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Comparative Study of Soft Computing and Metaheuristic Models in Developing Reduced Exhaust Emission Characteristics for Diesel Engine Fueled with Various Blends of Biodiesel and Metallic Nanoadditive Mixtures: An ANFIS–GA–HSA Approach

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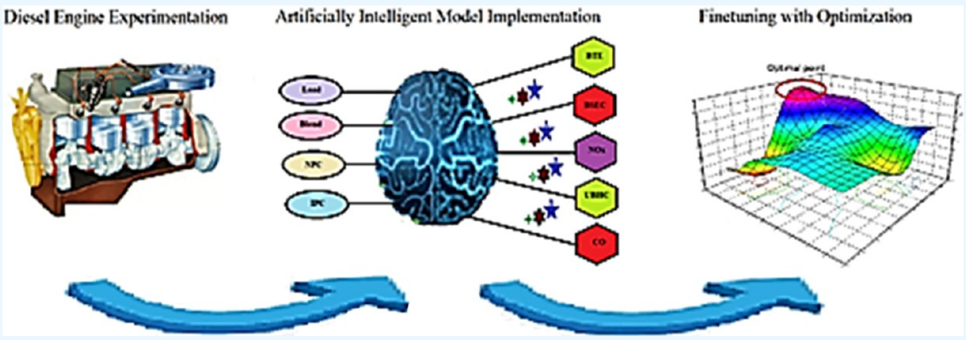

ABSTRACT: Since the discovery of petrol-based products, a surge in energy-requiring equipment has been established across the world. Recent depletion of the existing crude oil resources has motivated researchers to opt for and analyze potential fuels that could potentially provide a cost-effective and sustainable solution. The current study selects a waste plant known as *Eichhornia crassipes* through which biodiesel is generated, and its blends are tested in diesel engines for feasibility. Different models using soft computing and metaheuristic techniques are employed for the accurate prediction of performance and exhaust characteristics. The blends are further mixed with nanoadditives, thereby exploring and comparing the changes in performance characteristics. The input attributes considered in the study comprise engine load, blend percentage, nanoparticle concentration, and injection pressure, while the outcomes are brake thermal efficiency, brake specific energy consumption, carbon monoxide, unburnt hydrocarbon, and oxides of nitrogen. Models were further ranked and chosen based on their set of attributes using the ranking technique. The ranking criteria for models were based on cost, accuracy, and skill requirement. The ANFIS harmony search algorithm (HSA) reported a lower error rate, while the ANFIS model reported the lowest cost. The optimal combination achieved was 20.80 kW, 2.48047, 150.501 ppm, 4.05025 ppm, and 0.018326% for brake thermal efficiency (BTE), brake specific energy consumption (BSEC), oxides of nitrogen (NOx), unburnt hydrocarbons (UBHC), and carbon monoxide (CO), respectively, thereby furnishing better results than the adaptive neuro-fuzzy interface system (ANFIS) and the ANFIS–genetic algorithm model. Henceforth, integrating the results of ANFIS with an optimization technique with the harmony search algorithm (HSA) yields accurate results but at a comparatively higher cost.

1. INTRODUCTION

Diminishing oil reserves, escalating crude oil prices, and the ecological impact of conventional fuel utilization in engines have motivated researchers to discover feasible energy sources with a cleaner carbon footprint.[1,2] Besides the above problems, the transport-related zone, which is often considered an imminent player in the development of the economy of a nation, is often seen struggling when completely dependent on fossil resources.[3] The ever-increasing population has put surplus load on the existing crude oil resources, which are estimated to deplete before their allotted time period.[4] Combustion of fossil fuels is another problem that is responsible for degrading the environment and spreading viruses such as MERS, SARS, and COVID-

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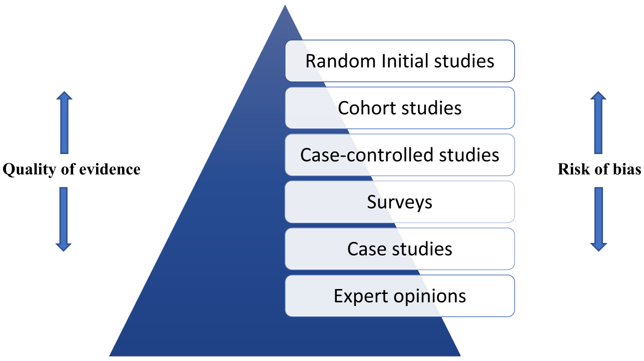

Figure 1. Hierarchy of literature selection and review process for the study.

19.[5] These particles are capable of amalgamating with existing emission particles, thereby spreading among communities. Thus, economic dependency, social insecurity, enormous petrodollar reserve, and effluents damaging the environment have led to various studies being carried out in nonconventional oil-based resources, which have been established as suitable and efficient alternatives for fossil oils in engines.[6]

In view of the above predicaments, investigators were inspired to find a feasible, justifiable alternative to petro-diesel, which could completely or moderately replace them. Among the several options of nonconventional resources, biofuels have found wide acceptance probably due to their similarities to diesel fuel with respect to physiochemical properties. Biodiesel has emerged as a viable alternative to crude oil as it can be directly used in the existing transportation sector without implementing major modifications in engine design.[7] People have started considering biofuel as an alternative to diesel fuel probably due to escalation in oil prices coupled with the excessive impact of combustion of fuel on the environment. Therefore, to move toward a sustainable category of fuel, the biodiesel production system has been enhanced as a result of growing popularity. This wide acceptance among the masses is probably due to biodiesel being biodegradable, easily available, nontoxic, readily available, portable, oxygenated, and environmentally safe.[8]

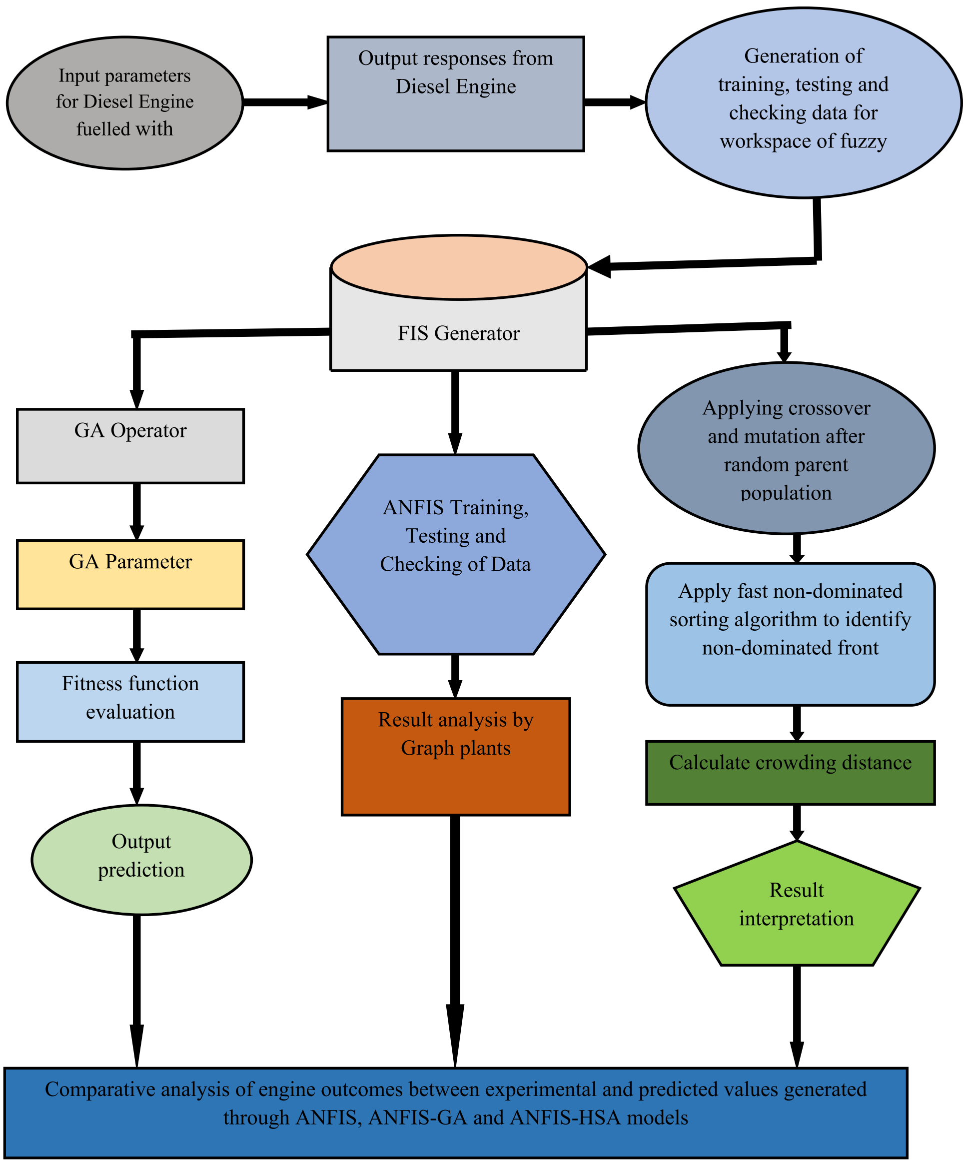

Figure 2. Structure of the research along with the flowchart for various models.

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This results in a small variation in engine performance as compared to engines running on only diesel.[9] This decrement in performance characteristics is often seen in consumption levels of the fuel, which increases probably due to the higher viscosity and density levels found in biofuels.[10] To further enhance performance of biodiesel in diesel engines, the mixing process is performed, where biodiesel is mixed with several potential nanoadditives.[11] This has been validated by several researchers in the past where engine performance was substantially enhanced and, in some cases, was even better than diesel engines while simultaneously decreasing the emission levels. The nanoparticle acts as a thermal bridge between the biodiesel and the nanoparticle as it increases the thermal conductance of the biofuel. This keeps in check the A/F ratio, mitigating the knocking process and simultaneously increasing engine life. The literature survey is comprehensively performed by considering several articles, case studies, expert opinions, etc. as shown in Figure 1.

Biodiesel can be attained from multiple resources that are both sustainable and environment-friendly, primarily from nonedible-based oils as they elude the food vs fuel debate. The production of biofuels can be accomplished using different types of raw materials by applying appropriate chemical reactions and extraction techniques. Örs et al.[12] examined the performance and emission levels of WCO biodiesel, amalgamated with titanium dioxide (TiO_2) in a diesel engine. The study established that the presence of nanoadditives aids in the burning process leading to a wholesome combustion process, which eventually results in lowered emission. Hoseini et al.[13] investigated the blends of Ailanthusaltissima biodiesel and graphene oxide for diesel engine performance and emission characteristics. An enhancement in BTE and reduction in BSFC, CO, and UBHC were observed since nanoparticle blended biofuels have superior air−fuel mixing properties, thereby changing the delay period for a stabilized combustion reaction. Gad et al.[14] applied blends of WCO enhanced with carbon nanoadditives for combustion and exhaust performance of diesel engines. The blends achieved lower emissions (NOx, smoke, and UBHC) while concurrently improving the ignition delay of the engine. This is quite evident since the presence of nanoparticles considerably reduces the evaporation time, eventually lowering the ignition delay effect and simultaneously enhancing ignition-based prospects of the blended biofuel. Rezania et al.[15] reported improved BTE and ignition pressure with lower emission levels for blends of lanthanum titanium dioxide ($LaTiO_3$) nanoparticles and mustard seed oil. The literature review specified above clearly presents an immediate desire and need to research and model diesel engines on the basis of various nanoparticles and its combinations with the aid of artificial intelligence, which still remains an unexplored zone in diesel engines similar to other problems of engineering.[16,17] If input parameters are designed and predicted based on a specified model while applying the optimization method, it will result in lowered biofuel production cost and time, thereby aiding in commercializing it at the global and industrial levels.[18,19]

This paper explains a technique to contemplate and predict the performance of diesel engines when fueled with nanoparticles and biodiesel in varying combinations through soft computing and metaheuristic techniques.[20] The elementary process comprises establishing a feasible relationship among multiple constraints over available outcomes in diesel engines established by employing various algorithms, thereby successfully predicting the performance and emission parameters of biofuel-induced engines.[21] This ultimately delivers effective models with enhanced performance and lower exhaust pollution. Application of prediction models effectively decreases the experimental runs in diesel engines, thus reducing the cost, labor, and time of experimentation.[22,23] The prediction models combined with optimization tools produce a pareto-optimal combination of inputs. Soft computing models are capable of applying the nonlinear framework on numerous constraints being interconnected among one another. Prior literature regarding the engine-related models being evolved soft computing methods tend to lessen the complete experimentation data with noteworthy results.[24,25] Additionally, the genetic algorithm technique is also applied to produce effective optimized results for performance and emission characteristics in diesel engine arrangement.[26−28] In earlier experimentation cases on large diesel engines, like marine engines, to build a feasible interrelationship between input and output variables, a large data set was required, with ∼10 000 to 12 000 values. This consumed time, cost, fuel, and labor. By application of smart models, the data can be predicted by training and testing the engine with a smaller data set. This would decrease the large experimentation process and furnish values with an uncertainty acceptable to the investigator.

Rahman et al.[29] discussed essential physicochemical characteristics of various biofuels and ranked them according to these properties based on performance outcomes in diesel engines. The study furnished Brassica Juncea, Cardoon, and poppyseed biodiesels as the most feasible biofuel feedstocks when applied in IC engines. Najafi et al.[30] explored the feasibility of waste cooking oil with the help of ANN and RSM techniques. Experimental parameters considered in this study were alcohol type, catalyst concentration, mixing intensity, and temperature within the production process. Anwar[31] ranked various biofuels by employing soft computing techniques by considering 15 various performance parameters such as economic aspects (extraction biofuel cost), technical aspects (physicochemical characteristics), and chemical structure (FFA content) of basic oil. Outcomes designate coconut as the most favorable biofuel, whereas soybean was established as the least performing biofuel in diesel engines. Khan et al.[32] optimized vital constraints of biodiesel in diesel engines with the aid of the ANFIS-RSM method on biodiesel hydrogen blends. Anwar[33] classified various biofuels with soft computing techniques on the basis of four criteria such as potential (microalgae oil), prevalent (palm oil), popular (soybean oil), and proven (coconut oil). Consequently, preceding established models clearly explain the importance of applying soft computing procedures and metaheuristic techniques as accurate predicting models with additional benefits of optimization, producing a human-like reasoning style of decisions.[34,35]

The current paper primarily employs the ANFIS model as the outcome predictor and additionally combines the hypothetical function by optimizing the outcomes with the assistance of genetic algorithms (GAs) and the harmony search algorithm (HSA). Preceding models established in earlier studies evidently validate the importance of combining the ANFIS prediction model with metaheuristic systems, which is capable of delivering an improved ideal grouping for engine performance and exhaust. Predicted responses achieved through the model implementation were in accordance with the achieved experimental values, thereby enabling an effective background. Hereafter, using a smaller set of input variables (load, blend percentage, nano-

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Figure 3. *E. crassipes* site (a) and *E. crassipes* stems (b).

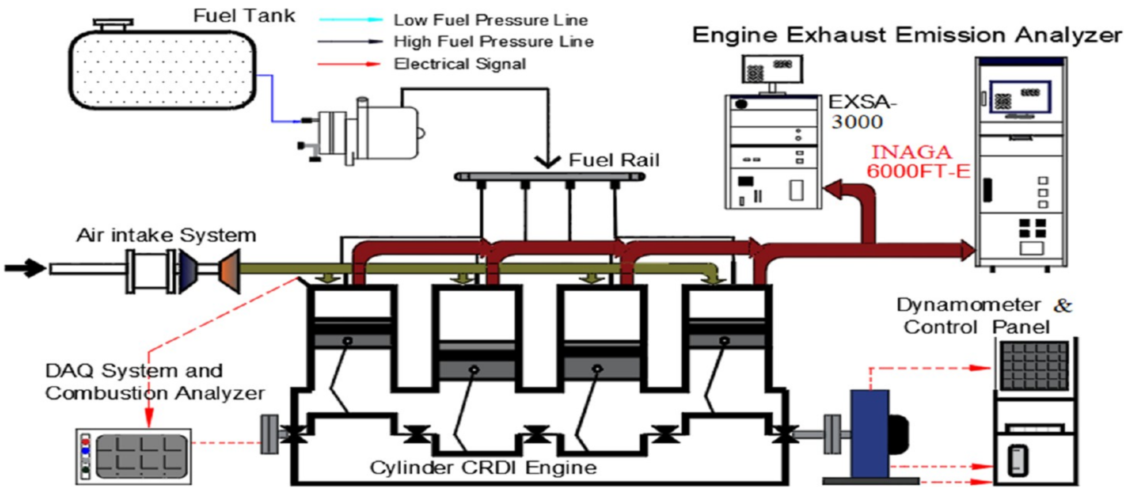

Figure 4. Experimental setup of the PETTER-AV engine.

particle concentration (NPC), and injection pressure (IP)) can efficiently estimate the outcomes by applying these models in a cost-effective manner. The projected outcomes from the ANFIS model were associated with data attained during engine investigation and were found to be in accordance with applied real-time values. The ANFIS-GA combination is undoubtedly proficient in duplicating the conventional experimental method for engine outcome assessments with reduced uncertainty levels. Additionally, one more optimization procedure called the harmony search algorithm (HSA) is combined with the initial ANFIS algorithm to examine the feasibility of the model, thus comparing the outcomes of each model with one another. Finally, considered models are ranked according to different criteria using the TOPSIS method to provide future researchers with some groundwork before opting for a prediction process.

Summarizing the above trends, the following points are coined and presented.

- Premixing EC oils with nanoadditives was found to be a reasonable and possible option to be used in diesel engines due to its easy accessibility and sustainable nature.
- Examination of engine outcomes for multiple nano-additives varied in different proportions, while engaging soft computing[36] and metaheuristic methods[37] such as ANFIS, ANFIS-GA, and ANFIS-HSA have seldom been addressed in the literature as per the authors' knowledge.
- Previous studies have emphasized the reputation of combining soft computing prediction models with metaheuristic models, yielding accurate engine characteristics with reduced effort, cost, labor, time, and energy.[38]

Literature studies specified above clearly indicate the prevalence of significant work in biofuel optimization and performance boost with the help of statistical software and soft computing techniques. The novelty of the existing study is prevalent since absolutely no previous work has been reported for boosting engine performance and reducing emissions (using nanoparticles) while employing prediction models (ANFIS) and optimization techniques (GA and HSA) for *Eichhornia crassipes* oils. The exceptional implemented model applied in diesel engines reduces the number of trial or experimentation runs with proper prediction, which happens by training and testing the data inputs, making the current work innovative, specific, and accurate. The application of artificial intelligence techniques integrated with optimization techniques will yield revolutionary results in the current field of petro-diesel engines. The structure of the research has been explained in Figure 2.

2. MATERIALS AND METHODS

After establishing the potential of biodiesels in diesel engines, researchers have moved toward experimental analysis of the

Table 1. Technical Details of the Engine

sl. no.	component	specification
1	engine make	PETTER-AV1
2	engine type	CRDI, 4-stroke, DI, water-cooled
3	bore	80 mm
4	stroke	110 mm
5	rated power	5 BHP at 1500 rpm
7	compression ratio	19:1
8	dynamometer	Eddy current
10	load sensor	load cell, type strain gauge
11	compression pressure	6.2 MPa

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Table 2. Comparison of Physiochemical Properties between Applied Test Fuels

properties	ABD	ZBD	*E. crassipes* biodiesel	diesel	ASTM limit
density at 15 °C (kg/m^3)	884	890	905	841	860−900
kinematic viscosity (cSt)	3.50	3.55	2.8	4.56	2.52−7.5
calorific value (MJ/kg)	49.8	47.3	41.93	44.85	min. 33
flash point (°C)	71.36	69.31	105	51	min. 130
FFA (%)			1.2	0.0014	max. 2
cetane number (°C)	59	57	55	51.3	min. 45

Table 3. CCRD Design for Engine Input Control Parameters

coded level	blending (%)	IP	NPC	load
−2	0	180	0	20
−1	5	190	5	40
0	10	200	10	60
1	15	210	15	80
2	20	220	20	100

prepared blends of fuel. To furnish the experimental values, a specified data set is prepared, which predicts and replicates the experimentation values. Primarily, the inputs and outputs of the research data are classified and categorized into different levels. Further, the interrelationship between variables and outcomes is established by modeling the parameters. The experimental inputs were load applied, blend percentage, nanoparticle concentration, and injection pressure. It is upon this benchmark that the input proposed will be evaluated for maximum brake thermal efficiency, minimum brake specific fuel consumption, and minimum emission exhaust gases such as CO, NOx, and UBHC. Soft computing techniques integrated with metaheuristic approaches have been explored in this research to compare the investigational and algorithm-derived data explained in four successive steps: (a) gathering the investigational data from the engine and grouping the data sets based on training and testing, (b) recognizing the finest performing model within the ANFIS network for evaluating the performance and exhaust attributes of diesel engines, (c) combining the outcomes of the ANFIS model with GA and HSA optimization techniques, and (d) finally, ranking the models on the basis of various criteria, which will provide a foundation to future researchers while opting for models.

2.1. Data Compilation. The investigational data set required for developing the prediction model was generated from the diesel engine test setup provided with EC biofuel. These oils were simultaneously combined with couple nanoparticles, namely, aluminum oxide (Al_2O_3) and zinc oxide (ZnO), in variable proportions. The performance and exhaust attributes were estimated for the developed couple mixtures on a petro-diesel engine, generating a data set based on various nanoparticle proportions for various blend fractions, engine loads, and injection pressures. Subsequent segments comprise a comprehensive explanation of the steps followed in information prediction.[39]

2.2. Material Preparation and Raw *E. crassipes* Oil Conversion into Biodiesel Analysis. One of the primary disadvantages of biofuels is that the availability of raw material to procure oils for production of biodiesel is nullified using waste products, which are easily and freely available in nature. This segment explains the production and mixing process of biodiesel−diesel blends with nanoparticles to form a hybrid and superior fuel. The EC plant was made available from local ponds near the New Delhi area, as depicted in Figure 3. Furthermore, chemicals such as methanol (99%), KOH (96%), and phenolphthalein indicator were readily available from the chemical laboratory of Al-Falah University. An ultrasonic system was also used to mix all chemicals thoroughly as the yield conversion was substantially low using conventional methods. Nanoadditives used in the study were received in the powdered form from Khari-bali, New Delhi.

The process begins with cutting down and collecting EC plants from the nearest pond. The EC leaves and stem are separated from each other. The stems are further shredded to required limits, while leaves are discarded. The shredded stems are then heated in a furnace at temperatures above 80 °C. The stems are treated with available chemicals such as potassium hydroxide and sulfuric acid for biofuel production. Although plants have lower free fatty acids (FFAs), a titration method is employed to validate the results. Roughly 50 g of EC oil was poured into a glass along with chemical additions such as propanol and a color indicator. The glass was further placed under a KOH solution where the solution was added until the final purple color persists even on shaking. The ultimate FFA was generated. The ultimate reaction mixture comprised biodiesel and glycerin, which separated into two distinct deposits. The proportions of acid and oil were kept at a persistent ratio of acid/oil = 20/200(w/w), whereas methanol was maintained at a ratio of 200 g/400 mL.

As discussed above, the shortcomings of biodiesel application in diesel engines can be addressed by mixing nanoadditives with biodiesel−diesel blends, which provide superior performance parameters. It has already been established through a literature survey that mixing nanoparticles enable a larger surface area with a potential drop in viscosity and density levels. Normally, nanoadditives and biodiesel cannot be mixed directly with each other. It requires a chemical catalyst and an energy-imparting process for effective mixing. This is furnished by mixing Surfactant 30 as the catalyst, while an ultrasonic horn provides the necessary energy addition to the reaction for boosting the intermixing capability. Metal-based particles are primarily transformed into nanofluids, which are easily miscible with biodiesels. Initially, the nanoadditives are weighed and combined with normal water to form nanofluids. The mixture is then positioned under an ultrasonic reactor at 90−100 kHz for 20 min. The size of nanoparticles applied in this investigation is around 30 nm. The colorless nanofluid is also further combined with biodiesel. The EC blend for the ultimate proportion of aluminum nanoadditive biodiesel (ABD) and zinc nanoadditive biodiesel (ZBD) contained 93% biodiesel, 4% nanofluid, and 3% surfactant volume basis.[40]

2.3. Setup of Test Engines. The engine setup employed for experimentation determined the performance and emission parameters for biodiesel-based fuels, as displayed in Figure 4. Primary investigations were performed on a common rail direct injection (CRDI) diesel stationary engine. The engine load can be altered by varying the speed of the engine to predict the performance and emission parameters. The engine loading is measured and varied by an eddy-current dynamometer. The resistive-type load panel consists of a voltmeter and a current meter. An eddy-current dynamometer in combination with the diesel engine was employed to regulate the engine torque in the range from 0 to 18 kgf. The temperature of the exhaust gas was

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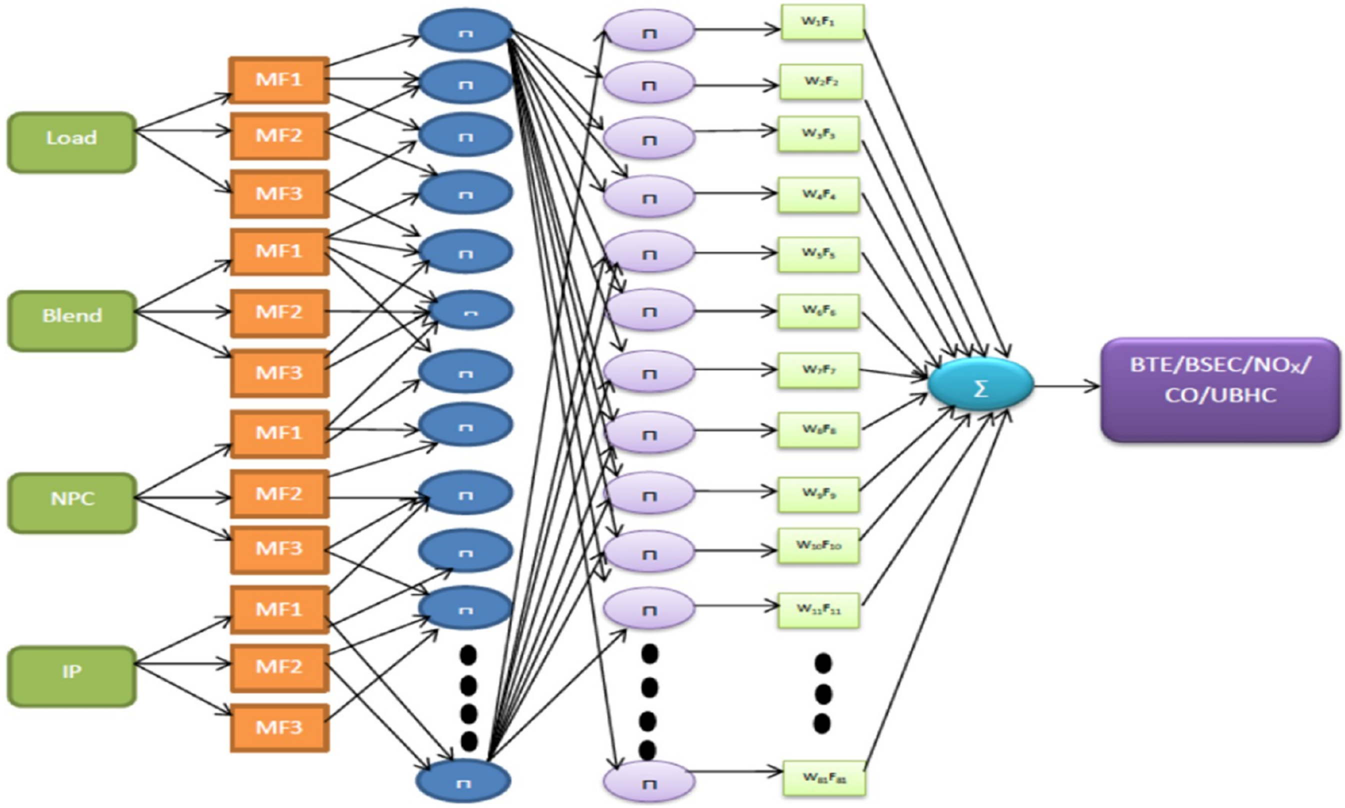

Figure 5. General approach applied in the ANFIS model.

measured by a K-type thermocouple. A separate panel box is included within the system specifying the measurements such as fuel tank, air box, transmitters for air, and fuel flow. The engine exhausts primarily include UBHC, CO, and NOx emissions, which were displayed on the screen of gas analyzers. Table 1 specifies the various technical details of the engine setup. In earlier experimentation cases on large diesel engines, like marine engines, to build a feasible interrelationship between input and output variables, a large data set was required, with ∼10 000 to 12 000 values. This consumed time, cost, fuel, and labor. By application of smart models, the data can be predicted by training and testing the engine with a smaller data set. This would decrease the large experimentation process and furnish values with an uncertainty acceptable to the investigator.

2.4. Physiochemical Characterization of Diesel Blends. Petro-diesel and nanoparticles were added in different concentrations to basically estimate the feasibility of the obtained fuel in a CI engine. The *E. crassipes* oil biodiesel physiochemical properties were quite identical to those of petroleum-derived diesel oil as demonstrated in Table 2, thereby prompting a study on its suitability for an engine. Additional benefits such as a higher calorific value further added to the fuel advantage in the heating process. The viscosity of the fuel blends was obtained by a capillary viscometer. A hydrometer was employed to determine the density of the fuel, while a bomb calorimeter apparatus specified the calorific value.[41] The final test blends of aluminum oxide (ABD) and zinc oxide (ZBD) were found to be in accordance with global ASTM and EN standards, apparent from their physiochemical properties presented in Table 2.

2.5. Experimentation Analysis Using the Response Surface Methodology Technique. Experimentation and investigation of diesel engine parameters have always remained an expensive proposition, especially in larger engines such as marine engines. Several input parameters need to be varied to obtain the required data set and also establish a feasible interconnection between the input constraints and output values. To furnish a smaller data set with a feasible relationship establishment between input and output variables, response surface methodology (RSM) is used. Application of the RSM method establishes a feasible approach to solving and interconnecting the input variables with required outcomes. This stage is decisive for developing a practical data set of input variables for attaining the optimal responses with limited access to experimental data sets. Prior problems solved by RSM in experiment-based investigations have well-found noteworthy enhancements in generating output responses with insignificant statistical uncertainties. This design planning is well considered to be the primary foundation among its other counterparts due to its proficiency in summing up experimental levels along all major coordinate axis in the opposite direction of origin and at a distance equal to the semidiagonal hypercube of the factorial architecture. Ranges developed for input parameters strongly influenced the output responses, beyond which the effects became marginal. The load variation ranged between 20 and 100%, with the biodiesel concentration at a maximum of 20%, injection pressure variation between 180 and 220 bar, and varying the nanoparticle concentration between 0 and 20%. The experiment was conducted between two different nanoparticles (Al_2O_3 and ZnO) so as to obtain the finest fuel that can be successfully applied in diesel engines based on output responses. A given set of input variables is available from the investigation, in which three readings were taken simultaneously to develop fool-proof values with minimum uncertainty. Lastly, their average value was applied as the experimental value for further analysis. The center input values as specified in Table 3 were suggested in the engine specifications when operated with neat diesel as fuel.[42]

The data set comprises a number of control factors; numerical and coded values are employed in the CCRD array, comprising a total of 60 runs.

2.6. Advantages of the Present Work. The present study is a novel work where diesel engine performance and emission parameters are predicted based on a relationship developed by hybrid models. To furnish accurate prediction, multiple models are applied and compared on different parameters. These models are further ranked for best performance and worst performance so as to provide a future framework for upcoming researchers. The following are a few benefits of this research.

- Utilization of waste resources for production of biofuel, thereby not harming the environment and providing a sustainable fuel for diesel engines.
- Furnishing a viable interrelationship with a smaller diesel engine data set with acceptable uncertainty levels.
- Prediction of missing data, simply by incorporating training and testing models separately.
- Experimentation at a comparatively lower cost and lower fuel consumption.
- Faster result generation using models that would consume substantial time by a conventional experimentation process.

3. MODELING AND OPTIMIZATION

The reading generated from the experimental setup is modeled with the help of the first-order Takagi−Sugeno artificial neuro-fuzzy interface system (ANFIS). The modeling was structured on the system consisting of four inputs as depicted in Figure 5 so as to evaluate the performance and exhaust parameters considered as the foremost objective functions. Previously, ANFIS-based models have been applied at various levels in the field of thermal engineering for developing an input−output framework and simultaneously understanding the relationship between unclear and difficult problems having a limited, nonlinear, and uncertain database. The popularity of ANFIS models has reached several folds mainly due to their capability to construct effective fuzzy rules, facilitating efficient surface plots for outcome responses. Practically, there is an urgent need to implement such artificial neural techniques in engine performance evaluations since this methodology may prove to be a faultless alternative to the conventional experimental techniques, thereby furnishing outcomes with enhanced accuracy and reliability. The general prototype of ANFIS comprises six different layers with an initial layer of input parameters, followed by a fuzzification layer, a rule consequent layer, a rule strength normalization layer, a rule consequent layer, and finally a rule inference layer. Constructing a feasible ANFIS structure indicates the presence of the fuzzy theory and membership frameworks. Data generation was furnished by developing five different FIS models for objective functions, i.e., BTE, BSEC, CO, NOx, and UBHC.[43] Approximately 60 values of input parameters were selected, and on that basis, data patterns were generated from the experiments categorizing them randomly into two subsets, i.e., 45 (≈75%) and 15 (≈25%), data for the training and testing ANFIS models, respectively. The framework of the single ANFIS model is explained in Table 4.

Table 4. Developed ANFIS Framework for Training Set of Data

parameters of the model	values
total number of nodes	193
number of linear parameters	81
number of nonlinear parameters	36
number of training data pairs	45
number of rules that are fuzzy	81
membership function	triangular

Table 5. GA Algorithm Framework

type of selection method	Roulette wheel
population scale	81
iterations	3200
crossover (%)	0.83
mutation rate (%)	0.83
level of mutation	0.8
selection pressure	10

The following equations of ANFIS were applied to generate different responses by modeling.

Layer 1 − fuzzification layer:

$$Q_{1,i} = \mu_{A_i}(x), \quad \text{for } i = 1, 2 \tag{1}$$

or

$$Q_{1,j} = \mu_{B_j}(y), \quad \text{for } j = 1, 2 \tag{2}$$

$$\mu_{A_i}(x) = \frac{1}{1 + \left[\left(\frac{x - c_i}{a_i}\right)^2\right]^{b_i}} \tag{3}$$

Layer 2 − product layer:

$$Q_{2,i} = \overline{w_i} = \mu_{A_i}(x)\mu_{B_i}(y), \quad \text{for } i = 1, 2 \tag{4}$$

Layer 3 − normalized layer:

$$Q_{3,i} = \overline{w_i} = \frac{w_i}{w_1 + w_2}, \quad \text{for } i = 1, 2 \tag{5}$$

Layer 4 − defuzzied layer:

$$Q_{4,i} = \overline{w_i}f_i = \overline{w_i}(p_i x + q_i y + r_i), \quad \text{for } i = 1, 2 \tag{6}$$

Layer 5 − total output layer:

$$Q_{5,i} = \text{overall output} = \sum_i \overline{w_i}f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{7}$$

$$f = \frac{w_1}{w_1 + w_2}f_1 + \frac{w_2}{w_1 + w_2}f_2 \tag{8}$$

$$f = \overline{w_1}(p_1 x + q_1 y + r_1) + \overline{w_2}\,(p_2 x + q_2 y + r_2) \tag{9}$$

$$f = (\overline{w_1}p_1 x + \overline{w_1}q_1 y + \overline{w_1}r_1) + (\overline{w_2}p_2 x + \overline{w_2}q_2 y + \overline{w_2}r_2) \tag{10}$$

Initially, modeling begins with prescribing the fitness function associated with engine outputs, which conforms with the complexity of the problem statement. Orthodox approaches employed to generate the fitness function for outcomes consume a considerable amount of time and labor. Nevertheless, the ANFIS approach establishes an acceptable objective function due to its ability to generate the data without requiring any preceding model history. Estimations and predictions determined from the ANFIS technique can be further perfected

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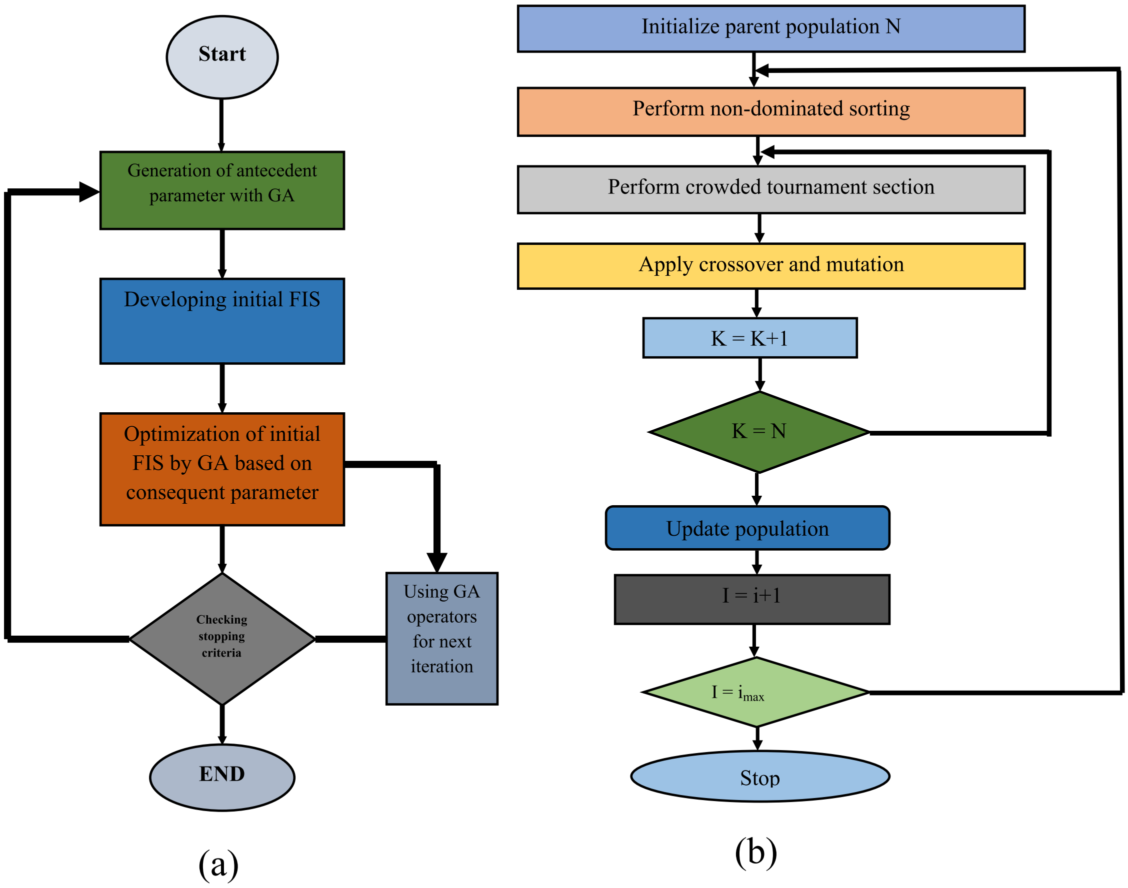

Figure 6. (a) Algorithm of ANFIS-GA and (b) HSA algorithm.

Table 6. Pearson's Correlation Coefficient of Five Engine Parameters

parameters	BTE	BSEC	CO	NOx	UBHC
BTE	1	−0.911	−0.852	−0.775	−0.727
BSEC	−0.911	1	−0.953	−0.884	−0.828
CO	−0.852	−0.953	1	−0.949	−0.917
NOx	−0.775	−0.884	−0.949	1	−0.965
UBHC	−0.727	−0.828	−0.917	−0.965	1

with improved precision and efficiency using the genetic algorithm in the final outcome values. The overfitting or convergence of the curve is avoided since the plot of training loss continues to increase with experienced data sets. Also, the plot of testing data increases continuously, thereby having no over-fitting among data.

The uncertainty levels found in the ANFIS model can be removed to some extent by employing optimization techniques. In the literature, application of the ANFIS approach has displayed a small extent of inaccuracy, mainly as the outcomes are caught within the local optima for multiobjective optimization problems. Also, the conflicting outputs complicate the model development. To overcome this complexity, hybrid techniques such as genetic algorithms are employed to optimize the problem rapidly and effectively. Application of a randomly searched GA algorithm facilitates cost-effective and efficient responses. Genetic algorithm is an adaptive combinatorial search algorithm working on the basic principle of biological evolution where the permutations are created based on parent—child combination. The model employs a data set to generate the finest combination of inputs facilitating the best outcomes, whose framework is specified in Table 5. Previous research have validated the application of GA compared with other multi-variate techniques that need longer periods to furnish outcomes even while employing a comprehensive nonparametric strategy, to recognize the ideal result for a comprehensive evaluation. Therefore, coupling prediction techniques with the GA-weighted sorting technique lowers the error levels in membership functions, enabling smooth improvisation within the basic Sugeno fuzzy model.[44] The simulation was executed by simple programming steps applied in MATLAB software (version R2018a). The flowchart of the ANFIS-GA algorithm is provided in Figure 6a.

The present research also incorporates an established optimization approach called the harmony search algorithm (HSA), which has gained considerable popularity, probably due to its improved convergence ability. Different nanoparticles (ABD and ZBD) are amalgamated to optimize the engine characteristics with the available small data set. Furthermore, results of HSA optimization were compared with previous evolutionary algorithm integrated prediction-optimization models (ANFIS and ANFIS-GA) based on the error associated with each solution. Also, the output solutions from these models should fulfill the criteria set by ASTM standards for diesel engines. The HSA approach has previously been successfully employed in several fields for multifunction optimization processes, which leads to faster convergence and appropriate sorting based on priority. The input data set is fed into neuro-fuzzy designer stipulating membership functions for input—output combinations. Further, the model is fine-tuned by

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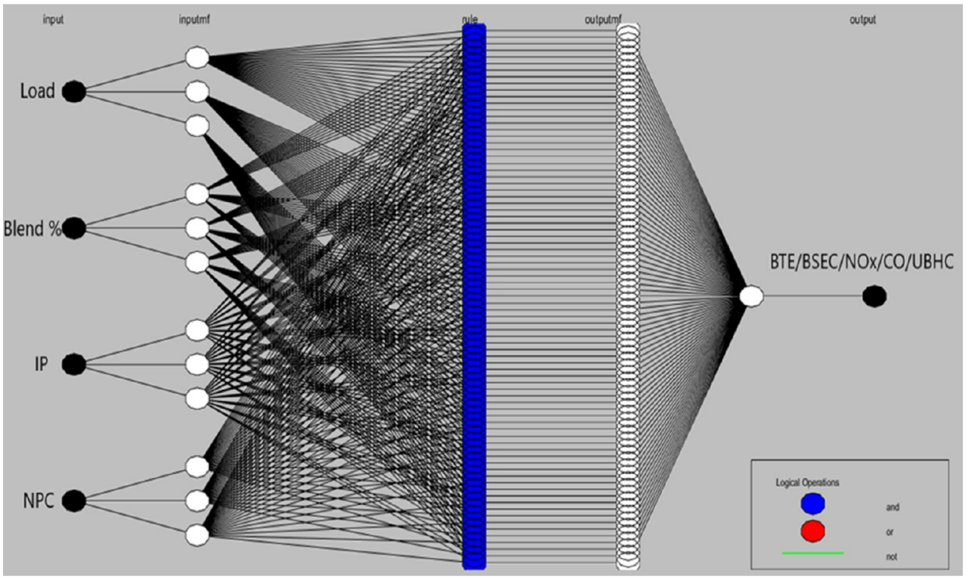

Figure 7. FIS framework with 81 rules for a particular set of inputs.

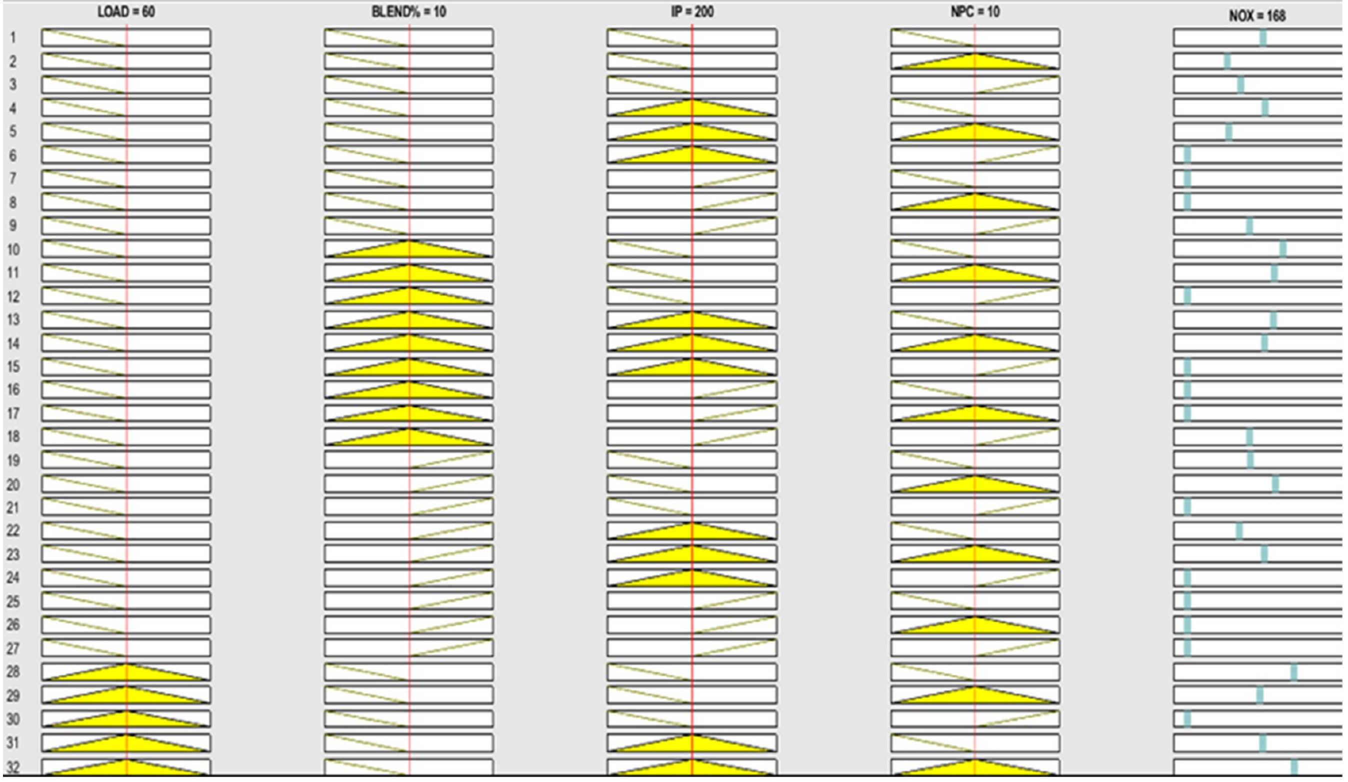

Figure 8. Some fuzzy rules developed in the ANFIS model.

incorporating the HSA algorithm into the predicted values, which successfully executes multiobjective optimization for all outcomes.

The primary aim of incorporating the optimization model into the neuro-fuzzy diesel system is to maximize the BTE, minimize the BSEC, and minimize the exhaust effluents (NOx, UBHC, and CO) concurrently. A comprehensive flowchart is presented in Figure 6b highlighting the steps involved in the HSA approach in generating a multiobjective output for performance and exhaust emission of *E. crassipes* oil biodiesel. The local optimization can significantly reduce the required number of iterations to achieve the optimal solution.

It is a common practice that engine outcomes might be interrelated to each other based on the fact that input conditions remain the same for all outcomes. Therefore, any adherent correlation between the five objective functions was evaluated with the aid of Pearson's correlation coefficient as shown in Table 6.

As apparent from the above table, the coefficient, when applied to the diesel engine model, ranges between 0 and ±1. The lowest value is allocated when no linear correlation is

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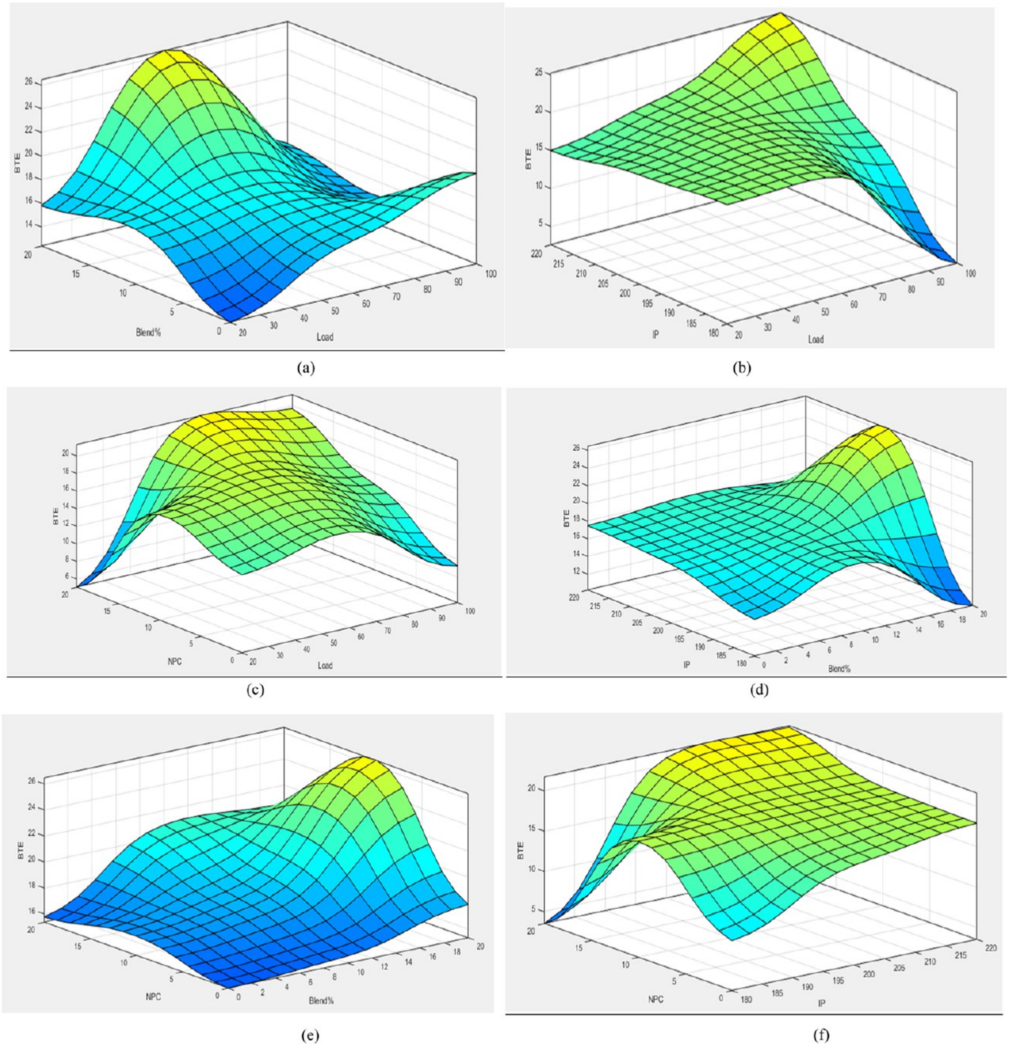

Figure 9. Surface plots for BTE vs input conditions (a−f).

established between any output variables, and the zenith value is assigned when the best linear correlation between any two variables is obtained. Similarly, the sign of the correlation establishes the direction of the relationship between the output parameters. However, insignificant relationship values were derived for all outcomes among each other as depicted in Table 10. Also, the mutual correlations developed between various outcomes were indirect and contradictory, thereby being incompatible with the original model. Henceforth, all five objective functions (outputs) were drafted in the optimization process so as to generate the best (optimum) input variables by trading off between the engine performance and emission characteristics. The output responses achieved for the ANFIS models, i.e., BTE (FIS1 (X)), BSEC (FIS2 (X)), CO (FIS3 (X)), NOx (FIS4 (X)), and UBHC (FIS5 (X)), were interfaced into the optimization technique.

HSA was applied to generate top-notch responses by optimizing the best interdependency matrix. The following steps were involved while employing the HSA algorithm.

Step 1: Parameter initialization, which includes harmony memory size (HMS), harmony memory considering rate (HMCR), bandwidth (BW), pitch adjusting rate (PAR), and the stopping criteria.

Step 2: Development of the harmony memory (HM) matrix using randomly generated solution vectors within the upper and lower bounds of design variables based on the associated cost function values.

Step 3: Modification or improvement of the decision variable (harmony) with every successive iteration that is created by jointly considering the harmony memory, pitch adjustment decision, and random selection procedure.

Step 4: Updating or interchanging the worst harmony of HM with the new vector if it furnishes a better solution (smaller cost function).

Keep repeating Steps 3 and 4 until the termination criterion (or maximum iteration number) is fulfilled.

Data generated through these models are compared with experimental values to provide a comparative analysis to sort out the best working model based on accuracy. The discrepancy in the developed model could be explained with statistical tools such as coefficient of determination (R^2) and mean-squared error (RMSE) provided in eqs 11 and 12, respectively.

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(P_i - E_i)^2} \tag{11}$$

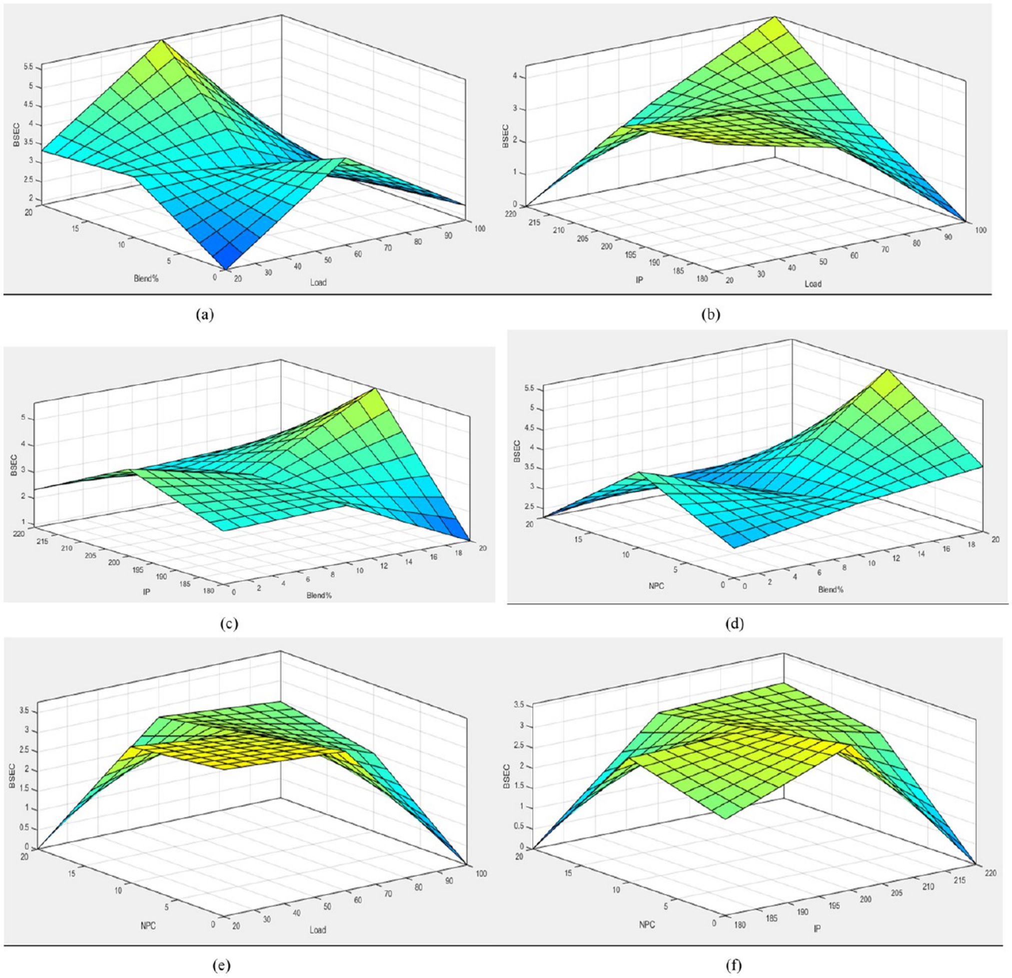

Figure 10. Surface plots for BSEC vs input conditions (a−f).

$$R^2 = 1 - \frac{\sum_{i=1}^{N} (P_i - E_i)}{\sum_{i=1}^{N} (P_i - E_m)} \tag{12}$$

where $E_m = \frac{\sum_{i=1}^{N} P_i}{N}$, RMSE is the root-mean-squared error, R^2 is the fraction of variance, P_i is the predicted value obtained from modeling, E_i is the experimental value generated, E_m is the mean of the predicted values generated from models, N is the available data, and i is the trial run value that needs to be calculated.

4. RESULTS AND DISCUSSIONS

4.1. Prediction of Engine Performance and Emission Parameters by ANFIS. The present research began with preparing blends of the EC plant biodiesel and metallic nanoparticles in varying combinations. Subsequently, due to the large levels provided in the blending proportion, the required data sets become extremely large. A substantial number of input−output data sets gets are generated with various permutations and combinations to accurately detect engine characteristics, thus consuming time, labor, energy, and fuel. Prediction models are applied to estimate the model interrelationship between constraints and outcomes, and subsequently, values are predicted on that relationship. The models were built on different concepts of AI and metaheuristic techniques, in which data was fed into the ANFIS prediction model. The ANFIS model is capable of estimating and establishing a viable interrelationship between variables of the study and its subsequent outcomes. The engine outcome parameters comprised performance attributes such as BTE and BSEC and exhaust attributes such as UBHC, NOx, and CO. The algorithm developed in this study offers an alternative to conventional technology for a fusion strategy (ANFIS), which facilitates effectual and operative output prediction even for a reduced data set with lower uncertainties in the system. The variables of the study were derived through RSM for different combinations and then fed to the ANFIS model in MATLAB. The data sets were divided into training and testing data sets and fed to the ANFIS structure. Array-based hybridization is executed to boost the mega-functionality of the framework designed for the experimental engine characteristics. Previous research have explored and simultaneously established the ANFIS framework to be a potential tool capable of predicting the interrelationship among four input variables and five layers to be successfully implemented in well-characterized complex engineering problems. The fuzzy interface system (FIS) structure is modeled for each output variable, which is distinctly designed for four input constraints in the ANFIS operation as shown in Figure 7. About 81 rules were automatically developed within the system, which is considered a viable analysis situs for associating the operational variables and desired parameters. Figure 7 displays the basic rules applied in the ANFIS model for the output parameters (e.g., NOx). In fuzzy interface system (FIS) development, the assertions formulated concerning the

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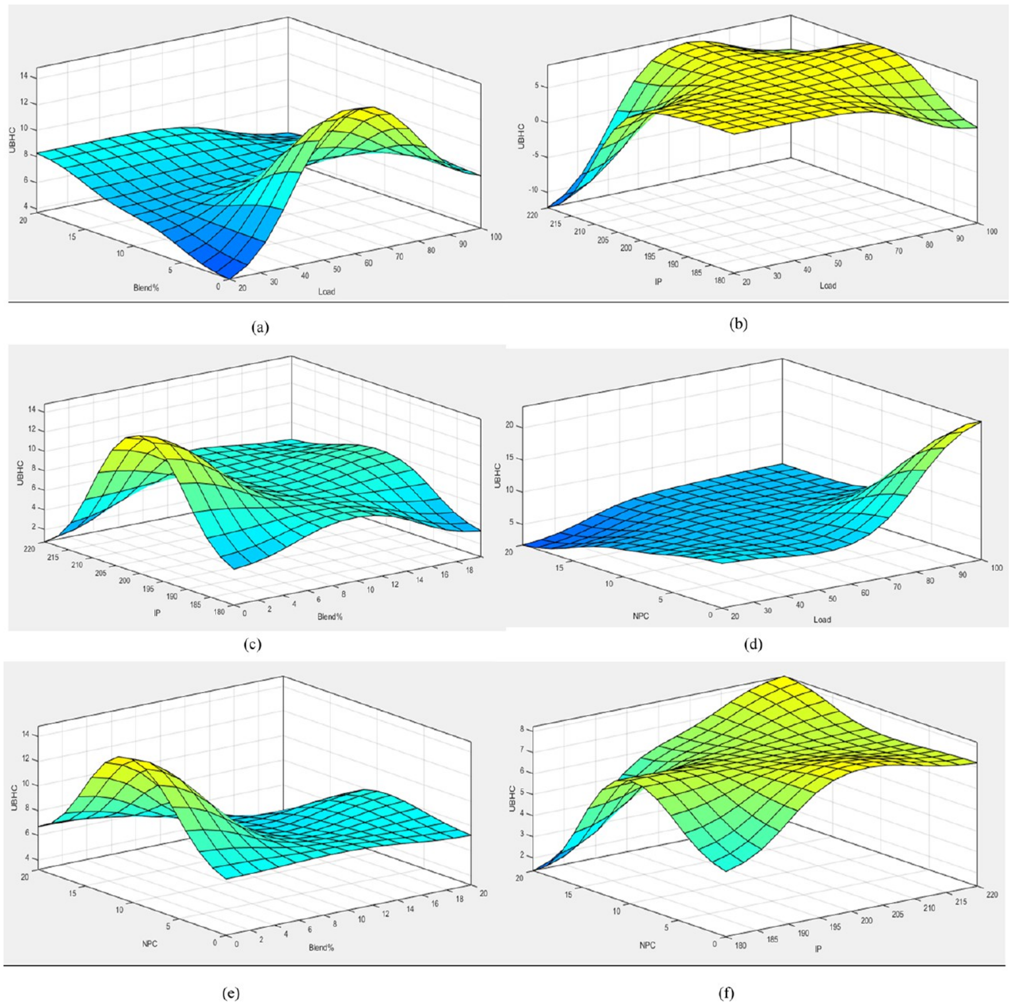

Figure 11. Surface plots for UBHC vs input conditions (a−f).

fuzzy rules in ANFIS are interrelated to the Sugeno model, which estimates the output values through predefined values obtained from the input responses as shown in Figure 8. For relations among outputs, 3D surface plots were developed indicating the relationship between any two inputs (out of four) and an output response. This makes things easier forthe curve tracing between input variables and outcome responses for superior nanoparticle additions (aluminum oxide) as provided below in Figures 9−13. Each rule and law developed in the Sugeno model after training and testing the data in the ANFIS model were validated by evaluating the mean square deviation and the fraction of variance approximation. Employing the ANFIS approach has successfully predicted reliable values similar to experimental engine outcomes. The accuracy or closeness of the predicted values is plotted against the original experimental engine values in Figures 14−18 to validate model consistency and accuracy.

4.2. Prediction of Engine Performance and Emission Parameters by ANFIS-GA. The results drawn from the previous ANFIS model can be further optimized based on a set of parameters of the study. Using optimization techniques in combination with intelligent approaches in prediction models improves the accuracy of the model by minimizing uncertainty. Values estimated above are additionally fine-tuned with better accuracy and efficiency. The implementation of ANFIS-GA eradicates any uncertainty present within the model, which may be due to the steep descent methodology of outcomes often caught within the local optima. Application of a randomly searched GA algorithm facilitates cost-effective and efficient responses. Genetic algorithm is an adaptive combinatorial search algorithm formulated on the basic principle of biological evolution, where the input combinations are reconstructed based on parent−child grouping. The model optimizes the ANFIS-generated outcomes, thereby obtaining the finest combination of inputs yielding the best outcomes. Studies (thermal engineering) have validated the application of GA compared with other multivariate techniques that consume a lot of time to estimate outcomes even when employing a comprehensive nonparametric strategy, to distinguish the ideal result for a comprehensive evaluation. Henceforth, employing a GA-weighted categorization approach in ANFIS-generated predictions lowers the uncertainty in membership functions, facilitating improvisation in Sugeno fuzzy-based rule structures.

Development of the fitness equation was managed by contemplating the average statistical error values for all trial runs between the experimental and predicted responses. When feeding values in the GA toolbox, the fitness function was evoked. The fitness equations obtained by all five models are given below

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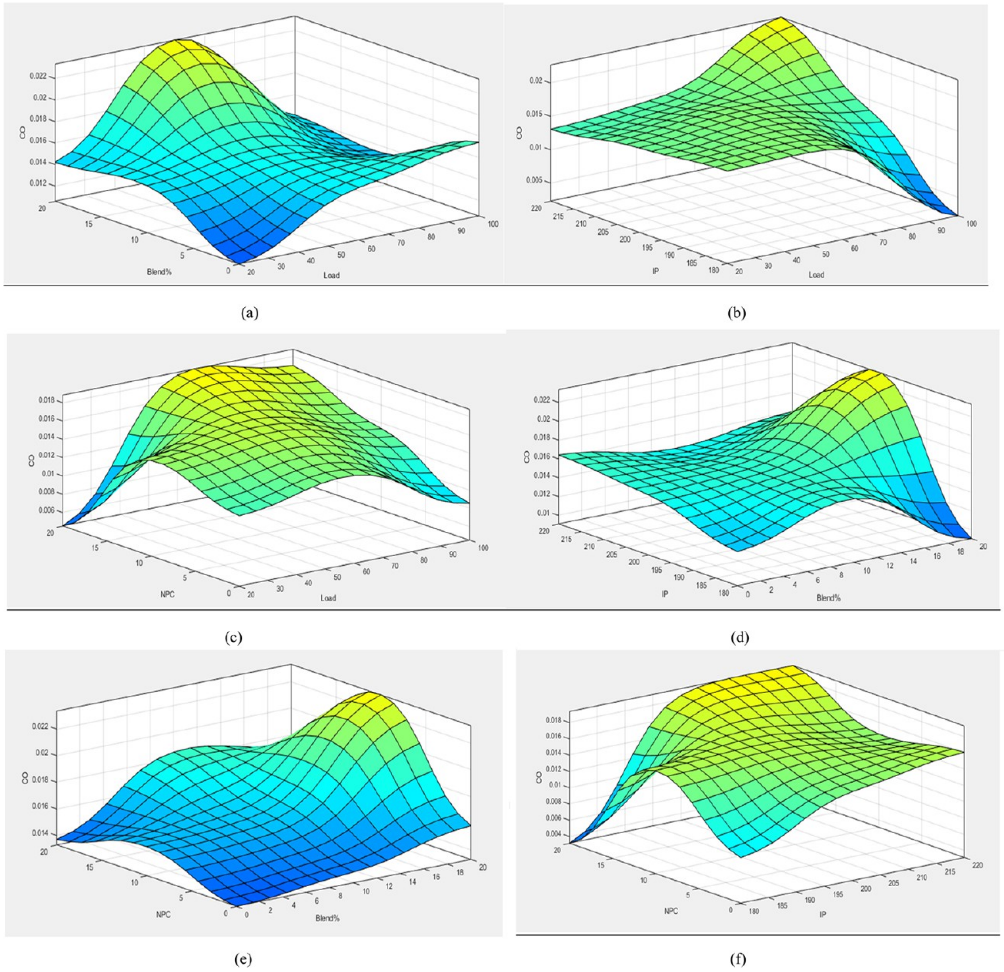

Figure 12. Surface plots for CO vs input conditions (a−f).

$$\begin{aligned}\mathrm{BTE} ={}& 45.6 - 0.0660\,\mathrm{LOAD} + 0.830\,\mathrm{BLEND\%} - 0.394\,\mathrm{IGN\ PRE} \\ &+ 0.630\,\mathrm{NPC} - 0.000050\,\mathrm{LOAD} \times \mathrm{LOAD} - 0.00224\,\mathrm{BLEND\%} \\ &\times \mathrm{BLEND\%} + 0.001121\,\mathrm{IGN\ PRE} \times \mathrm{IGN\ PRE} + 0.002671\,\mathrm{NPC} \\ &\times \mathrm{NPC} + 0.000337\,\mathrm{LOAD} \times \mathrm{BLEND\%} + 0.000593\,\mathrm{LOAD} \\ &\times \mathrm{IGN\ PRE} - 0.000814\,\mathrm{LOAD} \times \mathrm{NPC} - 0.003279\,\mathrm{BLEND\%} \\ &\times \mathrm{IGN\ PRE} + 0.00420\,\mathrm{BLEND\%} \times \mathrm{NPC} - 0.002259\,\mathrm{IGN\ PRE} \\ &\times \mathrm{NPC}\end{aligned} \tag{13}$$

$$\begin{aligned}\mathrm{BSFC} ={}& 2.775 - 0.006405\,\mathrm{LOAD} + 0.03416\,\mathrm{BLEND\%} \\ &+ 0.004270\,\mathrm{IP} - 0.04270\,\mathrm{NPC} + 0.000000\,\mathrm{LOAD} \times \mathrm{LOAD} \\ &- 0.000000\,\mathrm{BLEND\%} \times \mathrm{BLEND\%} - 0.000000\,\mathrm{IP} \times \mathrm{IP} \\ &- 0.000000\,\mathrm{NPC} \times \mathrm{NPC} - 0.000000\,\mathrm{LOAD} \times \mathrm{BLEND\%} \\ &+ 0.000000\,\mathrm{LOAD} \times \mathrm{IP} + 0.000000\,\mathrm{LOAD} \times \mathrm{NPC} - 0.000000 \\ &\mathrm{BLEND\%} \times \mathrm{IP} - 0.000000\,\mathrm{BLEND\%} \times \mathrm{NPC} + 0.000000\,\mathrm{IP} \\ &\times \mathrm{NPC}\end{aligned} \tag{14}$$

$$\begin{aligned}\mathrm{NOx} ={}& 108.22 + 0.34025\,\mathrm{LOAD} + 1.7973\,\mathrm{BLEND\%} + 0.2119\,\mathrm{IP} \\ &- 2.2502\,\mathrm{NPC} + 0.000008\,\mathrm{LOAD} \times \mathrm{LOAD} + 0.000241 \\ &\mathrm{BLEND\%} \times \mathrm{BLEND\%} + 0.000037\,\mathrm{IP} \times \mathrm{IP} - 0.000248\,\mathrm{NPC} \\ &\times \mathrm{NPC} - 0.000097\,\mathrm{LOAD} \times \mathrm{BLEND\%} - 0.000001\,\mathrm{LOAD} \times \mathrm{IP} \\ &+ 0.000029\,\mathrm{LOAD} \times \mathrm{NPC} + 0.000092\,\mathrm{BLEND\%} \\ &\times \mathrm{IP} + 0.000054\,\mathrm{BLEND\%} \times \mathrm{NPC} - 0.000078\,\mathrm{IP} \times \mathrm{NPC}\end{aligned} \tag{15}$$

$$\begin{aligned}\mathrm{UBHC} ={}& 37.1 - 0.0074\,\mathrm{LOAD} - 0.291\,\mathrm{BLEND\%} - 0.271\,\mathrm{IP} \\ &- 0.145\,\mathrm{NPC} - 0.00068\,\mathrm{LOAD} \times \mathrm{LOAD} + 0.00305\,\mathrm{BLEND\%} \\ &\times \mathrm{BLEND\%} + 0.000659\,\mathrm{IP} \times \mathrm{IP} - 0.00095\,\mathrm{NPC} \times \mathrm{NPC} \\ &- 0.000562\,\mathrm{LOAD} \times \mathrm{BLEND\%} + 0.000028\,\mathrm{LOAD} \times \mathrm{IP} \\ &+ 0.0099\,\mathrm{LOAD} \times \mathrm{NPC} + 0.0096\,\mathrm{BLEND\%} \times \mathrm{IP} + 0.0020 \\ &\mathrm{BLEND\%} \times \mathrm{NPC} + 0.036\,\mathrm{IP} \times \mathrm{NPC}\end{aligned} \tag{16}$$

$$\begin{aligned}\mathrm{CO} ={}& 0.0412 - 0.000055\,\mathrm{LOAD} + 0.000713\,\mathrm{BLEND\%} \\ &- 0.000358\,\mathrm{IP} + 0.000580\,\mathrm{NPC} - 0.000000\,\mathrm{LOAD} \times \mathrm{LOAD} \\ &- 0.000002\,\mathrm{BLEND\%} \times \mathrm{BLEND\%} + 0.000001\,\mathrm{IP} \times \mathrm{IP} \\ &+ 0.000002\,\mathrm{NPC} \times \mathrm{NPC} + 0.000000\,\mathrm{LOAD} \times \mathrm{BLEND\%} \\ &+ 0.000000\,\mathrm{LOAD} \times \mathrm{IP} - 0.000001\,\mathrm{LOAD} \times \mathrm{NPC} - 0.000003 \\ &\mathrm{BLEND\%} \times \mathrm{IP} + 0.000004\,\mathrm{BLEND\%} \times \mathrm{NPC} - 0.000002\,\mathrm{IP} \\ &\times \mathrm{NPC}\end{aligned} \tag{17}$$

The ANFIS-GA hybrid model approximated the predicted parameters, further ascertaining the fuzzy rules and association between input and output variables. The soft computing approach (ANFIS) coupled with an optimization model (GA) uses the best of both systems, therefore enabling a quicker and efficient architecture process. The intelligent model is applied to predict the performance parameters (BTE and BSEC) and emission parameters (UBHC, NOx, and CO) based on the association developed earlier with the available experimental data set, as displayed in Figures 14−18. Comparative analysis between the ANFIS-GA and ANFIS methods shows that the

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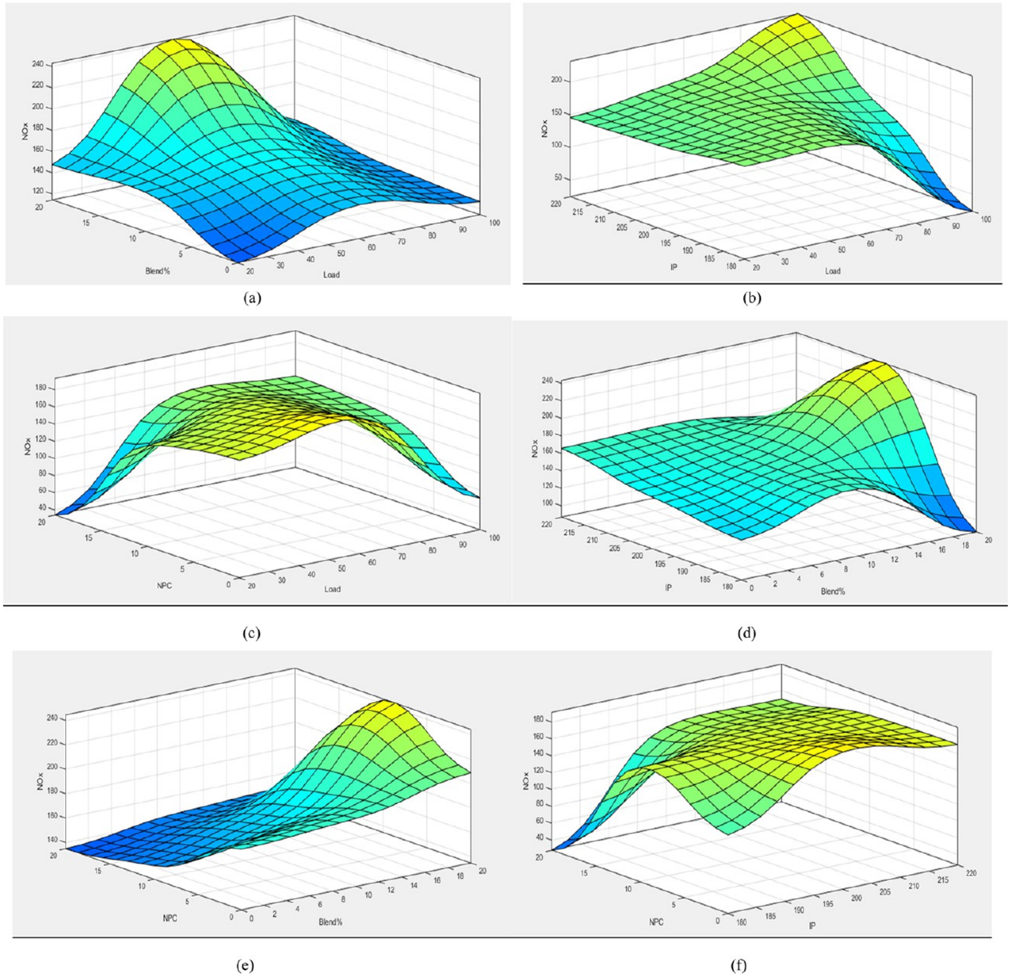

Figure 13. Surface plots for NOx vs input conditions (a−f).

former method outperformed the latter model based on the accuracy of prediction. Moreover, the major benefit of employing soft computing and optimization integrated methods lies in eradicating the overestimated or underestimated numbers. Thus, the ANFIS-GA algorithm has proved to be an influential instrument for modeling the engine performance and emission characteristics.

4.3. Prediction of Engine Performance and Emission Parameters by ANFIS-HSA. As explained in the previous section, values are generated from the ANFIS model to fine-tune the extreme conditions with the help of the HSA approach. The HSA estimates perfect operational input variables in accordance with ASTM standards for diesel engines. This particular optimization approach has previously been successfully employed in many fields of engineering for multifunction optimization, therefore yielding faster convergence and appropriate sorting based on the cost function.[28,29] The initial parameters such as harmony memory size (HMS), harmony memory considering rate (HMCR), bandwidth (BW), pitch adjusting rate (PAR), and stopping criteria are established in the model. Harmony matrix (HM) is established using randomly generated solution vectors within the upper and lower bounds of design variables based on the cost function. The solution having the best cost function replaces the worst one with every subsequent iteration. Generally, multiobjective optimization applied in diesel engines involves complex nonlinear equations with contrasting objectives. Therefore, to address this complexity in engine output responses, heuristic techniques such as HSA have been used to facilitate fast and efficient values. The simulation was performed by writing a code in MATLAB software (version R2018a), which worked on the ANFIS-HSA optimization method. The Pareto-optimal front set developed for engine parameters was attained at the best operating conditions. Table 9 depicts the results obtained by the above algorithm, also showing the best conditions to attain the required engine outputs. A comparative plot is displayed in Figures 14−1818, which displays the estimated and experimental outcomes for a fuzzy system for all models. The outcomes attained in this section were in close agreement with the generated experimental values, thereby displaying their dominance on similar models (ANFIS and ANFIS-GA) for data prediction. Therefore, the ANFIS-HSA integration proved to be a fruitful transition in predicting accurate results with a higher generalization capability for performance and emission characteristics for diesel engines.

The Pareto-optimal front established in the ANFIS-HSA approach is displayed (in bold line) in Table 7. Optimal conditions attained are an optimal trade-off between the five established outcomes defined in the model earlier. In all 60 trials, the best input conditions representing the ultimate trade-off between outcomes are presented in Table 9. The optimized responses generated from the above technique are displayed in the bolded line in the table, where the optimum load is 100%, the optimum blend percentage is 20%, the optimum nanoparticle

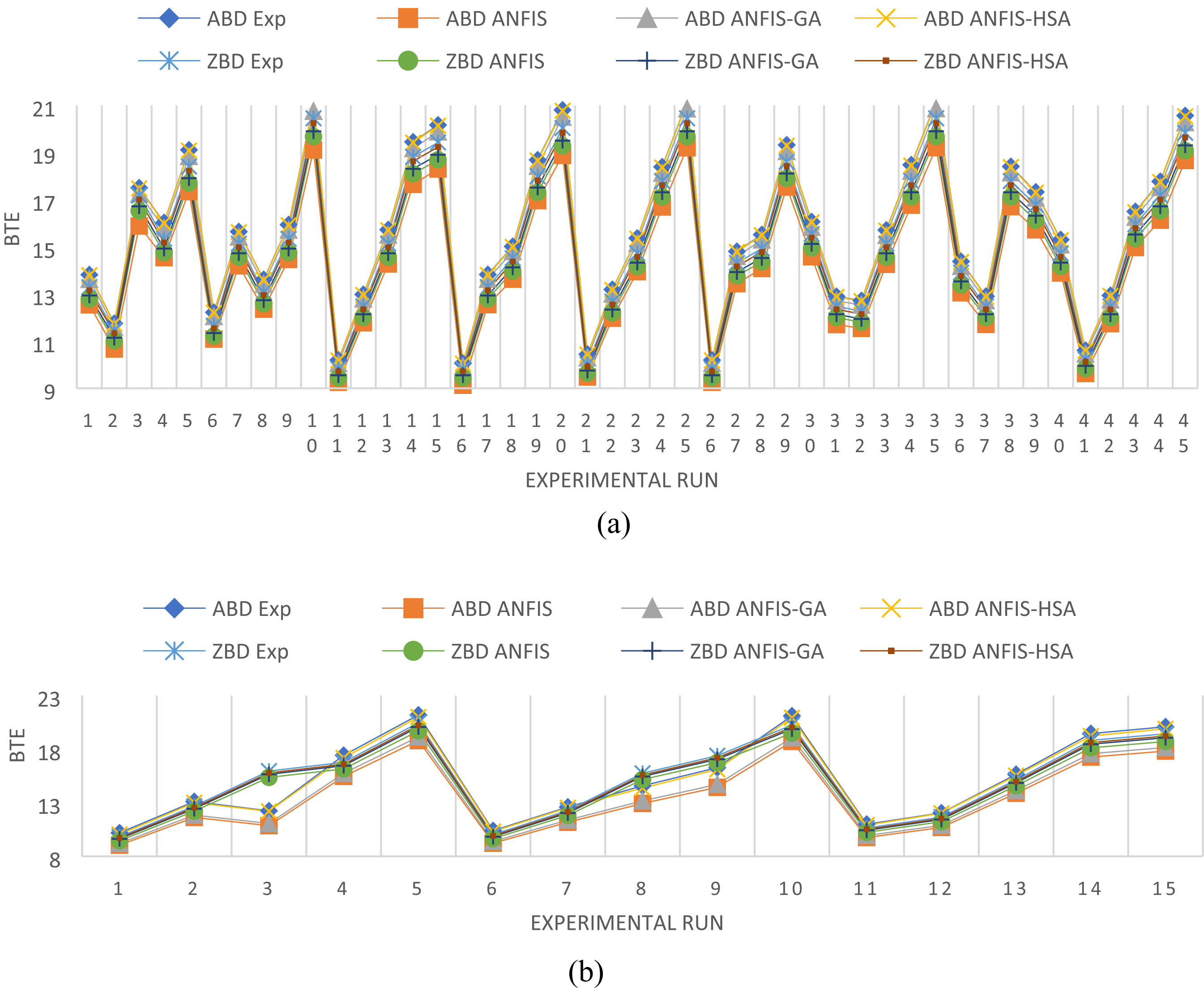

Figure 14. Comparative study of observational and expected outcomes for (a) BTE training and (b) BTE testing.

concentration (NPC) is 20 ppm, and the optimum injection pressure (IP) is 200 bar. These conditions yield BTE to be 20.80 kW, BSEC to be 2.48047, NOx to be 150.501 ppm, UBHC to be 4.05025 ppm, and CO to be 0.018326%, which is a trade-off between output values. A preference ranking was developed for the established outcomes, in which BTE was given the maximum preference, while BSEC, NOx, UBHC, and CO were considered equally. In addition, the rest of the factors (outputs) were satisfactory and in accordance with the ASTM standards and EN standards for diesel engines for these optimized conditions. Furthermore, substantial variation between optimum operating conditions and conventional operating conditions was registered. Henceforth, the above statement justifies and validates the suitability of engine characteristic analysis by employing the ANFIS-HSA model so as to analyze and optimize complex diesel engine parameters.

4.4. Comparative Study of the Predicted Values of the Developed Models. The results predicted by fuzzy optimized models (ANFIS, ANFIS-GA, and ANFIS-HSA) were compared with the original experimental values on the basis of regression methods such as root-mean-square error (RMSE) and fraction of variance R^2. The accuracy of the predictive model was validated by considering the regression formulas like RMSE and R^2. Figures 19–23 present a comparative analysis of the regression errors approximated from the predicted outcomes such as BTE, BSEC, UBHC, CO, and NO_X, respectively. The error values generated by the ANFIS-HSA model were quite parallel to the experimental responses in comparison to those obtained by ANFIS and ANFIS-GA modeling. Therefore, the predicted outcomes generated in the ANFIS-HSA framework are more reliable and exact in formulating the fuzzy relationship in comparison to its counterparts. The graphs plotted validate the usefulness of soft computing techniques as the estimated values are quite close to the experimental value, enabling an accurate fit. Also, better results were evaluated in the case of ANFIS-HSA integration in comparison to the single ANFIS model and the ANFIS-GA model.[45]

4.5. Ranking Analysis. The multiple attribute performance models furnished by the TOPSIS method were adopted in this research to enhance the performance of the diesel engine prediction models, which includes the following steps.

Step 1: Gather data from stakeholders regarding the essential evaluations of the outcome responses in linguistic terms such as extremely low, low, average, high, and extremely high from the experts.

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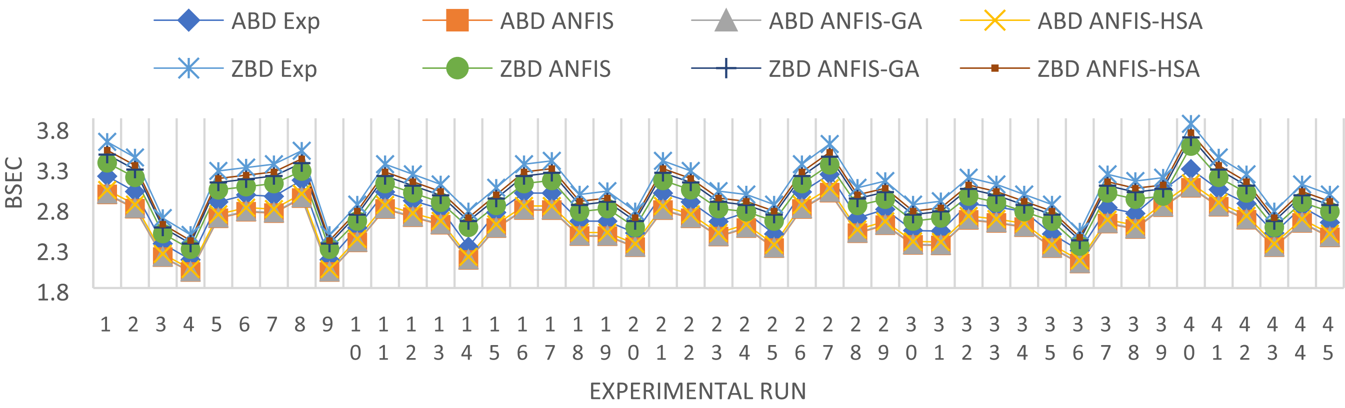
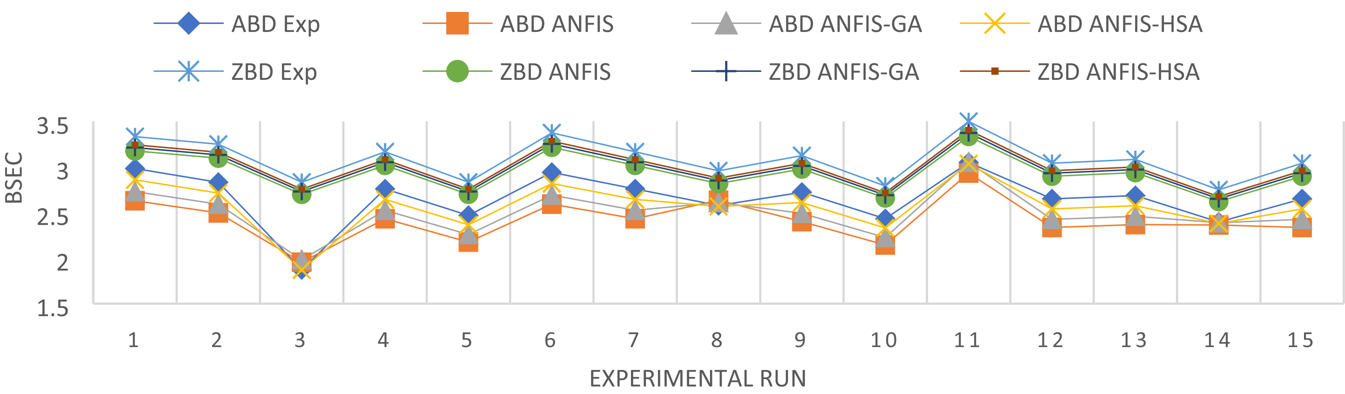


(a)



(b)

Figure 15. Comparative study of observational and expected outcomes for (a) BSEC training and (b) BSEC testing.

Step 2: Transform various linguistic values into numeral valuations.

$X_{abN} = (l_{abN},\cdots,)$, where $a = 1, 2, 3,\cdots, m$; $b = 1, 2, 3,\cdots n$, where

$$a = \min\{l_{abN}\},\quad b = \frac{1}{N}\sum_{N=1}^{N} P_{abN},\quad c = \max(u_{abN}) \tag{18}$$

Step 3: evaluate the outcome responses for the combined weights.

$$B = [P_{ij}]_{m\times n} \tag{19}$$

Here, $i = 1, 2, 3,\cdots, m$; $j = 1, 2, 3,\cdots, n$

$$P_{ij} = \left(\frac{a_{ij}}{c_j^*}\right);\quad c_j^* = \max c_{ij} \tag{20}$$

$$P_{ij} = \left(\frac{a_j^-}{c_{ij}}\right);\quad a_j^* = \min a_{ij} \tag{21}$$

Step 4: standardize the overall output matrices.

$$V = [v_{ij}]_{m\times n},\quad \text{where } i = 1, 2, 3, \cdots,\ m;\ j = 1, 2, 3, \cdots,\ n \tag{22}$$

Here

$$v_{ij} = p_{ij}(\times)w_j \tag{23}$$

Step 5: compute the standardized weighted matrices.

$$A^+ = \{v_1^+, \cdots, v_n^+\} \tag{24}$$

where

$$v_j^+ = \{\max(v_{ij}) \text{ IF } j \in J;\ \min v_{ij} \text{ IF } j \in J'\},\ j = 1, 2, 3, \cdots, n \tag{25}$$

$$A^- = \{v_1^-, \cdots,\ v_n^-\}, \text{ where } v_j^- = \{\max(v_{ij}) \text{ IF } j \in J;\ \min v_{ij} \text{ IF } j \in J'\},\ j = 1, 2, 3, \cdots, n \tag{26}$$

Step 6: establish the optimal solutions that are both positive and negative.

$$d_i^+ = \left\{\sum_{j=1}^{n}(v_{ij} - v_{ij}^+)\right\}^{1/2};\ i = 1, 2, \cdots, m \tag{27}$$

$$d_i^- = \left\{\sum_{j=1}^{n}(v_{ij} - v_{ij}^-)\right\}^{1/2};\ i = 1, 2, \cdots, m \tag{28}$$

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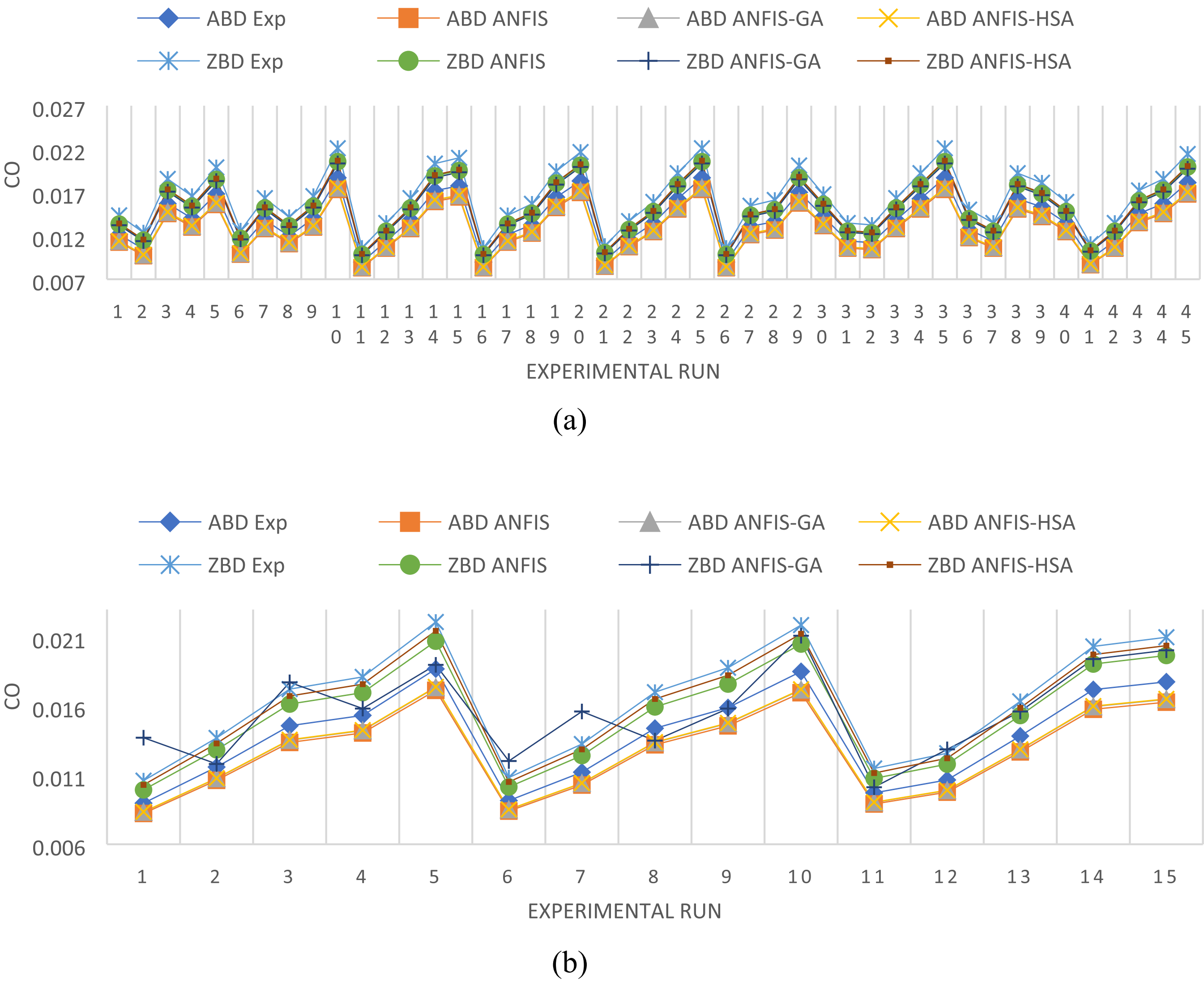

Figure 16. Comparative study of observational and expected outcomes for (a) CO training and (b) CO testing.

Step 7: compute the differences between the actual data collected from the ideal both positive and negative.

$$CC_i = \frac{d_i^-}{d_i^- + d_i^+};\ i = 1, 2, \cdots, n \tag{29}$$

Step 8: estimate the closeness coefficient (CC) data and evaluate the pre-experimental studies based on them, starting with research having the maximum CC value marked with the highest rank. The rank degrades with decreasing CC value.

Table 8 illustrates the linguistic equivalents assigned to the outcome reactions of the significance levels.

The essential weightage assigned to each attribute in linguistic equivalents was independently evaluated by a decision-making committee of key experts of the industry.

The performance score of each model was calculated after calculating the ideal best and ideal worst and the Euclidean distance in respective steps as shown in Table 9. Table 10 establishes the rank for each model used.

This study finally establishes the dominance of one model over another and optimizes the criteria for the prediction model based on performance attributes among the models and finds that the best model is ANFIS-HSA, followed by ANFIS-GA, and finally, the least favorite is ANFIS.[46]

4.6. Discussion.

The results predicted by fuzzy optimized models (ANFIS, ANFIS-GA, and ANFIS-HSA) were compared with the original experimental values on the basis of regression methods such as root-mean-square error (RMSE) and fraction of variance R^2. The accuracy of the predictive model was validated by considering the regression formulas like RMSE and R^2.

The error values generated by the ANFIS-HSA model were quite parallel to the experimental responses in comparison to those obtained by ANFIS and ANFIS-GA modeling. Therefore, the predicted outcomes generated in the ANFIS-HSA framework are more reliable and exact in formulating the fuzzy relationship in comparison to its counterparts. The graphs plotted validate the usefulness of soft computing techniques as the estimated values are quite close to the experimental value, enabling an accurate fit. Also, better results were evaluated in the case of the ANFIS-HSA integration in comparison to the single ANFIS model and the ANFIS-GA model. This study finally establishes the dominance of one model over another and optimizes the criteria for the prediction model based on performance attributes among the models and finds that the best model is ANFIS-HSA, followed by ANFIS-GA, and finally the least favorite is ANFIS.

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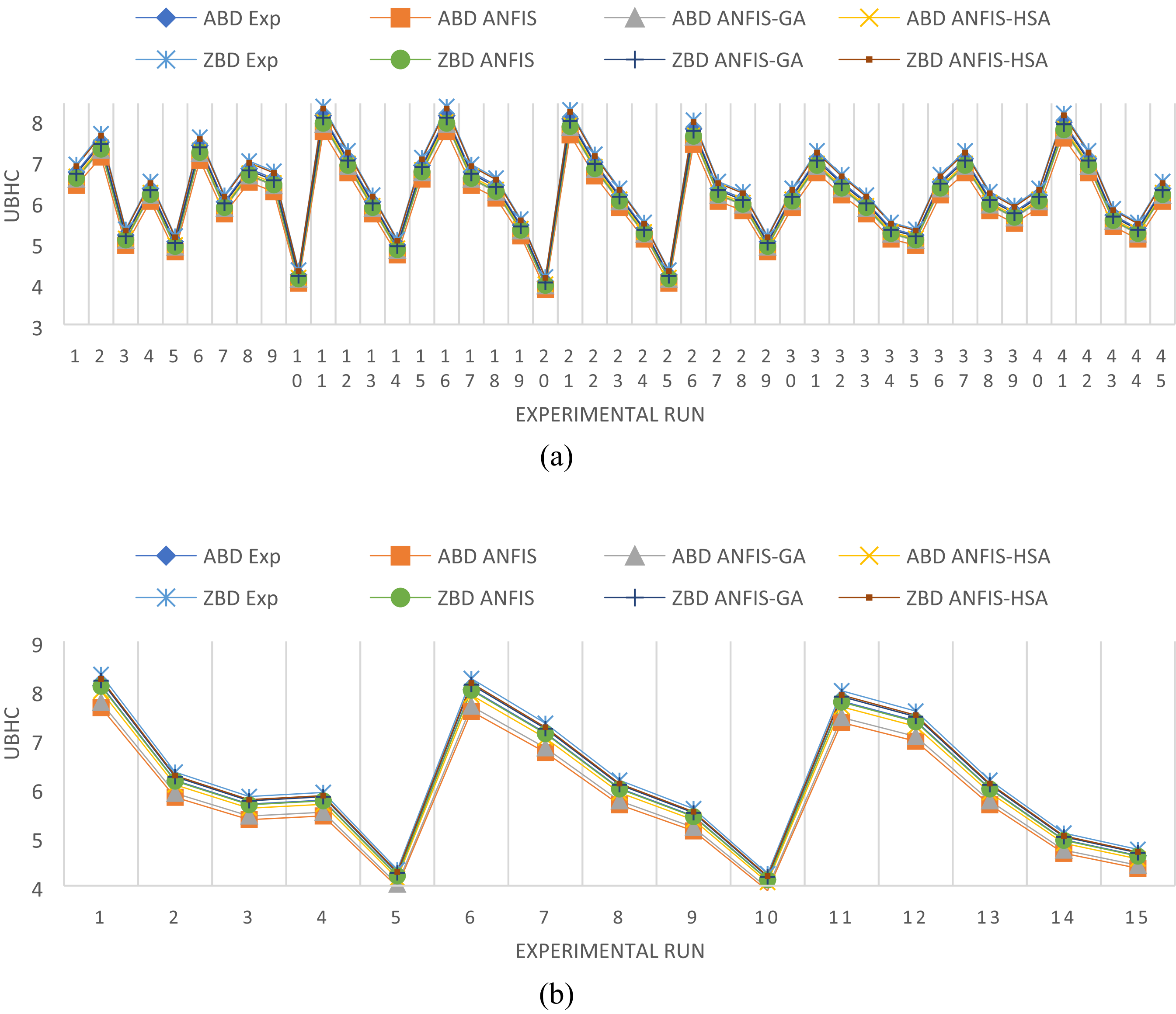


Figure 17. Comparative study of observational and expected outcomes for (a) UBHC training and (b) UBHC testing.

5. VALIDATION OF THE PROPOSED MODEL WITH PREVIOUS STUDIES

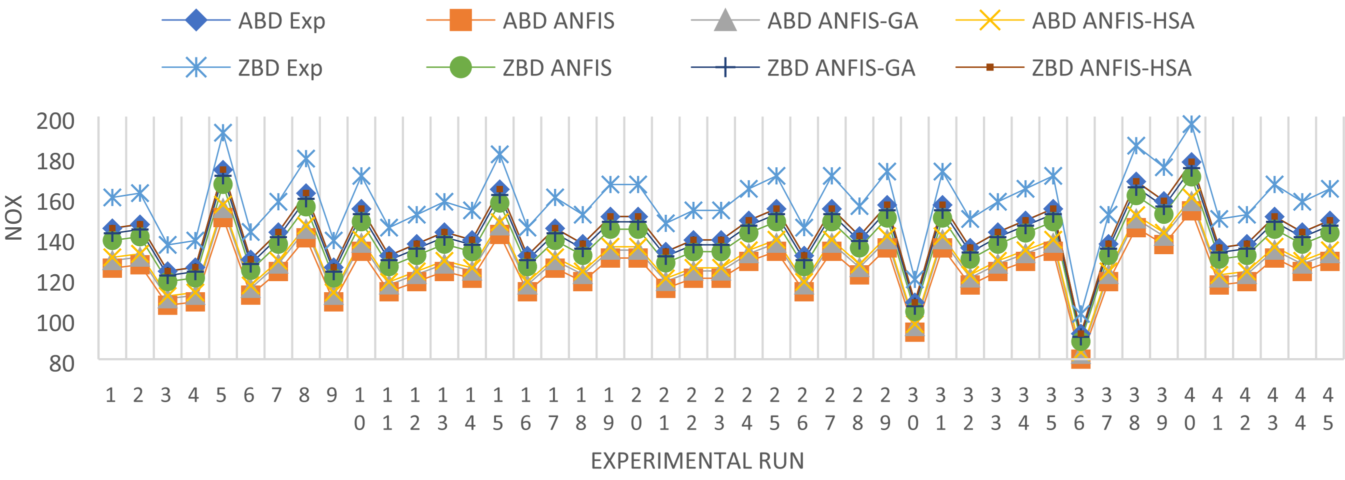
The intelligent-optimized models prepared in this study were compared to other model integrations in thermal engineering applications on the basis of statistical errors (RSME and R^2). The values generated by ANFIS-HSA were deemed quite close and parallel to experimental values when compared to other previous models that applied ANFIS or a similar framework to predict output values.[47] Therefore, the model furnished a comprehensive R^2 value approaching 1, showing its accuracy. To validate and defend the selection of the ANFIS-HSA model, previous thermal engineering-related models were recollected and compared, as presented in Table 11. In accordance with earlier models, the present model has shown the same pattern of higher accuracy (lowered RSME with a higher R^2) in the ANFIS-HSA model, thereby validating the proposed fuzzy-optimization integrated framework.

6. ACADEMIC CONTRIBUTION OF THE RESEARCH

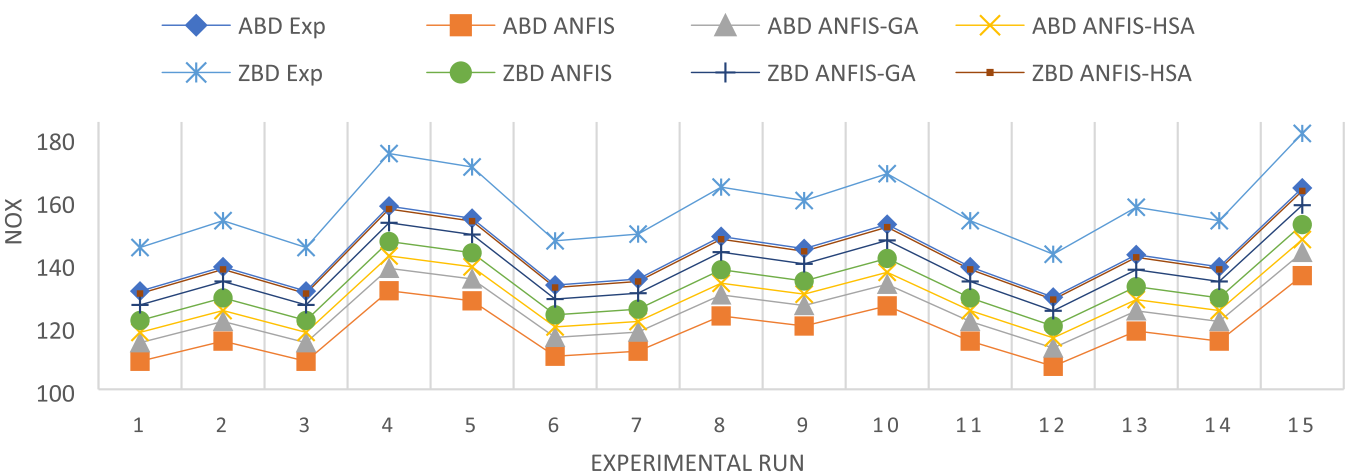
The ongoing COVID-19 pandemic is unquestionably one of the most devastating events in the last few decades or so. One of its major spread contributors is exhaust gas effluents, whose molecules bind with the virus, making it spread at a higher rate than normal. The second and third lockdowns are the primary examples of the spread. Henceforth, using a sustainable fuel and researching the experimental data through hybrid models will counter the spread of this virus by lowering exhaust gases as the pandemic has influenced people in all parts of the world.[48] At an individual level, everyone can contribute by using such sustainable fuels with a smaller data set. Also, future researchers will have a feasible model that can yield efficient valuable experimental values for potential upcoming feedstocks being sustainable in nature.[49−51]

7. CONCLUSIONS, LIMITATIONS, AND SCOPE FOR FUTURE WORK

7.1. Conclusions. This study explored the potential of waste EC plants, which are widely found in tropical countries, to be



(a)



(b)

Figure 18. Comparative study of observational and expected outcomes for (a) NOx training and (b) NOx testing.

Table 7. Pareto-Optimal Front Set[a]

trial run	load	blend, %	IP	NPC	BTE	BSEC	UBHC	CO	NOx
50	100	20	220	20	24.87	2.9036	4.9556	0.022	181.6
9	80	0	210	15	15.94	2.1499	6.5614	0.014	125.42
20	**100**	**20**	**200**	**20**	**20.802**	**2.4805**	**4.0503**	**0.018**	**150.5**
26	20	0	180	0	10.198	2.9886	7.7765	0.009	131.21
36	20	0	180	20	14.38	2.2627	6.4804	0.013	92.616

[a]Bolded line shows the best operational condition for corresponding engine outputs.

used in diesel engines by employing smaller and faster data sets generated through soft computing and metaheuristic techniques. The attained values through the prediction system were compared with experimental values. Input constraints considered were blend proportion, load application, ignition pressure (IP), and nanoadditive concentration (NPC). Furthermore, the biodiesel is intermixed with a couple of metallic nanoadditives so as to achieve the best engine characteristics among the different blends. The outcome parameters comprised both engine performance and exhaust parameters, which were compared with values attained by employing hybrid models discussed earlier. The primary reason for predicting model-based engine outcomes is the complexity of attaining values of different and large data sets in the case of diesel engines, which also seems to be a tedious job. Thus, the present research validates the practicability of such models in diesel engines as the outcomes predicted achieved utmost accuracy with a cost-effective framework. The mixed model employed the AI system to generate real models so as to predict engine responses efficaciously. The models were later ranked on the basis of attributes and criteria to provide future researchers with some groundwork. Furthermore, optimization techniques yielded a

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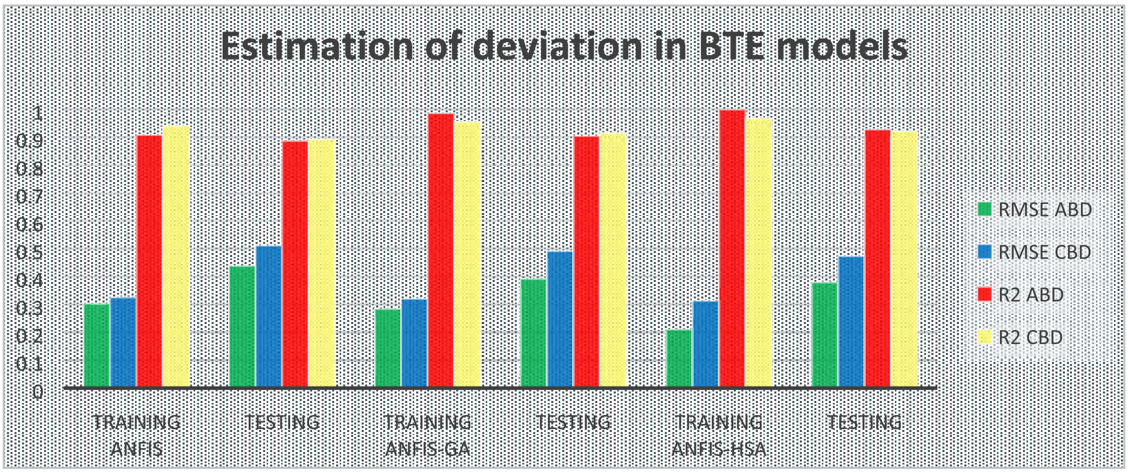

Figure 19. Comparative error study of various BTE models.

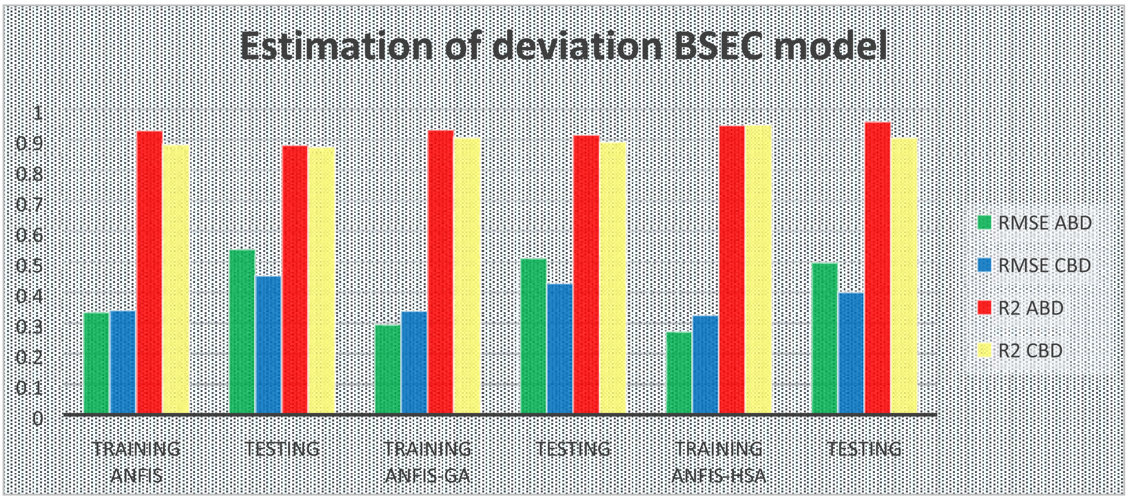

Figure 20. Comparative error study of various BSEC models.

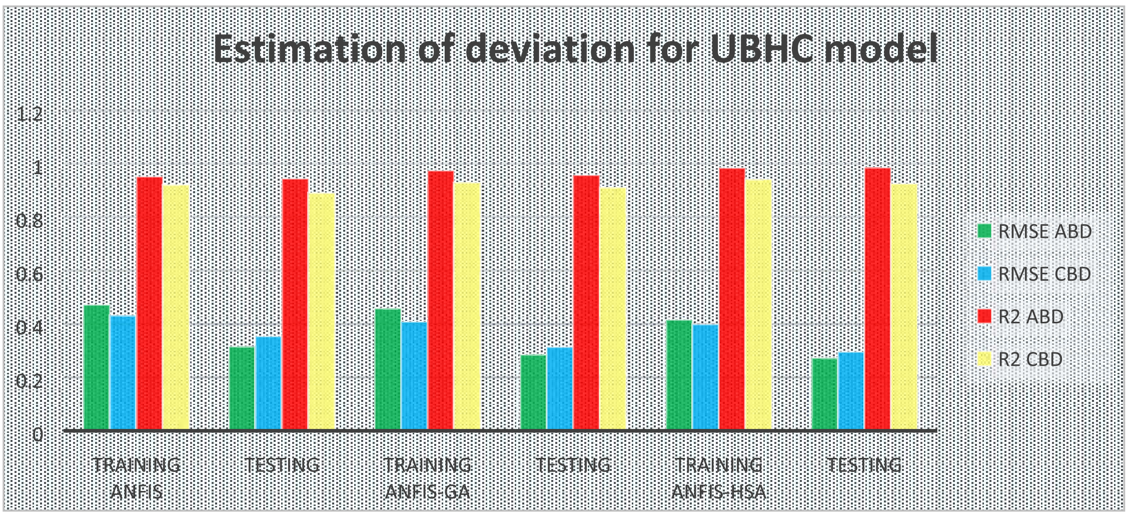

Figure 21. Comparative error study of various UBHC models.

perfect engine input combination, which furnished the best possible input conditions for the biodiesel and its blends employed in diesel engines. The scientific study might be implemented in the real world by setting proper equipment for collection of EC plants and converting them into sustainable biodiesels. Furthermore, various feedstock performance can be

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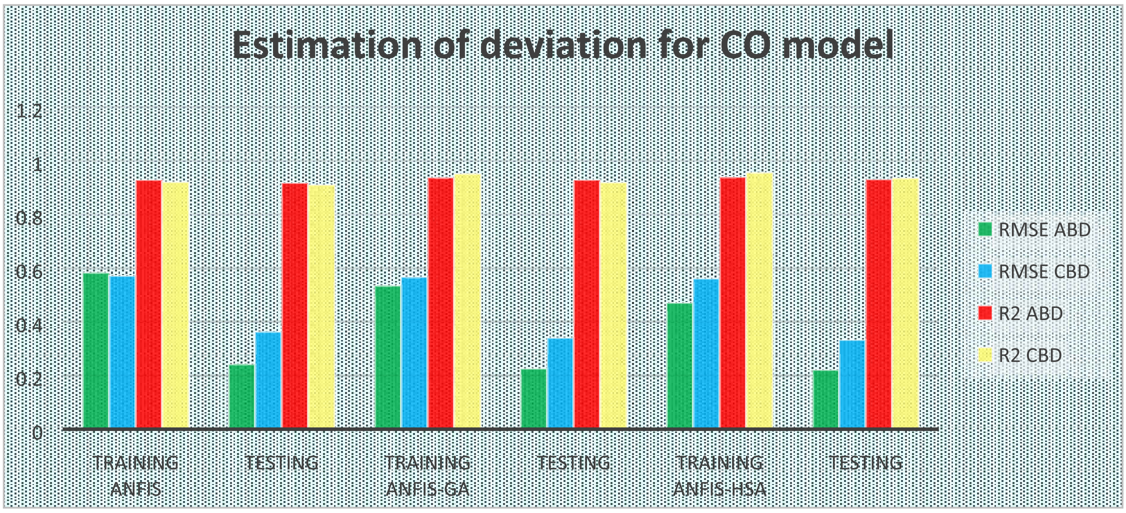

Figure 22. Comparative error study of various CO models.

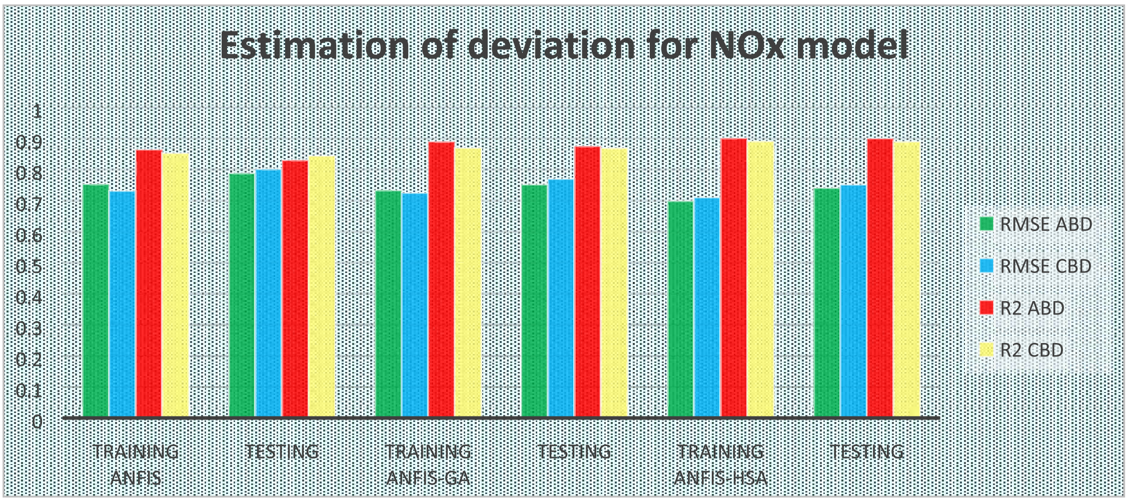

Figure 23. Comparative error study of various NOx models.

Table 8. Linguistic Equivalents Assigned to the Outcome Reactions of the Significance Levels

models/attributes	cost	accuracy	skill requirement	time
importance	nonbeneficial	beneficial	nonbeneficial	nonbeneficial
ANFIS-HSA	3	5	4	2
ANFIS	4	4	1	3
ANFIS-GA	4	4	4	4

easily computed by smart models (ANFIS-HSA) by adopting strategies that yield faster results at a lower cost and high accuracy. This research will aid the community by providing a cleaner fuel and thereby safeguarding the environment from exhaust gases. The main results of the research are enumerated as follows.

Table 10. Ranking of Models' Selection Process in Solar Radiation

models	P_i (score)	rank
ANFIS-HSA	0.70155	1
ANFIS-GA	0.55798	2
ANFIS	0.48323	3

- The general framework of the research was based on hybridization of models with AI and metaheuristic techniques to probe diesel engine characteristics with multiple combinations of biodiesel blends and NPC, which successfully replicated the original experimental data sets, proving the model's replicability in diesel engines.

Table 9. Positive and Negative Ideal Solution Matrix along with Performance Score

models/attributes	cost	accuracy	skill requirement	time	P_i
ANFIS-HSA	0.02275702	0.260308	0.163439159	0.04117143	0.70155
ANFIS	0.03034269	0.208247	0.04085979	0.06175714	0.48323
ANFIS-GA	0.03034269	0.208247	0.163439159	0.08234286	0.55798

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Table 11. Comparison of the Prediction Capability of Various Models and Developed ANFIS-HSA

references	model	RMSE	R^2
Mostafaei[40]	ANFIS	0.28	0.94
Callejon-Ferre et al.[42]	ANFIS-GA	3.470	0.38
Naderloo et al.[18]	ANFIS	0.32	0.87
Gupta et al.[44]	ANFIS-GA	0.34	0.96
Aghbashlo et al.[47]	ANFIS-ALFIMO	0.423	0.92
BTE (current study) (ABD)	ANFIS-HSA	0.210	0.9981
BSEC (current study) (ABD)	ANFIS-HSA	0.272	0.9463
NOx (current study) (ABD)	ANFIS-HSA	0.698	0.9002
CO (current study) (ABD)	ANFIS-HSA	0.470	0.9214
UBHC (current study) (ABD)	ANFIS-HSA	0.415	0.9842

- Uncertainty developed among the models was assessed by statistical tools such as RSME and R^2, where the ANFIS-HSA hybrid model-achieved values were better predicted as compared to other models.
- Appreciable and superior models have been prepared that select the best combinational input characteristics, which lower the engine emissions with a small experimentation data set quickly and efficiently.
- This study also takes into consideration various nanoparticles such as aluminum oxide and zinc oxide in different concentrations, thereby evaluating the best among them in the required combination to reduce emission rates. Aluminum oxide was estimated to be the best nanoparticle with an optimum concentration of 20%.
- This study finally establishes the dominance of one model over the other and optimizes the criteria for the prediction model based on performance attributes among the models and finds that the best model is ANFIS-HSA, followed by ANFIS-GA, and finally the least favorite is ANFIS.
- The established hybrid algorithms are capable of predicting quicker results with utmost efficiency for more future biofuel combinations, thereby enabling researchers to minimize errors and develop a perfect fuel that can provide a cleaner emission process.

7.2. Limitations. Research studies always lag in some respect. Numerous limitations are associated with each research due to which the research might remain incomplete and might be potentially explored by other examiners. Corresponding to other studies, the following are some primary limitations of this study.

- Nonmetallic nanoadditives are seldom explored to prepare biodiesel−diesel and nanoadditive blends.
- Other possible waste sources of biodiesel might be interlinked with the current research.
- Limited parameters were considered in the present study.
- Only one type of engine was used without considering bigger engines.
- Combustion parameters were not considered in the research.

7.3. Scope for Future work. The restrictions or constraints of the research give proper ideas to future researchers for conducting forthcoming research. Previous studies have also suggested possible works for the soft computing field with successful results.[43] Subsequent suggestions may be considered as scope for future research.

- Combustion parameters can be incorporated in the next possible research.
- A new model, the neuro-optimization technique, might also be explored in the diesel engine field since in other engineering applications the results were noteworthy.[43]
- More input constraints might be considered to build a possible framework.
- Different types of engines might be considered for future research.

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Notes

The authors declare no competing financial interest.

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NOMENCLATURE

ASTM	American Standard Test Method
B0	0% blending (*E. crassipes* biodiesel) with diesel
B5	5% blending (*E. crassipes* biodiesel) with diesel
B10	10% blending (*E. crassipes* biodiesel) with diesel
B15	15% blending (*E. crassipes* biodiesel) with diesel
B20	20% blending (*E. crassipes* biodiesel) with diesel

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EB *E. crassipes* biodiesel
EC *E. crassipes* plant
RSM response surface methodology
BTE brake thermal efficiency
BSEC brake specific energy consumption
UBHC unburnt hydrocarbons
NOx oxides of nitrogen
CO carbon monoxide
FIS fuzzy interface system
ANFIS adaptive neuro-fuzzy inference system
A/F air−fuel ratio
GA genetic algorithm
RMSE root-mean-square error
ABD aluminum oxide biodiesel
ZBD zinc oxide biodiesel

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