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Adaptive Neuro-fuzzy-based modeling of exhaust emissions from dual-fuel engine using biodiesel and producer gas

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Abstract. The dual-fuel technology, which uses gaseous fuel as the main fuel and liquid as the pilot fuel, is an appealing technology for reducing the exhaust emissions. The current study proposes emission models based on ANFIS for a dual-fuel using producer gas (PG)-diesel engine. Emissions measurements were taken at different engine load levels and fuel injection timings. The proposed model predictions were examined using statistical methods. With R^2 values in the range of 0.9903 to 0.9951, the established ANFIS model was found to be consistently robust in predicting emission characteristics. The mean absolute percentage deviate in range 1.9 to 4.6%, and mean squared error varies in range 0.0018 to 13.9%. The evaluation of the ANFIS model developed shows a reliable claim of intrinsic sensitivity, strength, and outstanding generalization. The presented meta-model can be used to simulate the engine's operation in order to create an efficient control tool.

Keywords: alternative fuels; emission; machine learning; renewable energy sustainability

1. Introduction

Global population growth, increased energy consumption, reliance on imported fossil fuels, and climate change all give opportunities for the utilization of biodiesel in diesel engines as an alternative fuel sourced from locally accessible oil feedstock (Saengsuriwong *et al.* 2021). Diesel engines are extensively employed in the power generation and transportation sectors due to their dependable performance and improved fuel economy and performance (Ong *et al.* 2021). However, the functioning of diesel engines is being closely monitored owing to their exhaust emissions, which is blamed for greenhouse gas (GHG) emissions. To reduce GHG emissions, the European Union ratified the Kyoto Protocol in 2002, emphasizing the importance of future technological advancements that have yet to be achieved (Miyamoto and Takeuchi 2019). Several ways have been tried in the past by researchers to mitigate the hazardous emissions from diesel engines. Among the many approaches of applying additives, alternative fuels, and design improvements, alternative fuel research has been at the forefront. The utilization of the PG (Sharma 2011) and diesel or biodiesel via dual-fuel technology is a significant approach.

Biodiesel fuel substitution in conventional diesel engine has got widespread acceptance as a

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viable alternative for fossil diesel fuel. Low level blending of biodiesel in diesel fuel (i.e., upto 20%) does not demand significant modification/adjustments in hardware (Sharma and Sahoo 2022). It may be produced from a number of crops and has many advantages over fossil fuels, including being renewable, ecologically friendly, non-toxic, sulfur-free, and renewable (Sharma and Sharma 2020). Its thermophysical properties and rating as a fuel are comparable to those of standard fuel with a high oxygen concentration. Its higher density and viscosity contribute to issues such as clogging of fuel injectors, poor shelf life, and adhesion of piston ring. Overall, its power output and thermal efficiency are comparable to fossil diesel. First-generation biodiesel is produced from the oils derived from edible sources such as palm, sunflower, cotton seed, soybean, peanut, linseed, and mustard (Fuess et al. 2021). However, the application of edible oil for biofuel preparation is causing increase in the prices of edible oils and thus affecting human food chain. Consequently, the employment of non-edible oils to produce biofuel is preferable since it reduces dependency on edible oil. A substantial effort is observed towards the production of potential biodiesel feedstock from non-edible oil seeds i.e., Karanja, Mahua, Rubber seed, Jatropha, waste cooking oil, Tamanu, and others. Among these the waste cooking oil has been gaining prominence as it is a waste product and its direct disposal to soil/dump yard or water bodies is environmentally hazardous process (Singh *et al.* 2021).

Dual-fuel operation, which uses a gaseous fuel as the main energy source and liquid fossil fuel/biofuel as a pilot fuel, is gaining popularity over single-fuel single fuel operation. The gaseous fuels are favored because because of their clean combustion characteristics leading to less polluting emissions (i.e., NOx and CO2), which are two fuels that create less NO_x and CO_2, the two principal contributors to the GHG. Various gaseous fuels like Syngas, Natural gas, Hydrogen, Liquefied petroleum, Biogas, and Oxyhydrogen have been successfully utilized partly or totally replace diesel fuel in diesel engines. Dual fuel powered diesel engines are generally known for to fossil fuel replacement (Gobbato *et al.* 2015). Many investigations revealed reduced reduction in engine performance with lowered NO_x and CO_2 emissions, but an increase in HC in dual fuel modes. Although, the major attraction with dual-fuel operation is considerable diesel fuel saving (i.e., in range of 70–85%), yet it suffers from engine duration (i.e., loss in power). Numerous literary works have addressed the fuel characteristics and their influence on dual fuel mode (Simsek *et al*. 2022).

Biofuel research has sparked considerable attention in recent years, owing to the many benefits it offers. Several tactics are used to increase biofuel efficiency. While different methodologies may provide a range of conclusions, experimental research provides a direct examination of a real-world system. However, they are often resource-intensive and need significant engineering expenditures in terms of both money and time (Sharma and Sahoo 2022b). Alternatively, although analytical methods by definition give proof of concept, they also rely on approximations and assumptions and that may be unsuitable for real-world applications in certain instances. While computational techniques fail to account for physical and geometrical complexity in the majority of cases, they do propose additional viable solutions via the use of geographically constrained approximations(Chen *et al.* 2021). Additionally, predictive modeling of engine emissions is considered for determining the optimal fuel mix. The practice of producing outcomes based on statistical strategies and probability assumptions is known as predictive modeling. The combination of contemporary machine processing power and the availability of modern machine learning algorithms has created a lot of momentum in this subject (Said *et al.* 2022). In order to get accurate results, this approach requires certain input data. More experimental data fed into the algorithm improves forecast accuracy. The precision of forecast is the most significant factor (Milidonis *et al.* 2021).

Sharma and Sahoo (2022a) employed a combination of ANFIS-RSM technique for prognostic modeling of dual fuel engine using syngas-diesel combinations. The syngas (i.e., combination of H_2 and CO) combustion, a unique synthetic gaseous fuel, was examined. ANFIS coupled with RSM prediction-optimization models were developed using observed data of exhaust emission and performance acquired over the complete engine loading range. Though ANFIS outperformed RSM in terms of model forecasting, RSM was instrumental in establishing a link between engine input and response variables. The ANFIS-based prediction model is reported to be robust as R^2 value of correlation was reported in range of 0.9918–0.997, which followed by low residuals levels reported by root means squared error in the range of 0.008–5.9. The ANFIS was used to develop a prognostic model for a natural gas-powered combined cycle power plant following Dirik *et al*. (2022). The data collected from the pollution monitoring system was used for ANFIS-GA based predictive modeling.

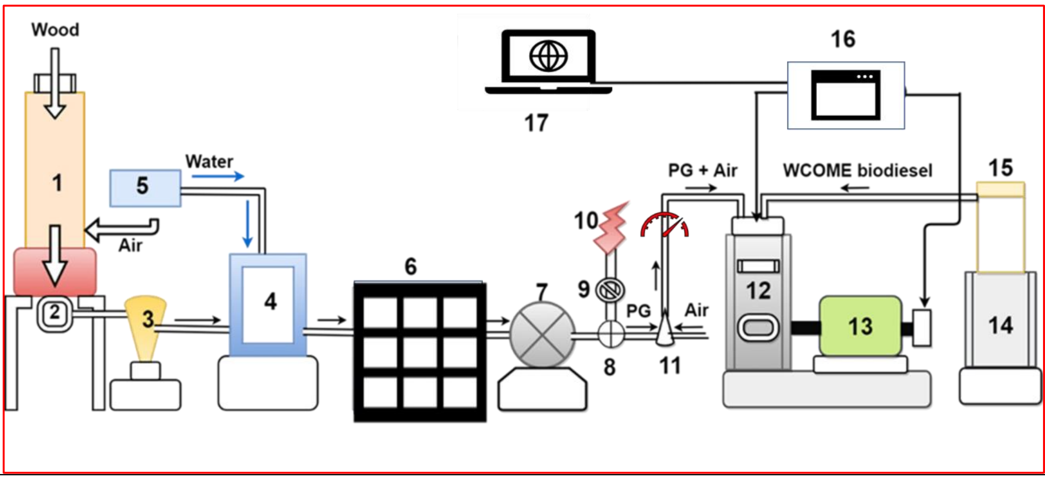
The developed model was used to anticipate NO_x emissions. First, ANFIS-based model was created by using fuzzy based C-Means, and model parameters were subsequently modified by using genetic algorithm (GA) in order to reduce inaccuracy. The results show that the R^2 value for training and validation was between 0.8 and 0.904. In a similar study by Singh *el al*. (2020) a jojoba biodiesel/diesel blends powered engine was used to generate the performance and emission data. An ANFIS- Particle swarm optimization hybrid scheme was used to model development and parametric optimization emission of performance characteristics. The input control factors chosen in the study were fuel injection timing and pressure, biodiesel blend ratio, and engine load settings. The BTE and emission characteristics (NO_x and UHC) were chosen as response variables. The R^2 value-based prediction model efficacy shows a significant increase in consistency. Several other authors (Aghbashlo *et al*. 2021, Saravanakumar and Prakash 2020, Razavi *et al.* 2019) reported the robust prognostic efficiency of the ANFIS technique.

Several researchers have reported successful implementation of machine learning methods such as artificial neural networks, boosted regression tree, Gaussian process regression, Neuro-fuzzy, Gene expression programming, and Response surface methodology for modeling of the emission-performance paradigm of a biodiesel-diesel powered gas-engine in dual fuel mode. The majority of investigations have achieved more than 99% prediction accuracy, resulting in the development of a surrogate model. However, the use of these strong prognostic methodologies in the realm of dual-fuel engines is uncommon, particularly in the case of a PG-waste cooking oil biodiesel (WCOB) fuel fuelled dual-fuel engine. As a result, the current research is an attempt to model and anticipate the exhaust emission scenario of a dual-fuel engine driven by a carbon neutral producing gas with WCOB as a pilot fuel. The ANFIS was used as a better neuro fuzzy based modeling approach. ANFIS combines the best of both worlds, since it combines the superior training ability of neural networks with the logical ability of the fuzzy technique.

2. Materials and methods

2.1 Test setup

A mid-sized diesel engine, extensively used in Indian rural areas for farming and irrigation activities, was chosen for this work and modified into gas-engine in dual-fuel mode. To deliver a measured amount of gas, an in-house built swirl-type air-producer gas mixer was employed. The inlet manifold of the gas-engine was connected to gas supply line from the downdraft gasifier. Fig. 1 depicts the schematic layout of the gasifier-engine test setup, which include a downdraft gasifier system and gas-engine in dual fuel mode. In order to mitigate the experimental error/uncertainty, the



1. Downdraft gasifier	2. Grate assembly	3. Cyclone	4. Cooling towers
5. Water tank	6. Sand bed filter	7. Blower	8. Gate valve
9. Fire arrester	10. Burner	11. Air-PG carburetor	12. Diesel engine
13. Eddy current dynamometer		14. Computerized engine test bench	

Fig. 1 Gasifier-Engine test setup

Table 1Technical specification of test bed

	Parameter	Specification
Test engine	Ratio of Compression	17.5: 1
	Make and model	Kirloskar, TV1, 225
	Power rating	5kW / 7 HP, @ 1500 rpm
	Bore and stroke	0.0875 m and 0.11 m
	Fuel injection pressure	210 bar
	Emission analyzer	Omega make, 5 gas analyzer
	Loading type	dynamometer (Eddy current)
Pressure sensor	Type and range	Piezoelectric and 250 bar
	Sensitivity of sensor	-17 pC/bar
	Range of temperature	-20 to 400 (°C)
Encoder	Type and resolution	Optical and 720/ 0.5°CA

engine combustion data was acquired in real-time using a high accuracy measuring instruments. A five-gas analyzer was used to obtain data on exhaust emissions. Table 1 shows the technical specifications of the test rig with exhaust emission measuring kit.

2.2 Test fuel

The research include three fuel combinations: in-house prepared-WCOB from waste frying oil, diesel purchased from Indian Oil outlet at Sonipat, Haryana, India, and producer gas (PG) was obtained by a downdraft gasifier. Table 2 includes the lists the of fuels specifications (i.e., diesel, WCOB and

Table 2 Properties of diesel and WCO biodiesel

Properties	WCOB	Diesel	PG
Specific gravity @ 15.6°C	0.893	0.831	--
Cetane number	55	49.2	--
Lower heating value, kJ/kg	38600	43550	35.14
Pour point, °C	-11.5	3.1	--
Fuel density @ 15°C, $Kg.m^{-3}$	874	849	--
Kinematic viscosity @ (40°C), cSt	3.86	2.86	--
Flash point, °C	156	77.4	--

PG). On a volumetric basis, WCOME was mixed with diesel in two ratios: B10 (Diesel 90% + WCOB 10%) and B20 (Diesel 80% + WCOB 20%). The fuel was carefully chosen to ensure the nearby availability from the locals. So, in the current research, biodiesel was made from waste cooking oil, and PG was made from waste wood from the Babool tree. To derive PG from Babool wood, an in-house designed and built downdraft gasifier was employed.

2.3 Adaptive neuro-fuzzy inference system

Neuro-fuzzy is a hybrid machine learning technique that combines neural networks with fuzzy logic. ANFIS combines logical/decision making ability of fuzzy logic with neural network's learning efficiency. It can be trained using observed experimental data. Once the algorithm is trained, the optimal ANFIS structure for tackling the related problem is determined. The developed fizzy inference system (FIS) is then examined with a set of new data (previously unknown) to the FIS for validation. The ANFIS network architecture is primarily separated into two parts i.e., the *premise* and the *effect*. The ANFIS training demands an optimization approach in order to find the parameters related with these modules. The ANFIS uses existing pairs of data for control and response variables during its training phase. Then, fuzzy IF-THEN rules are created to explain how these parts are connected. Fuzzy inference systems (FIS) are identified as fuzzy controllers, fuzzy-rule based systems, and fuzzy associative memory in the literature pertinent. A typical FIS is constituted by the five functional elements: a rule base with numerous fuzzy if-then rules; a database specifying the membership functions of a processing unit that conducts the inference; and a unit responsible to execute the inference. A fuzzification interface then converts crisp input information into fuzzy inputs, and a defuzzification step converts these fuzzy inputs into the output. Basically, such knowledge-base is a hybrid of the rule-base and the database. The ANFIS was trained and validated using commercial software MATLAB in the present study.

Once the predictive model is developed its performance can be measured using statistical indices i.e., coefficient of determination (R^2), mean absolute percentage deviation (MAPD) and mean squared error (MSE). These are essential evaluation variables in regression analysis that examines the relationships between the predicted and observed outputs. A higher R^2 values ~1 followed by lower MSE and MAPD values indicates to good fitting or correlation. The following expression were used to estimate these criteria (Sharma 2021, Taghavi *et al*. 2019)

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{n}(x_o - x_p)^2}{\sum_{i=1}^{n}(x_o)^2}\right) \tag{1}$$

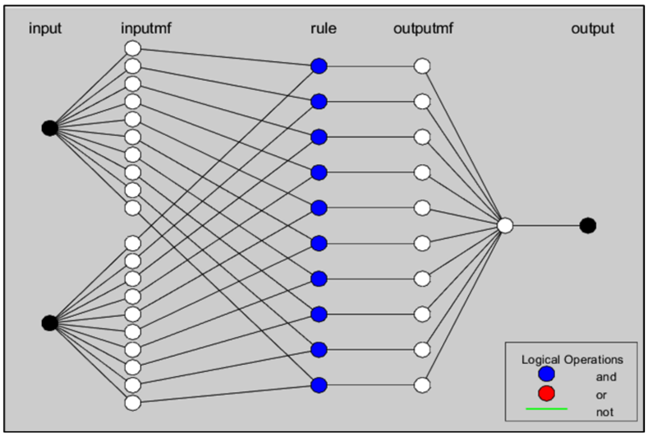


Fig. 2 ANFIS architecture

$$\mathrm{MAPD} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{x_p - x_o}{x_o}\right| \times 100 \tag{2}$$

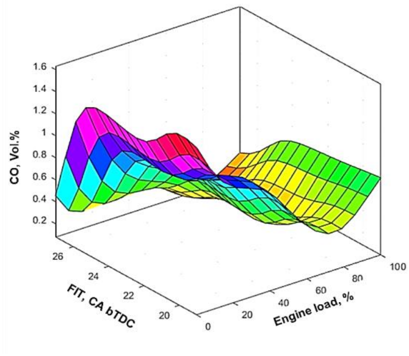
$$MSE = \frac{\left[\sum_{i=1}^{n}(x_o - x_p)^2\right]}{n} \tag{3}$$

Herein, x_o and x_p represents observed and ANFIS-based model predictions values, subscript n represents the number of data points.

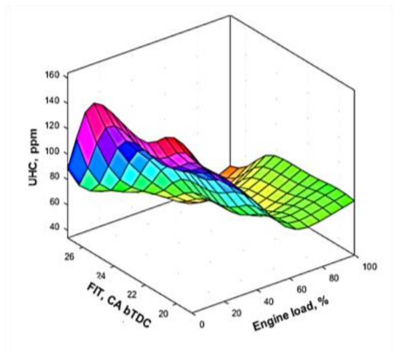
3. ANFIS-based model development

The data set acquired from experimental phase, consisting of 54 input data points and their outputs, was used to develop ANFIS-based model. The data is grouped into two sets; the first set (i.e., 70% of data) was used to train the model itself while the second set (i.e., 30% of data) was employed for model testing or validation. Two input variables define the output characteristics of the test engine namely the engine load (%) and fuel injection timing (°CA bTDC). Included in the output measurements of the test engine are exhaust characteristics CO, UHC, CO_2 and NO_x emissions. In present work, the ANFIS model was developed in MATLAB environment. Herein, a subtractive fuzzy clustering was employed to establish a rule-based linkage between the control factors and response variables. The ANFIS architecture used in the present investigation is shown in Fig. 2. The layer 1 shows the input variable, the layer 2 shows the input membership function used for generation of fuzzy inference system. The layer 3 denotes the fuzzy rule applied and layer 4 shows the output membership function. The last layer denoted as 'output' represent the output of ANFIS. Once the model was developed it was used to generate the surface diagrams for model output. The Fig. 3, depicts the surface diagrams for each output.

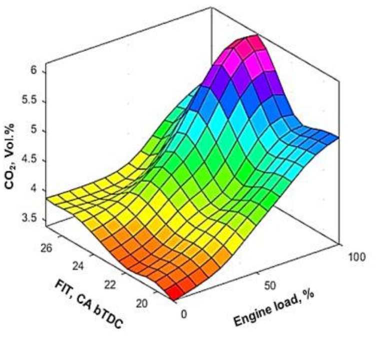
These surface diagrams show the mapping of output emission characteristics with engine control factors (load and FIT). The Fig. 3(a) shows the surface diagram for CO emissions. Highest CO emissions is observed at lower engine loads with retarded injection timings. The surface diagram for UHC emissions is illustrated in the Fig. 3(b). Likewise, the highest UHC emissions is observed



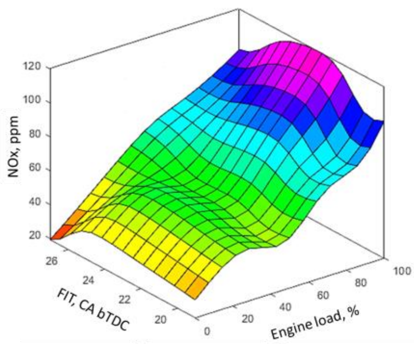
(a)



(b)



(c)



(d)

Fig. 3 Surface diagrams

Table 3 Statistical indices for the model development

Model	R^2	MAPD (%)	MSE
CO	0.9951	4.6	0.0018
UHC	0.9941	3.0	13.9000
CO_2	0.9903	1.9	0.0146
NO_x	0.9940	2.9	4.9290

at lower engine loads with retarded injection timings while lowest emissions of UHC was observed at 60-70% engine load condition and 23°CA bTDC. Herein, the CO_2 sub-model shows at designed FIT (24 °CA bTDC) and full engine load condition, in contrast the lowest emission was observed at low engine load and 24°CA bTDC FIT (refer Fig. 3(c)). The NO_x sub-model developed with ANFIS is shown in the form of surface diagram (Fig. 3(d)). The highest NOx is observable at full engine load condition and 24°CA bTDC FIT. These sub-models have been used to predict the engine emission at entire engine load range. The comparison of observed and model predicted emission values are shown in Fig. 4. The R^2 value for each model is also shown on the respective graph. The statistical analysis of model performance is listed in Table 2. The statistical indices as well as the graphs (Fig. 4) shows that ANFIS can create robust prognostic model.

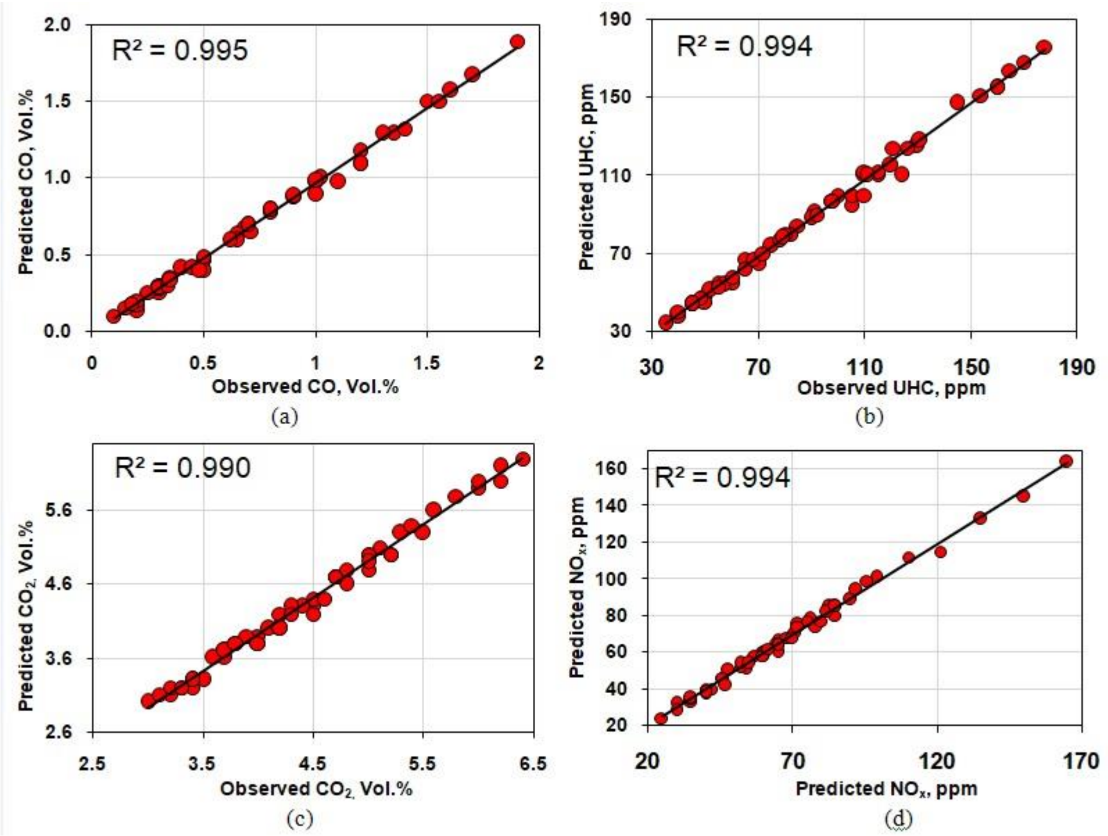


Fig. 4 Observed vs ANFIS predictions for (a) CO (b) UHC (c) CO_2 and (d) NO_x

4. Conclusions

The present research proposes ANFIS-based emission ub-models for PG-diesel fuelled gas-engine in dual-fuel mode. The database for exhaust emissions was collected at different engine loads and injection timings. The model predictions were examined using statistical methods. The established ANFIS model was observed to be consistently robust in predicting the emission characteristics as R^2 was in the range of 0.9903 to 0.9951. The deviation in mean absolute percentage is observed in the range of 1.9 to 4.6% and range of mean squared error varies from 0.0018 to 13.9. The assessment of the constructed ANFIS model demonstrates a realistic claim of inherent sensitivity, robustness, and superior generalization. The current model may be used to simulate the engine operation in order to create an effective simulation and control tool.

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