the lower viscosity and density of the TCB30 mixture make the fuel combustion as efficient (Baranitharan et al. 2019). At top load condition, the CR 18:1 shows that the maximum BTE for TCB30 blend (33.52%) is highest among other TCB blends and is 1.25% less than that of neat diesel fuel. Generally, the TCB blends are combusted at higher CR 18:1, resulting in increased compression pressure and the temperature to shorten the ignition delay (ID) period and enhance the test fuel volatility promoting higher BTE (Wamankar et al. 2015). But, the CR 16:1 and 17:1 result in lower BTE for all test fuels.

#### Brake specific fuel consumption (BSFC)

BSFC measures test fuel efficiency and the ratio of total fuel consumption (TFC) to engine BP output (Nanthagopal et al. 2019). An interaction between TCB blend, CR, and BP on the BSFC is shown in Fig. 8. It indicates that the variation of CR from 16:1 to 18:1 decreases the BSFC for an increase in BP. But, the rise in TCB blend ratio on neat diesel fuel

| Table 5 Engine technical specifications |
|----------------------------------------|
| **Engine make and model** | **Kirloskar and TV1** |
| **Type** | Single-cylinder, 4-stroke, water-cooled, direct injection, variable compression ratio, diesel engine |
| **Bore (B) x stroke (L)** | 87.5 mm x 110 mm |
| **Compression ratio (CR) range** | 16:1 to 18:1 |
| **Rated power output** | 5.2 kW at 1500 rpm |
| **Engine displacement volume** | 661 cc |
| **Fuel injector opening pressure (FIP)** | 20 MPa |
| **Fuel injection timing (FIT)** | 23° bTDC |
| **Connecting rod length (l)** | 234 mm |
| **Combustion chamber design** | Hemispherical type |
| **Fuel injector nozzle hole and diameter** | 3 holes and 0.3 mm |
shows more BSFC for full power outputs due to the decreasing trend of green diesel heating value which resulted in higher BSFC (Venugopal et al. 2018). Furthermore, the CR which varied from 16:1 to 18:1 decreases the ID period for all operated test fuels making the highest decrement in BSFC (Hosamani and Katti 2018). Higher CR 18:1 shows that the minimum BSFC was observed as 0.264 kg/kWh for diesel, 0.27 kg/kWh for TCB30, 0.287 kg/kWh for TCB50, 0.311 kg/kWh for TCB70, and 0.326 kg/kWh for TCB100 operated at peak power outputs. The high mean effective pressure developed inside the combustion chamber promotes the combustion as complete for all test fuels resulting in the efficient power output at minimum BSFC (Lahane and Subramanian 2014). But these BSFC values are maximum at lower CR of 16:1 and 17:1, because inadequate mixing and atomization of test blends caused incomplete combustion, leading to higher BSFC (Vellaiyan 2020).

**Exhaust gas temperature (EGT)**

Figure 9 shows the variation of EGT with brake power operated at CR 16:1, CR 17:1, and CR 18:1. It was
observed that the increase in BP shows an increasing trend of EGT for all the test fuels. Similarly, the EGT is raised with a higher CR 18:1 because the operating temperature is more for higher compression ratios (Shivakumar et al. 2011). EGT for green diesel is more when correlated with neat diesel fuel, and it increases as the proportion of TCB is increased. It may be credited due to higher physical ID period, increased viscosity, and poor volatility of TCB blend (Senthil Kumar et al. 2019). At top load engine operation, the value of EGT for TCB100 is 411.23 °C, 394.24 °C, and 382.48 °C operated at the CR 16:1, CR 17:1, and CR 18:1, respectively. This could be because TCB100’s higher oxygen content (O₂) produces higher EGT when compared to pure diesel fuel (Dhinesh et al. 2016). The engine operating at a higher CR 18:1 results in lower EGT for neat diesel and TCB blends. This could be owing to the fact that air enters at a higher compression ratio during the suction stroke, which raises the air temperature. The increased air temperature aids in greater fuel atomization and optimum air–fuel mixing, resulting in complete fuel combustion and a reduction in EGT (Wamankar et al. 2015).

**In-cylinder gas pressure (p-θ)**

The in-cylinder gas pressure is a crucial metric for determining peak pressure generation during fuel combustion (Ashok et al. 2018). Figure 10 depicts the variations of in-cylinder gas pressure with respect to crank angle at maximum power output for CR 16:1, CR 17:1, and CR 18:1. The findings reveal that increasing the TCB blend ratio on diesel fuel causes a progressive decline in combustion chamber pressure. This is because a rise in the kinematic viscosity and density of the TCB blends, which lowers the in-cylinder pressure formation, affects the fuel mixing rate, atomization, evaporation, and spray penetration during the uncontrolled combustion phase (Dhinesh et al. 2016). A similar pattern was observed for all of the TCB test fuels associated with neat diesel. Despite this, the peak pressure of TCB blends was lower than that of pure diesel fuel. TCB100 offers the lowest peak pressure of all the TCB blends for all compression ratios, with observed peak pressures of 47.32 bar, 48.65 bar, and 50.53 bar for CR 16:1, CR 17:1, and CR 18:1, respectively. Because of TCB100’s higher viscosity and low heating value, less fuel is prepared during the ID period, resulting in the lowest peak pressure. The air–fuel mixture ratio was enhanced by increasing the compression ratio, resulting in better combustion quality and higher cylinder pressure. As a result, the compression ratio 18:1 had the highest peak pressure of all the test fuels, compared to CR 16:1 and CR 17:1. Notably, the recorded peak pressures at CR 18:1 are 69.09 bar for diesel, 65.75 bar for TCB30, 61.63 bar for TCB50, 56 bar for TCB70, and 50.53 bar for TCB100.

**Heat release rate (HRR)**

During diesel engine combustion, the rate at which chemical energy released from the test fuel is turned into heat energy is known as HRR. It was calculated using the first law of thermodynamics and the conservation of energy concept (Heywood...
The HRR can be derived from the in-cylinder gas pressure data with respect to a crank angle using Eq. (2).

\[
\frac{dQ_{net}}{d\theta} = \left( \frac{\gamma}{\gamma - 1} \right) \times P(\theta) \times \left( \frac{dV}{d\theta} \right) + \left( \frac{1}{\gamma - 1} \right) \times V(\theta) \times \left( \frac{dP}{d\theta} \right)
\]

where \( \frac{dQ_{net}}{d\theta} \) = HRR (J/deg CA), \( \gamma \) = proportion of specific heats \( c_p/c_v \) (\( \gamma = 1.3 \)), \( P \) = in-cylinder gas pressure (bar), and \( V \) = in-cylinder volume (m\(^3\)).

Figure 11 depicts the relationship between HRR and crank angle for diesel and TCB blends at various compression ratios. The diesel fuel emitted more HRR in the premixed combustion phase than TCB blends, and vice versa in the diffusion stage, when the engine was run at the CR 16:1, 17:1, and 18:1, respectively. It is mainly for the diesel fuel lower viscous nature and high volatility (Prabakaran et al. 2021). However, the TCB100 releases lower HRR in the premixed combustion stage for all compression ratios and vice versa in the diffusion phase. The higher viscosity and density of the TCB100 affect the fuel atomization, the size of the fuel droplets is slightly larger, and there is less fuel penetration inside the combustion chamber (Thiruvenkatachari et al. 2021). As a result, less fuel is consumed during the ignition delay period for premixed combustion, resulting in more fuel being burned later in the combustion process. At CR 18:1, the neat diesel fuel had higher HRR (36.31 J/deg CA), and the remaining fuel blends of TCB30 (34.29 J/deg...
CA), TCB50 (29.11 J/deg CA), TCB70 (26.4 J/deg CA), and TCB100 (23.39 J/deg CA) showed significantly lower HRR in the premixed phase. The availability of O₂ (15.68%) content in the neat TCB structure develops slow combustion, resulting in higher HRR at the diffusion combustion. It is evident from the HRR figure that a significant percentage of TCB blends are combusted in the diffusion phase and produce more HRR instead of the premixed combustion phase (Hoang et al. 2019).

**Hydrocarbon (HC) emission**

Figure 12 portrays the variation of HC emission with the influence of different compression ratios (CR 16:1, CR 17:1, and CR 18:1) operated at low load (1.3 kW) and full load (5.2 kW) conditions. Generally, the unburned HC emission is formed during rich mixture combustion, penetration of fuel spray across the combustion chamber wall, and leakages in the fuel injector system (Annamalai et al. 2016). At low load engine operation, more HC formation was observed for all test fuels operated at different compression ratios of CR 16:1, CR 17:1 and CR 18:1. More accumulation of fuel molecules in the combustion chamber reduces engine combustive products reaction temperature is a credible reason for higher HC emission (Prasada Rao et al. 2017). An increase in BP and CR makes a significant reduction in HC formation. Likely, the rise in green diesel percentage on neat diesel fuel reduces the formation of unburned HC emissions due to the greater cetane number of green diesel, which increases the rate of air–fuel mixing and vaporization. (Balasubramanian et al. 2019).
At peak power outputs, HC formation is decreased by 39.13% for diesel, 43.07% for TCB30, 46.04% for TCB50, 42.59% for TCB70 and 37.06% for TCB100 when compared to low load condition operated at the CR 18:1. At higher compression ratio 18:1, better mixing of air–fuel takes place due to enhanced swirl motion in the engine combustion chamber. As a result, fuel undergoes efficient combustion and decrement in HC emissions was observed with increase in compression ratio (Dhingra et al. 2014).

**Carbon monoxide (CO) emission**

The variations of CO emission with CR 16:1, CR 17:1, and CR 18:1 running at low load and full load conditions are plotted in Fig. 13. It shows that more CO formation in the neat diesel fuel operation equated with green diesel blends. The deficiency of $O_2$ content in the neat diesel fuel forms higher CO operated at low and peak power outputs (Musthafa et al. 2018). However, the presence of oxygen content in the green diesel promotes complete oxidation of CO into $CO_2$ which reduces the formation of CO emission at different modes of CR operations (Dhinesh et al. 2016). At low load conditions, all the test fuels (diesel, TCB30, TCB50, TCB70, and TCB100) have resulted in higher CO emission operated at the compression ratios of 16:1, 17:1, and 18:1. The important reasons are lower operating temperature, and the A/F mixture in the combustion chamber exhibited higher.
CO formation (Hawi et al. 2019). Notably, the CO emissions are diminished by 43.06\% for diesel fuel, 44.78\% for TCB30, 48.39\% for TCB50, 51.67\% for TCB70, and 45\% for TCB100 operated at CR 18:1 when correlated with top load state. The higher the in-cylinder air temperature and pressure were generated at CR 18:1, which shortens the ID period results in the complete burning of the test fuels with less CO formation. But, the CO levels are higher for other compression ratios of 16:1 and 17:1 (Shameer and Ramesh 2017).

**Nitric oxide (NO) emission**

The NO formation in the CI engines is influenced by the rate of air–fuel mixing, in-cylinder combustion temperature, and O\textsubscript{2} content in the intake air and test fuel (Manimaran et al. 2019). Figure 14 shows the variation of NO emission with the influence of different input variables (BP, CR, and TCB blend) under low load and high load operations. The graph observed that the increase in compression ratio increases the NO formation for all test fuels. The engine at high load operation produces higher incylinder temperature leading to NO formation. Similarly, an increase in the green diesel ratio on neat diesel increases the formation of NO. This is due to the proportional increment of O\textsubscript{2} molecules, density of the green diesel leading to peak in-cylinder gas temperature, and most negligible radiative heat losses developing higher NO (Rashed et al. 2016).
The test engine operated at the CR 18:1 generates a higher temperature inside the combustion chamber during the compression stroke resulting in more NO (Koten 2018). However, the engine operated at lower CR 16:1 produces lesser NO emission due to a reduction in flame formation temperature, and localized in-cylinder gas temperature leads to NO as small during low load engine operations (Sathiyamoorthi and Sankaranarayanan 2016). At CR 18:1 with full load condition, the TCB30 blend emits less NO emission than other TCB blends, and it was reduced by 7.82% than TCB50 and 10.89% than TCB70, respectively. On the other hand, the TCB100 exhibits a reduction in NO emissions for all compression ratios, which is attributed to the TCB100’s lower calorific value and lower peak pressure (Vigneswaran et al. 2018).

**Smoke opacity emission (%)**

In general, the smoke opacity was formed due to the disproportion of the A/F ratio and unavailability of O₂ in the fuel-rich pockets. The formation of fuel-rich zones in CI engines due to the heterogeneous nature of the mixture was the primary cause for smoke emissions (Ramesh et al. 2019). Figure 15 illustrates the variation of smoke opacity for different compression ratios and fuel blends, namely TCB30, TCB50, TCB70, and TCB100 at low load and full load conditions. An increase in brake power gradually raises the test fuel admission into the engine cylinder to keep the engine speed constant at 1500 rpm, resulting in a higher smoke level (Anand et al. 2010). But, the increase in green
diesel percentage on neat diesel fuel resulted in minimal smoke opacity except for TCB100. Green diesel blends with no aromatic compounds and a lower C/H ratio have improved fuel atomization, and effective combustion in fuel-rich zones lowers smoke opacity formation (Ashok et al. 2018). On the other hand, TCB100 produces more smoke at low and full load condition due to its higher viscosity and larger fuel droplet size (Ganesan et al. 2020). At peak load condition, the CR 18:1 resulted in lower smoke levels, and it was diminished by 14.43% for TCB30, 24.87% for TCB50, 36.04% for TCB70, and 12.52% for TCB100 when compared to neat diesel. The enhanced combustion chamber pressure and temperature as a result of reduced clearance volume are the reasons for reduction in smoke opacity emission operated at CR 18:1 (Maurya et al. 2018). But, the lower CR of 16:1 and 17:1 results in more smoke emission than CR 18:1. It may be credited to longer ID which makes slow-burning, and lower in-cylinder gas temperature causes fuel combustion as incomplete, resulting in increased smoke emission (Gnanamoorthi and Devaradjane 2015).

**Carbon dioxide (CO₂) emission**

Figure 16 depicts the variation of CO₂ emission against different CR and TCB blends operated at the minimum and maximum loading conditions. The
graph shows that increasing the CR from 16:1 to 18:1 gradually raises CO₂ emissions levels for all test fuels. This is owing to the fact that complete combustion of test fuels increases CO₂ emissions by converting CO to CO₂ (Ramalingam et al. 2020b). Correspondingly, increasing the percentage of green diesel in diesel fuel promotes more CO₂ emissions. It is possible that raising the percentage of O₂ content in the TCB blend which oxidizes the shape of CO into CO₂ produces a higher amount of CO₂ emission in green diesel combustive products (Parida et al. 2019). At CR 18:1 with maximum power output, the value of CO₂ emission is lower for diesel fuel (7.81%), and the remaining test blends of TCB30 (9.21%), TCB50 (9.52%), TCB70 (9.77%), and TCB100 (9.01%) show higher CO₂ emissions. But, the CR 16:1 and 17:1 show lower CO₂ formation for all the test fuels. Notably, the CO₂ emissions are increased by 17.93%, 21.89%, 25.1%, and 15.36% for TCB30, TCB50, TCB70, and TCB100, respectively, when compared to neat diesel fuel. The main reason for above findings is the development of combustion temperature at 1500 °C; the more availability of O₂ content in the green diesel improves the combustion rate, resulting in more CO₂ formation functioning at CR 18:1 (Pradhan et al. 2017). However, the TCB100 emits lower CO₂ at all power conditions.
outputs and compression ratios, owing to the lower calorific value and higher density of the TCB100 which causes incomplete combustion to produce less CO$_2$ (Dhinesh et al. 2016).

**Artificial neural network (ANN)**

ANN uses an interconnected collection of neurons to create a significant regression model that may be used to handle forecasting and decision-making challenges (Venugopal et al. 2018). In comparison to simulation software and mathematical models, the ANN approach is unique in its ability to forecast engine process parameters. However, choosing an appropriate network is vital for ANN model precision (Uslu and Celik 2020). An ANN model is made up of three layers: an input layer, a hidden layer, and an output layer. Initially, the input layer is linked to the output layer via the hidden layer. After that, bias and weights are updated in the hidden layer and the difference between the experimental and predicted values is calculated until the error is small.

For all input parameters, a trained ANN model was simulated to achieve the corresponding outputs. The regression correlation coefficient ($R^2$), MAPE, and RMSE were calculated using the ANN model’s targets and outputs in the following Eqs. (3)–(5)

$$ \text{MeanAbsolutePercentageError(MAPE)} = \frac{100}{n} \sum_{i=1}^{n} \left| \frac{x_i - y_i}{y_i} \right| \% $$

(4)

$$ \text{RootMeanSquareError(RMSE)} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (x_i - y_i)^2} $$

(5)

where $x$—actual value, $y$—predicted value, and $n$—number of marks in the data group.

The proposed ANN model workflow chart is displayed in Fig. 17. In part 1, the input factors of TCB blend (B), engine load (L), and compression ratio (CR) was introduced for network creation. Randomly, 53 data (70%) chosen from the experimental results were used for the training set, 11 data (15%) was selected for the validation set, and the remaining 11 data (15%) was used in the testing set. Secondly, it has been trained with this input information to obtain the best ANN model to evaluate the training, validation, and test cycles. The last part is applied for ANN accuracy control and collection of data.

**ANN modeling**

The neural network tool in MATLAB has been selected for this research work to predict diesel engine performance and emission characteristics. The ANN model is developed based on the FFBP (feed-forward back propagation algorithm), the most commonly used algorithm. It is used for the training of experimental test data. Levenberg–Marquardt (TRAINLM) has applied to predict the MSE (mean square error) directed neural network loss function. The hyperbolic
tangent sigmoid (TANSIG) transfer function produces better results, making the ANN model more significant. The proposed topology for the prediction of engine output variables is 3–12-8, as shown in Fig. 18.

Initially, the 3 neurons of TCB blend (B), engine load (L), and compression ratio (CR) located in the input layer, and the output layer consists of 8 neurons which are performance (BTE, BSFC, and EGT) and emission (HC, CO, CO₂, NO, and smoke) parameters. The generation of unique code optimizes the hidden layer and is observed by the variation of RMSE with respect to the number of neurons, as shown in Fig. 19. It indicates the maximum error trained with a minimum number of neurons known as the under fitting zone. As the number of neurons is maximum, the training error decreases. But, the gap between training, validation, and testing error increases, represented as the over fitting zone. From the above observations, the error and gap between all data sets are minimum at the optimal neuron of 12. It has been selected as the optimal neuron in the hidden layer of the neural network.

Based on input and output variables, the multiple regression model was generated using ANN. Figure 20 indicates the overall regression fit for training, validation, and test sets. It shows that the correlation coefficient ($R^2$) values of training, validation, test, and overall are 0.99798, 0.99619, 0.99092, and 0.99673, respectively. These obtained $R^2$ values are about 1, which indicates the high precision of the ANN model output responses.

**Sensitivity analysis of ANN model**

Sensitivity analysis evaluates the effect of specific input factors to grade their importance equivalent to the output responses. According to the importance of input factors, efficient and inefficient variables are evaluated. The inefficient variables are eliminated from the ANN model. It will simplify the numerical model and reducing training time (Ibrahim et al. 2019). The backward stepwise was found from the literature reviews as the simple method for ANN model sensitivity analysis. The engine load, TCB blend, and compression ratio were used to conduct the ANN model’s sensitivity analysis. The engine load, TCB blend, and compression ratio were used to conduct the ANN model’s sensitivity analysis. From Table 7, ANN model 1 trained with all the input factors gives $R^2$ and RMSE values of 0.99445 and 7.5126. Removal of the compression ratio from the training data set moderately increases the RSME value. It shows that the effect of compression ratio is inefficient for the
the TCB blend was omitted, and their $R^2$ and RMSE data are 0.97712 and 21.0544, which implies the lesser contribution in the ANN model. Finally, model 4 resulted in the $R^2$ of 0.44173 and RMSE of 140.7514, which presents the importance of engine load. The $R^2$ value is drastically decreased, with error increases (RMSE). Therefore, it was concluded that the engine load is the most efficient variable on the ANN model.

### Performance of ANN model

Figure 21 indicates the evaluation of experimental values with ANN predicted values for engine performance parameters. Notably, the $R^2$ values of BTE, BSFC, and EGT are 0.9988, 0.9996, and 0.9983, respectively. Similarly, the RSME values are minimum for all performance outputs. The correlation coefficient ($R^2$) values are closer to 1 which indicates the high accuracy of the proposed ANN model. It shows that using the proposed ANN model is ample to predict the engine performance parameters of BTE, BSFC, and EGT.

The engine emission parameters are evaluated by interpretation of experimental and predicted values which are shown in Fig. 22. The correlation
coefficient ($R^2$) values were found as 0.9968, 0.9994, 0.9996, 0.9636, and 0.9994 concerning emission variables of HC, CO, NO, smoke opacity, and CO$_2$. The error and correlation output responses are obtained from the proposed ANN model which is minimum. It indicates that the proposed ANN model is enough to forecast exhaust emissions.

Conclusions

In this study, the effect of brake power (L), TCB blend (B), and compression ratio (CR) on diesel engine performance and emission parameters is tested and predicted. The following conclusions are made based on the experimental and ANN model results obtained from the engine input factors and output responses.

- The green diesel with the yield of 92.7 ± 0.4% was produced from mature/waste *Trichosanthes cucumerina* fruit seeds, and their fuel characterization was done.
- The different proportions of TCB blends (TCB30, TCB50, TCB70, and TCB100) and neat diesel fuel are used in the VCR engine operations and obtain their performance and emission results. At full load conditions, all the TCB blends showed improved engine performance and reduced emission levels operated at the CR 18:1.
The TCB30 blend shows an improved BTE of 33.52% correlated with other test fuels at full load conditions. But, it was decreased by 1.25% of BTE with the increment of BSFC by 2.27% than neat diesel fuel operated at the CR 18:1. Similarly, a higher EGT was obtained for all TCB blends.

At higher CR 18:1, the TCB30 blend shows that the HC, CO, and smoke opacity were decreased by 13.51%, 10.82%, and 14.43%, respectively. But, the NO and CO₂ emissions are increased by 14.56% and 15.2% compared to neat diesel fuel operated at peak power outputs.

The multiple regression ANN model was developed to forecast the engine performance (BTE, BSFC, and EGT) and emission (HC, CO, NO, smoke opacity, and CO₂) parameters. In the proposed ANN model, around 75 combinations of engine input and output variables are used for training, validation, and test operations.

The $R^2$ values of training, validation, test, and overall are obtained as 0.99798, 0.99619, 0.99092, and 0.99673. These $R^2$ values are about 1, which provides exact output responses of the ANN model. It can reduce the experimental efforts and act as an effective tool for forecasting the engine process parameters under different operating conditions.

Finally, the green diesel (TCB) and its blends are successfully operated in the selected VCR engine. It can be revealed that the TCB30 blend operated with CR 18:1 results in better engine performance and reduced exhaust emissions among all other TCB blends and compression ratios.
Future scope of the research work

- EGR and emulsion techniques can be used to control NO formation in a diesel engine.
- Addition of oxygenated additives with higher latent heat of vaporization could reduce NO emissions.
- Particulate matter (PM) emissions will be measured, and NO and PM emissions from diesel engines will be reduced simultaneously using appropriate after treatment devices.
- The existing diesel engine can operate in a dual fuel mode using TCB as the pilot fuel.
- The current experimental research can be extended to multi-cylinder engines operated with variable speeds.

Abbreviations

ASTM: American Society for Testing and Materials; ANN: Artificial neural network; BTE: Brake thermal efficiency; BSFC: Brake specific fuel consumption; CO: Carbon monoxide; CO₂: Carbon dioxide; EGT: Exhaust gas temperature; GC-MS: Gas chromatography-mass spectroscopy; HC: Hydrocarbon; NO: Nitric oxide; TCO: Trichosanthes cucumerina Bio-oil; TCB: Trichosanthes cucumerina Biodiesel; TCB30: 30% Trichosanthes cucumerina Biodiesel + 70% diesel; TCB50: 50% Trichosanthes cucumerina Biodiesel + 50% diesel; TCB70: 70% Trichosanthes cucumerina Biodiesel + 30% diesel; TCB100: 100% Trichosanthes cucumerina Biodiesel
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