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Research Article

Radial-Basis-Function-Network-Based Prediction of Performance and Emission Characteristics in a Bio Diesel Engine Run on WCO Ester

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Radial basis function neural networks (RBFNNs), which is a relatively new class of neural networks, have been investigated for their applicability for prediction of performance and emission characteristics of a diesel engine fuelled with waste cooking oil (WCO). The RBF networks were trained using the experimental data, where in load percentage, compression ratio, blend percentage, injection timing, and injection pressure were taken as the input parameters, and brake thermal efficiency (BTE), brake specific energy consumption (BSEC), exhaust gas temperature (T_{exh}), and engine emissions were used as the output parameters. The number of RBF centers was selected randomly. The network was initially trained using variable width values for the RBF units using a heuristic and then was trained by using fixed width values. Studies showed that RBFNN predicted results matched well with the experimental results over a wide range of operating conditions. Prediction accuracy for all the output parameters was above 90% in case of performance parameters and above 70% in case of emission parameters.

1. Introduction

The world is presently confronted with a twin crisis of fossil fuel depletion and environmental degradation. Indiscriminate extraction and lavish consumption of fossil fuels have led to a reduction in underground-based carbon resources. The search for an alternative fuel which promises a harmonious correlation with the sustainable development, energy conservation, and management has become highly pronounced in the present context. The fuels of bio-origin like vegetable oils can provide a feasible solution to this crisis. The energy density, cetane number, and heat of vaporization of vegetable oils are comparable to diesel values. It is renewable, available everywhere, and has proved to be a cleaner fuel and more environment friendly than the fossil fuels [1–3]. Also from the literature, it is revealed that the emissions from the biodiesel engines are comparatively lesser from the engines with the petroleum-based fuels [4–6]. But the higher viscosity of vegetable oils affects the flow properties of fuel such as spray, atomization, and consequent vaporization and air fuel mixing.

Heating and blending of vegetable oils may reduce the viscosity and improve the volatility of the vegetable oils, but its molecular structure remains unchanged. Literature survey revealed that converting vegetable oils into methyl esters will overcome all problems related with vegetable oils [7, 8].

However, high cost of biodiesel is the major obstacle for its commercialization. The biodiesel produced from vegetable oil or animal fat is usually more expensive than petroleum-based diesel fuel from 10 to 50%. Moreover during 2010, the prices of virgin vegetable oils have nearly doubled in relation to the early 2000. This is of great concern to biodiesel producers, since the cost of feedstock comprises approximately 70–95% of total operating costs at a biodiesel plant. Compared to neat vegetable oils, the cost of waste cooking oils (WCO) is anywhere from 60% less to free, depending on the source and availability. WCOs constitute a major waste generated in hotels and other public eateries.

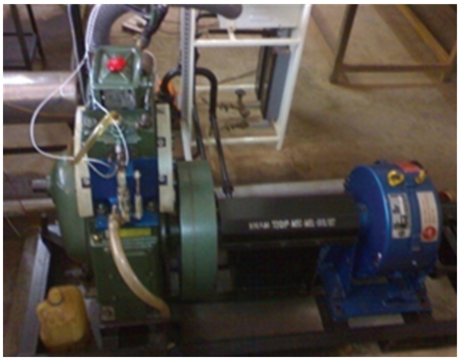

Figure 1: Photograph of the experimental setup.

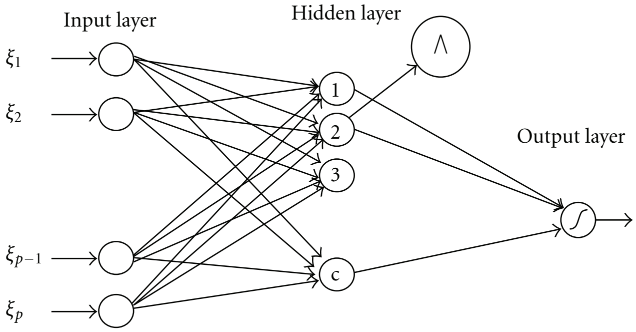

Figure 2: General architecture of RBF network.

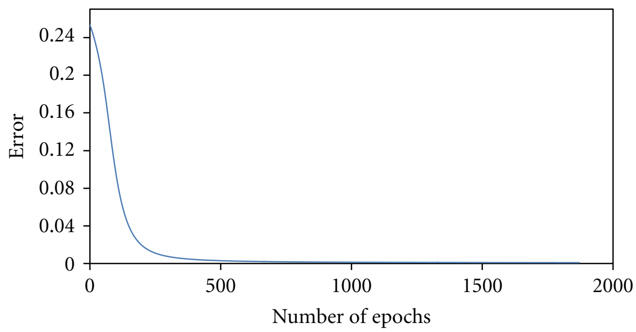

Figure 3: Variation of error during RBF training with 275 hidden neurons for the WCO methyl ester model.

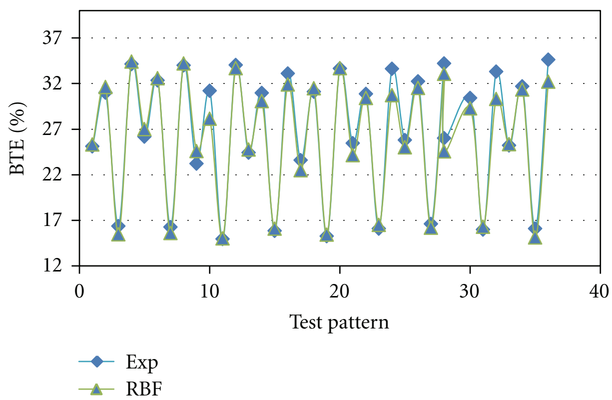

Figure 4: Comparison of experimental and network predicted values for BTE.

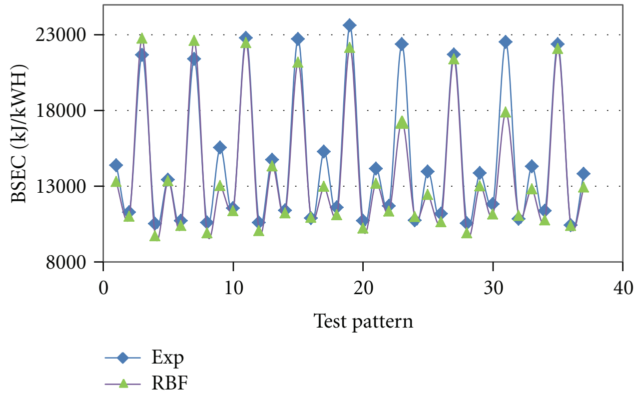

Figure 5: Comparison of experimental and network predicted values for BSEC.

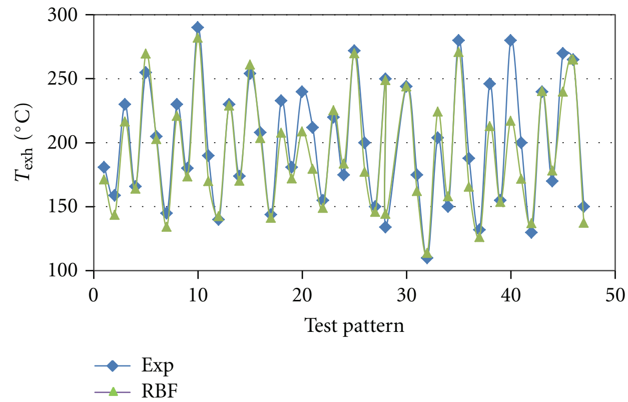

Figure 6: Comparison of experimental and network predicted values for T_{exh}.

This will be more often recycled for human consumption. The chemicals present in the recycled oil may cause health problems to human beings.

An alternative way for disposal of WCO is by recycling it. The main use of recycled WCO is in the production of animal feeds and in a much smaller proportion in the manufacture of soaps and biodegradable lubricants. Some health risks can be traced from the use of recycled cooking oils in animal feeding. Alternatively, WCO can be used as a fuel in CI engines after suitably modifying the fuel properties [9–12].

Manufacturers and engine application engineers usually want to know the performance of a C.I engine for various proportions of blends, for various compression ratios, and at different injection timings and injection pressures. This requirement can be met either by conducting comprehensive tests or by modeling the engine operation. Testing the engine under all possible operating conditions and fuel cases are both time consuming and expensive. On the other hand, developing an accurate model for the operation of a C.I engine fuelled with blends of biodiesel is too difficult due to the complex nature of the processes involved. As an alternative, engine performance and exhaust emissions can be modeled using Artificial Neural Networks (ANNs). This technique can be applied to predict the desired output

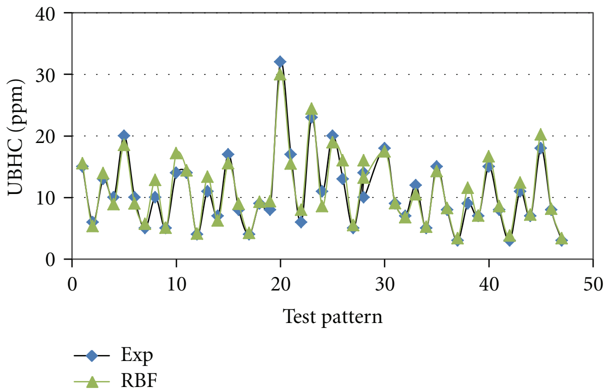

Figure 7: Comparison of experimental and RBF predicted values for test data for UBHC.

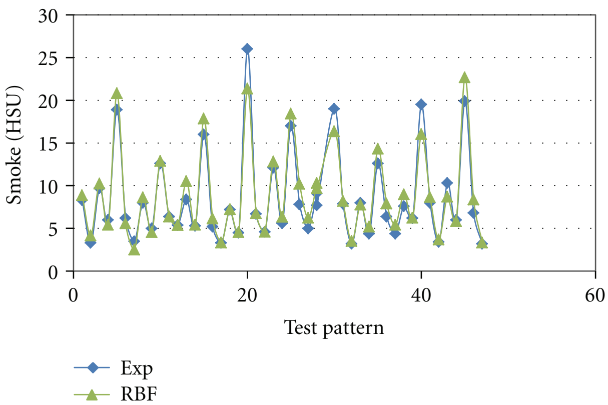

Figure 8: Comparison of experimental and network predicted values for smoke.

Table 1: Specifications of the engine.

Engine	Four stroke, single cylinder, water cooled, and constant speed diesel engine.
Rated power	3.2 KW
Speed	1500 rpm
Bore	87.5 mm
Stroke	110 mm
Compression ratio	12 to 18 : 1
Crank angle sensor	Resolution 1°
Engine indicator	For data scanning and interfacing with Pentium III processor
Swept volume	661cc
Temperature indicator	Digital PT-100

parameters when enough experimental data is made available.

ANNs are used to solve a variety of problems in science and engineering particularly in some areas where conventional modeling fail. The predictive capability of ANN results from training on experimental data and then validation by independent data. Various authors have investigated the

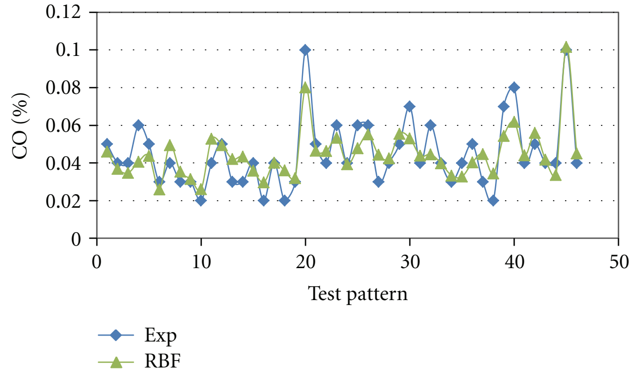

Figure 9: Comparison of experimental and network predicted values for CO.

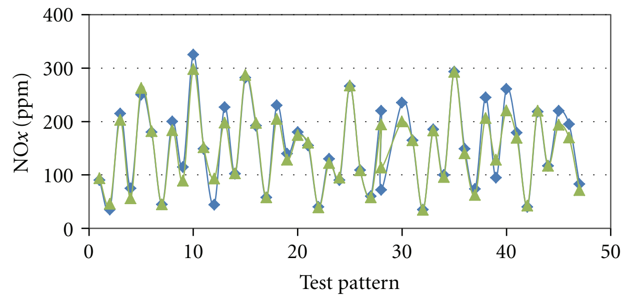

Figure 10: Comparison of experimental and network predicted values for NO_x.

Table 2: Experimental conditions using WCO methyl ester blends.

S. No	Operating parameters	Variations				
1	Engine load (%)	0	25	50	75	100
2	WCO blend (%)	10	15	20	25	
3	Compression ratio	16	17.5	18		
4	Injection timing (°BTDC)	24	27	30		
5	Injection pressure (bar)	160	190	220		

Table 3: Variation of MSE with the number of centers.

Number of centers	100	150	200	250	275	280
MSE	0.001985	0.00163	0.00149	0.0011	0.00100	0.0011

application of ANN to different thermal systems including internal combustion engines [13–17]. In a study carried out by Alonso et al. [18], ANN were employed as predicting tools for prediction of brake specific fuel consumption (BSFC), NO_x, and CO emissions. They developed individual models for emissions using the experimental data. Best prediction was obtained for BSFC and NO_x emissions. Ghobadian et al. [19] developed an ANN model to predict the engine emissions from a diesel engine using WCO as a fuel. They found fairly good results for the prediction of torque, specific fuel consumption, carbon monoxide (CO), and unburnt hydrocarbon (UBHC) emission. Yusaf et al. [20] used ANN to predict the engine torque, power, BSFC,

Table 4: Performance of RBF network with fixed centers selected at random for variable width.

S No	Variable	Training accuracy (%)	Test accuracy (%)
1	BTE	100	96
2	BSEC	99	94
3	T_{exh}	98	90
4	NO_x	88	82
5	Smoke	85	77
6	CO	72	69
7	UBHC	73	69

Table 5: Variation of MSE with the RBF width.

Width value	0.02	0.05	0.08	0.09	0.12	0.15
MSE	0.0015	0.0012	0.0010	0.0010	0.008	0.2977

Table 6: Performance of the network for optimized number of centers and width.

S No	Variable	Training accuracy	Test accuracy
1	BTE	100	96
2	BSEC	99	94
3	T_{exh}	98	90
4	NO_x	91	81
5	Smoke	85	78
6	CO	72	69
7	UBHC	72	70

and emissions from a diesel engine fuelled with CNG and diesel. ANN modeling was done with multilayer perceptron (MLP). They observed that the model was able to predict the performance and emission characteristics with a correlation coefficient of more than 0.9. Sayin et al. [21] developed ANN models to predict engine emissions from a SI engine. They observed that developed ANN models were able to predict accurately the emission parameters. Arcaklioğlu and Çelikten [22] demonstrated that ANN models accurately predict the performance parameters and emissions from a diesel engine when the engine was run on neat diesel. They took engine operating parameters as the inputs and the corresponding performance parameters and emissions as outputs for the network. The literature review reveals that use of MLP for modeling engine performance and emission characteristics is common [18–22]. But the application of radial basis function (RBF) networks for modeling of thermal systems is very limited [23–26]. In this context RBF technique has been used for modeling performance and emission characteristics of a biodiesel engine. RBFNN was developed based on the random selection of centers of the RBF units. The widths of RBF units were calculated using two approaches and a comparison has been carried out with regard to their prediction accuracy.

Table 7: Test pattern numbers corresponding to the specific engine loading condition.

Loading condition	Test patterns
25%	3, 7, 11, 15, 19, 23, 27, 31, 35
50%	1, 5, 9, 13, 17, 21, 25, 29, 33, 37
75%	2, 6, 10, 14, 16, 18, 22, 24, 26, 30, 32, 34
100%	4, 8, 12, 20, 28, 36

2. Experimental Setup

Since the direct use of vegetable oil poses problems during the running of the engines because of its higher viscosity, it is subjected to a process called as transesterification which reduces the viscosity and improves its volatility. Biodiesel is prepared from waste cooking oil using the transesterification process. Prepared biodiesel is mixed with neat diesel in various concentrations (10%, 15%, 20%, and 25%) by volume which has been termed as B10, B15, B20, and B25, respectively, and used as fuel to run the engine.

The performance and emission tests were conducted on a computerized 5.2 kW single cylinder, four stroke, naturally aspirated, direct injection, variable compression ratio, and water cooled diesel engine test rig. Figure 1 shows the photograph of the experimental setup. It is a single cylinder, four stroke compression ignition engine connected to an eddy current dynamometer. It is provided with temperature sensors for the measurement of temperatures of jacket water, calorimeter water, calorimeter exhaust gas inlet, and outlet temperature. It is also provided with pressure sensors for the measurement of combustion gas pressure and fuel injection pressure. An encoder is fixed for crank angle record. The signals from these sensors were interfaced with a computer to display P-θ, P-V, and fuel injection pressure versus crank angle plots. There is also a provision for the measurement of volumetric fuel flow. The built in software in the system calculated indicated power, brake power, thermal efficiency, volumetric efficiency, and heat balance. An AVL Digas 444 exhaust gas analyzer was used to measure the CO, HC, and NO_x emissions in the engine exhaust. An AVL 437C smoke meter was used to measure the smoke intensity in the engine exhaust. Specifications of the engine are given in Table 1. Experiments were conducted initially by using neat diesel at various loads and then with WCO methyl ester blends. Experiments were repeated by changing the compression ratios, injection timings, and injection pressures as shown in Table 2.

3. Neural Network Modeling

A neural network is a massively parallel distributed processor made up of simple processing units, which has a natural propensity for strong experimental knowledge and making it available for use. They can learn from examples and are fault tolerant in the sense that they are able to handle noisy and incomplete data. They are able to deal with nonlinear problems and once trained can perform prediction and generalization at high speeds [27]. They differ from conventional modeling approaches in their ability to learn about the system without the prior knowledge of the process relationships. The prediction by a well-trained ANN is much faster than the conventional simulation programs or mathematical models as no lengthy iterative calculations are needed to solve differential equations using numerical methods. One of the advantages is their ability to model complex nonlinear relationships between multiple input variables and required outputs. In the case of diesel engine modeling using blends of biodiesel, where complex interactions between the different variables are not yet completely understood, ANN approach for modeling is well suited. It consists of large number of neurons and interconnections between them. According to the structure of the connections, they have been identified as feed forward and recurrent networks. Feed forward networks have one-way connections, from the input to the output layer. They are most commonly used for prediction and nonlinear function fitting. Here the neurons are arranged in the form of layers. Neurons in one layer get inputs from previous layer and feed their outputs to the next layer. The last layer is called the output layer. Layers between the input and output layers are called hidden layers and are termed as multilayered networks. In the present study, modeling has been done by using radial basis function neural networks (RBFNNs), which is a feed forward network.

4. Radial Basis Function Neural Networks (RBFNNs)

RBF networks, a class of feed forward networks have universal approximation capabilities. The design of this network is viewed as a curve fitting approximation problem in a high dimensional space. According to this view point, learning is equivalent to finding a surface in a multidimensional space that provides the best fit to the training data. In its most basic form it involves 3 layers with entirely different roles. Input layer is made of source nodes that connect the network to its environment. Second is the hidden layer which applies a nonlinear transformation from the input space to the hidden space, which is of high dimensionality. Output layer is linear, supplying the response of the network to the activation patterns applied to the input layer. Figure 2 shows the general architecture of the RBF network. An RBF is symmetrical about a given mean or center in a multidimensional space. Each RBF unit has two parameters, a center x_j, and a width σ_j. This center is used to compare the network input vector to produce a radially symmetrical response. The width controls the smoothness properties of the interpolating function. Response of the hidden layer are scaled by the connection weights of the output layer and then combined to produce the network output. In the classical approach to RBF network implementation, the basic functions are usually chosen as Gaussian and the number of hidden units is fixed based on some properties of the input data. The weights connecting the hidden and output units are estimated by linear least squares method (LMS) [27].

There are different learning strategies available for the design of an RBF network, depending on how centers of the radial basis functions of the network are specified [28, 29]. In the present study, Random initialization method has been used for RBF modeling.

The simplest approach is to design RBFNN. In this, the number of radial-basis functions defining the activation functions of the hidden units are fixed. Specifically, the locations of the centers may be chosen randomly from the training data set. The RBFs use Gaussian activation function which is defined as $\phi_j(x) = \exp(-\|x_j - \xi_i\|^2/2\sigma_j^2)$, where x_j is the center and σ_j is the width (standard deviation), $j = 1, 2, \ldots, c$, where c is the number of centers. The only parameter that would need to be learned in this approach is the linear weights in the output layer of the network. The weights are learned using a simple LMS algorithm. The algorithm to train the network by using random initialization method is the following.

(1) Select the number of RBF centers arbitrarily.

(2) Initialize their centers from input data randomly.

(3) Set $E_{\text{tot}} = 0$.

(4) Choose the input output pair $(\xi_{\text{i}}^{\mu}, \zeta_{\text{k}}^{\mu})$, where $\mu = 1, 2, 3, \ldots n$ are the number of patterns and $i = 1, 2, 3, \ldots p$ are the number of input features, k is the output feature.

(5) Compute the hidden layer output $v_j = e^{\|x_j - \xi_i\|^2}/2\sigma_j^2$, where x_j is the center and σ_j is width of the RBF unit.

(6) Compute the output using $O_k = 1/(1 + e^{-\sum w_{kj} V_j})$.

(7) Compute the square error $E = (O_k - \zeta_k) \times (O_k - \zeta_k)$ and $E_{\text{tot}} = E_{\text{tot}} + E$.

(8) The change in the output layer weights are calculated as

$$\begin{aligned} \partial_k &= (O_k - \zeta_k) \times O_k \times (O_k - \zeta_k) \\ \Delta w_{kj} &= \partial_k \times v_j \times \alpha \times \eta, \end{aligned} \tag{1}$$

where η and α are learning rate and momentum parameters, and

$$w_{kj}^{\text{new}} = w_{kj}^{\text{old}} + \Delta w_{kj}. \tag{2}$$

(9) If $E_{\text{tot}} > E_{\text{min}}$ then go to step 4.

(10) Save weights, centers, widths, and exit [29].

For training the networks, load percentage, compression ratio, blend percentage, injection timing, and injection pressure were taken as the input parameters and brake thermal efficiency, brake specific energy consumption, exhaust gas temperature and engine emissions NO_x, smoke, and CO and UBHC were used as the output parameters. The training of the network has been done with different number of RBF units. The widths of the RBF units were determined using a P-nearest neighbor heuristic (each RBF unit has a different width value) [28] and studies have been carried out. The simulation parameters η and α were fixed as 0.85 and 0.05, respectively, and were maintained constant for all the studies. The data set was divided into two groups—training data set, used for training the network with about 85% of the data selected randomly, and test data set with the remaining data used for testing the network performance. For the different number of selected centers MSE have been tabulated in Table 3. It is clear from the table that the error decreases as the number of centers increased and reached a minimum for 275 beyond which the error increased. Hence, 275 was selected as the optimum number of centers. The variation of error with the number of epochs during training with 275 RBF units is shown in Figure 3.

Mean square error (MSE) has been used for evaluating the network performance. Error limit of 5% was considered for performance parameters and 10% for emission parameters [20–22]. Based on these values the prediction accuracy of the network for both training and test data is as shown in Table 4.

In another study, widths have been kept (fixed) constant for all the RBF units and the network was trained for different values of widths. Table 5 shows the MSE of RBF network with different values of widths, for 275 RBF units. It is clear from the table that the error decreased with the increase in the value of the width. The optimum value of width has been chosen as 0.08, since the MSE was least corresponding to this width. Beyond this value of the width the error started to increase. Using the above width, the network was trained and network results so obtained have been tabulated in Table 6.

On comparing the prediction accuracy of the network results, fixed widths for RBF units gave better performance prediction than variable width. The prediction accuracy for the emission parameters are relatively lower than that for the performance parameters. This could be attributed to the error made during the emission measurements and the complexity involved in the combustion process. Figures 4, 5, 6, 7, 8, 9, and 10 shows the plot of experimental and RBF network predicted results for the test data selected randomly from the entire experimental data. The results indicate that ANN predicted values are very close to the experimental values for the test data under different loading conditions (25%, 50%, 75%, and 100%). Table 7 shows the test pattern number and the corresponding loading condition with respect to BSEC. Hence RBFNN can be used for effectively predicting the performance and emission parameters of a biodiesel engine fuelled with WCO methyl ester.

5. Conclusions

In this paper an attempt has been made to model engine performance parameters and emissions using RBF neural network. Experiments were conducted on a four stroke CI engine using different biodiesel blends. Load percentage, compression ratio, blend percentage, injection timing, and injection pressure were taken as the input parameters. Brake thermal efficiency, brake specific energy consumption, exhaust gas temperature and engine emissions NO_x, smoke, UBHC, and CO were used as the output parameters. RBF neural networks which are a new class of networks not very widely used for these applications have been used in this work. Centers of the RBF units were selected randomly. Fixing the widths of RBF units rather than using variable widths calculated using P-nearest neighbor heuristic gave better results. RBF network results matched closely with the experimental results for the test data with the prediction accuracy of more than 90% for performance parameters and around 70% for emission parameters. Hence, it can be concluded that RBFNN can be effectively used for modeling a biodiesel engine.

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