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Performance and Emission Prediction in a Biodiesel Engine Fuelled with Honge Methyl Ester Using RBF Neural Networks

Shivakumar, G. S. Vijay, P. Srinivas Pai, B. R. Shrinivasa Rao

***Abstract*—**In the present study, RBF neural networks were used for predicting the performance and emission parameters of a biodiesel engine. Engine experiments were carried out in a 4 stroke diesel engine using blends of diesel and Honge methyl ester as the fuel. Performance parameters like BTE, BSEC, Tex and emissions from the engine were measured. These experimental results were used for ANN modeling.

RBF center initialization was done by random selection and by using Clustered techniques. Network was trained by using fixed and varying widths for the RBF units. It was observed that RBF results were having a good agreement with the experimental results. Networks trained by using clustering technique gave better results than using random selection of centers in terms of reduced MRE and increased prediction accuracy. The average MRE for the performance parameters was 3.25% with the prediction accuracy of 98% and for emissions it was 10.4% with a prediction accuracy of 80%.

***Keywords*—**Radial Basis Function networks, emissions, Performance parameters, Fuzzy c means.

I. Introduction

RAPID depletion in the world petroleum reserves and uncertainty in the petroleum supply have stimulated the search for alternatives to petroleum based fuels especially diesel and gasoline. Bulk of these petroleum fuels are being consumed by agricultural and transport sectors for which diesel engine happens to be the preferred prime mover. Vegetable oils have properties comparable to diesel and can be used to run compression ignition engine with little or no modification [1], [2].

Vegetable oils have higher viscosity than the diesel fuels. It will contribute to the formation of deposits, degradation of materials or plugging of filters on long running. Transesterification is one method by which viscosity and the gum content in the vegetable oils could be drastically reduced and could be adapted for use in diesel engines. This form of fuel which is chemically altered is known as biodiesel. Various vegetable oils both edible and non-edible can be considered as alternative sources for diesel engines. In most of the developed countries sunflower, peanut, palm and several other feed stocks are used as alternative sources, which are edible in the Indian context. There are concerns that they may compete with the food supply in the long term. Hence use of non-edible oils when compared with edible oils is very significant in developing countries like India, because of tremendous demand for edible oils as food and also they are quite expensive to be used as a fuel in the present conditions.

The production of biodiesel from different non edible oil seed crops has been extensively investigated over the last few years [3], [4]. Therefore in the developing countries like India, it is desirable to produce biodiesel from non-edible oils which can be extensively grown in the waste lands of the country *Pongamia pinnata* (Karanja or Honge) is one of the forest based tree borne non edible oil seed with a production potential of 135,000 metric tons per year in India. It is a medium sized, fast growing tree reaching an average height of 40 feet. It is a fast growing leguminous tree with the potential for high oil seed production and there is an added benefit of its ability to grow on marginal land (Fig. 1). These properties support the suitability of this plant for large scale oil production required by a sustainable biodiesel industry. Native to humid and subtropical environments, it thrives in areas having annual rainfall ranging from 500- 2500 mm [5]. Flowers are pink, light purple or white (Fig. 2). The trees produce seeds containing 30-40% oil. Pods are elliptical, 3 – 6 cm long and 2-3 cm wide, thick walled and usually contain a single seed. Seeds are 10-20 mm long, oblong shaped and light brown in color. A thick yellow orange to brown, bitter, nondrying, non-edible oil is extracted from the seeds. The properties of honge oil have been compared with the neat diesel and are shown in Table I. Since the properties are comparable with diesel (except viscosity) this will considered to be a promising alternative fuel for diesel engines after suitably modifying the fuel properties. Oil was subjected to transesterification and hence the viscosity of honge oil was reduced from 56 cst to 5.4 cst which is very close to the diesel. Although the diesel engines are fuel efficient, they have a negative impact on the environment, mostly related to high exhaust pollutant emissions.

TABLE I
Properties of Diesel and Karanja oil

S.No	Properties	Diesel	Honge oil
1	Densiy (kg/m^3)	840	927
2	Calorific value (kJ/kg)	43,000	35800
3	Viscosity (cst)	2-5	56
4	Flash point (ºC)	75	187
5	Cetane number	45-55	40

Shiva Kumar is with Manipal Institute of Technology, Manipal, India, 576104. (Mobile: +919449269099, e-mail: shiva_katipalla@yahoo.co.in)
Vijay G.S is with Manipal Institute of Technology, Manipal, India, 576104
Srinivasa Pai.P and Srinivasa Rao are with NMAMIT, Nitte, India, 574110.

Fig. 1 *Pongamia pinnata* tree

Fig. 2 *Pongamia pinnata* seeds

Hence an issue of major concern for the automotive industry is to achieve stringent emission regulations, while maintaining the engine performance. In this context, there is a need for prediction of performance parameters and emissions at different operating conditions from diesel engines. In case of CI engine fuelled with biodiesel, manufacturers and engine application engineers usually want to know the performance of the engine for various proportions of blends, for various operating parameters such as compression ratios, injection timings and injection pressures. This requirement can be met by different methods. The first option is by conducting comprehensive tests. Testing the engine under all possible operating conditions and fuel cases are both time consuming and expensive. The second option is by developing a mathematical model. In engineering domain, algebraic and differential equations are used to describe the behavior and functional properties of real systems and to create mathematical models to represent them [6]. Such approaches require accurate knowledge of system dynamics and use of estimation techniques and numerical calculations to emulate the system operation. The complexity of the problem itself may introduce uncertainties which make the modeling nonrealistic or inaccurate. As an alternative, engine performance and exhaust emissions can be modeled by using Artificial Neural Networks (ANNs). They have many advantages over conventional modeling techniques such as fast prediction responses, noise suppression capabilities, ability to handle large amounts of data, ability to model complex relationships between the inputs and the outputs without the need for having knowledge about the underlying distributions in the data. Several researchers have predicted the performance and emissions of the diesel engine using multilayer perceptron neural network. [7], [8]. Gholamhassan Najafi et al. [9] conducted a comprehensive combustion analysis on a direct injection, water cooled, two cylinders, in line, naturally aspirated diesel engine using WCO as the fuel. ANN model was developed based on this data. MLP was used for nonlinear mapping between the input and output parameters. Engine speed and percentage of blend were used as the input parameters and torque, BSFC, HC and CO emissions were used as the output parameters. Network was trained by using back propagation algorithm. It was found that R^2 values were high for all the predicted parameters. They concluded that ANN modeling can be applied for predicting the engine performance parameters and emissions. Erol Aracaklioglu et al. [10] used MLP to predict the emissions from the diesel engine. RMS error values were smaller than 0.02 and average R2 values for all the predicted variables were about 0.98, which were considered to be within the acceptable range. Jose M. Desantes et al. [11] used neural networks to predict and minimize NOx emissions and particulate emissions from a direct injection high speed diesel engine. They considered fuel mass, start of injection, EGR, nozzle diameter as the input variables and NOx, particulate emission and BSFC as the output variables. Instead of using a single network, individual networks were constructed for each output. MLP with back propagation algorithm was used for training the network. One hidden layer was considered with the number of neurons ranging from 9–11. Results showed that R^2 values were very close to 1, showing good relation between the input and the output variables. Literature regarding the use of Radial Basis Function networks for the prediction of performance and emission parameters was limited. Hence in the present study RBF neural networks were used to model the engine parameters using the experimental results. Two different learning strategies were used for the initialization of centers of the RBF units, random initialization and by using fuzzy c means. Network was trained by using fixed and varying widths for the RBF units in both the methods. The evolved network results were compared with the experimental results in terms of MRE and prediction accuracy and have been presented.

II. Experimentation

Engine experiments were conducted in in a single cylinder 4 stroke diesel engine using blends of diesel and honge methyl ester biodiesel. Experiments were conducted for different blend percentages, loads, various compression ratios, Injection timings and injection pressures. Matrix of the experimentation has been given in Table II. Performance parameters like BTE, BSEC, Tex, and emissions (NOx, UBHC, CO and smoke) were measured for the above conditions. These experimental results were used for training networks.

III. RBF Modeling

There are different forms of designing a supervised neural network. The back propagation algorithm for the design of a multi-layer perceptron (under supervision) can be viewed as an application of an optimization method known in statistics as stochastic approximation. Another approach can be viewing the design of a neural network as a curve-fitting problem in a high dimensional space. This involves finding a surface in a multi-dimensional space that provides a best fit to the training

data, with the criterion for "best fit" being measured in some statistical sense [12]. Correspondingly generalization is equivalent to the use of this multi-dimensional surface to interpolate the test data. This is indeed the motivation behind the method of radial-basis functions. The construction of a radial basis function network in its most basic form involves three entirely different layers. The input layer is made up of source nodes (sensory units). The second layer is a hidden layer of high enough dimension, which serves a different purpose from that in a multi-layer perceptron. The output layer supplies the response of the network to the activation patterns applied to the input layer. The transformation from the input space to the hidden-unit space is non-linear, whereas the transformation from the hidden-unit space to the output space is linear.

TABLE II
MATRIX OF ENGINE EXPERIMENTS

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

The RBF network is a single hidden-layer feed forward neural network. Each node of the hidden layer has two parameters, a center x_j and a width σ_j. This center is used to compare with the network input vector to produce a radially symmetrical response. The width controls the smoothness properties of the interpolating function. Network was trained by using two different learning strategies.

A. Fixed Centers Selected at Random

The simplest approach is to assume fixed radial-basis functions defining the activation functions of the hidden units. 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 $\Phi_j(x) = e^{\frac{-||x_j-\xi_i||^2}{2\sigma_j^2}}$ where x_j is the center and σ_j is the width (standard deviation), j = 1, 2 …c where c is the number of centers. The only parameters that would need to be learned in this approach are the linear weights in the output layer of the network. The weights are learned using a simple LMS algorithm or the gradient descent approach. The width of the basis function σ_j is given by the RMS distance of the given cluster center x_j to the P nearest neighboring centers, given by $\sigma_j = \sqrt{\left(\frac{1}{p}\sum_{p=1}^{p}\|x_j - x_{jp}\|^2\right)}$ [13]. Another heuristic is to choose all the σ_j to be equal. Out of the total 280 experimental patterns, 47 patterns were selected randomly for testing purpose and the remaining data were used for training the network. Load percentage, blend percentage, injection timing, compression ratio and injection pressure were used as the input parameters and Brake thermal efficiency, Brake specific energy consumption, exhaust gas temperature, NOx, smoke, UBHC and CO were used as the output parameters. MATLAB 8 has been used for developing the code for RBF network implementation. The RBF units for training the network were selected arbitrarily and each unit was assigned an input pattern randomly, thus initializing the centers. The momentum coefficient and learning rate were taken as 0.85 and 0.05 respectively. The maximum number of epochs was set to 2000 and the MSE goal was set to 0.001. Training was stopped when either of the performance goals was reached. Training of the network has been done with different number of RBF units. The widths of the RBF units were determined using P-nearest neighbor heuristic. The network error for the different numbers of selected centers has been shown in Fig. 3. It is clear from the Figure that the error decreased as the number of centers increased and reached a minimum for 277, beyond which the error increased. Hence 277 was selected as optimum number of centers. Network was trained by using above number of centers. For testing the performance of the developed RBF model, Mean Relative error (MRE) were calculated, which is defined by MRE = $1/N\sum_{i=1}^{N} 100(\frac{ai-pi}{ai})$, where N is the number of data in the data set, a_i is the actual or experimental value and p_i is the predicted value by ANN model.

To understand the prediction capability of the developed models, experimental data not used for modeling, called as test data were used and the MRE for different responses were calculated and are tabulated as shown in Table III. MRE of 10% has been assigned as the upper limit for determining the prediction accuracy for all parameters. Based on this value, prediction accuracy for both training and test data were calculated and were shown in table.

TABLE III
PERFORMANCE OF RBF MODEL (CENTERS SELECTED RANDOMLY, VARIABLE WIDTH)

S No	Variable	Training MRE (%)	Test MRE (%)	Training Accuracy (%)	Test Accuracy (%)
1	BTE	2.78	3.08	99	96
2	BSEC	2.56	3.33	98	94
3	T_{exh}	3.79	4.93	98	90
4	NOx	9.02	9.37	88	80
5	Smoke	9.15	10.82	85	77
6	CO	12.89	13.4	72	71
7	UBHC	11.83	13.34	73	71

Instead of having varying widths, network was trained using fixed values of widths. For various values of widths the network error was analyzed as shown in Fig. 4. From the graph it is clear that for a width of 0.08, the error was minimum. The network was trained with optimum number of centers determined from the random selection method and a width of 0.08. Results for the various performance and emission parameters are presented in Table IV. From Table IV it can be observed that RBF training with fixed width there is a slight improvement in results as the MRE reduced slightly with a marginal increase in prediction accuracy.

TABLE IV
PERFORMANCE OF RBF MODEL (CENTERS SELECTED RANDOMLY, FIXED WIDTH)

S No	Variable	Training MRE (%)	Test MRE (%)	Training Accuracy (%)	Test Accuracy (%)
1	BTE	2.75	3.06	100	96
2	BSEC	2.51	3.33	99	94
3	T_{exh}	3.53	4.85	98	92
4	NOx	8.98	9.12	90	80
5	Smoke	8.88	10.93	85	79
6	CO	12.5	13.17	72	71
7	UBHC	11.2	13.20	73	70

B. Centers Selected Using Fuzzy c Means Algorithm

In this approach, the radial-basis functions are permitted to move the locations of their centers in a self-organized fashion, the weights of the output layer are computed using a supervised learning rule. The network undergoes a hybrid learning process. The self-organized component of the learning process serves to allocate network resources in a meaningful way by placing the centers of the radial-basis functions in only those regions of the input space where significant data are present. The self-organized selection of the centers is done using clustering algorithms like the fuzzy c-means (FCM). FCM is a clustering technique, which assigns feature vectors xi into c clusters, which are represented by prototypes vj. The certainty of the assignment of the feature vector xi into various clusters is measured by the membership functions uj(xi) = uij $\in$ [0,1], 1<=j<=c, which satisfy the property $\sum$cj=1 uij =1. The M x c matrix U = [uij] $\in$ υ is a fuzzy partition in the set υ defined as υ = { U $\in$ RMc | uij $\in$ [0,1], $\forall$ i, j ; $\sum$cj=1 uij =1, $\forall$i; 0< $\sum$Mi=1 uij < M, $\forall$j}, where x $\in$ Rn are M feature vectors. [14].This has been used to iteratively select the optimum number of centers for the RBF network. The centers so determined have been used for training the RBF network. The training of the fuzzy c-means algorithm has been carried out with different number of centers; Fig. 3 shows the variation of MSE for different number of centers. Error decreased as the numbers of centers were increased and for 250 the MSE was found to be minimum. This was considered to be the optimum number of centers used for training the network. There has been a decrease in the number of centers required for optimal performance using fuzzy c-means algorithm, when compared to fixed number of centers selected randomly as s indicated by Fig. 3.

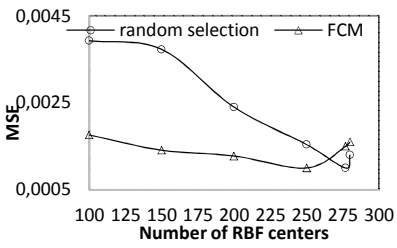

Fig. 3 Variation of MSE with RBF centers for random initialization

TABLE V
PERFORMANCE OF RBF MODEL (CENTERS SELECTED BY FCM, VARIABLE WIDTH)

S No	Variable	Training MRE (%)	Test MRE (%)	Training Accuracy (%)	Test Accuracy (%)
1	BTE	2.65	3.00	100	98
2	BSEC	2.41	2.81	100	98
3	T_{exh}	3.42	3.95	97	96
4	NOx	8.76	9.21	90	85
5	Smoke	8.93	9.53	87	81
6	CO	11.57	11.93	75	74
7	UBHC	10.25	11.31	76	76

Table V presents the results of the RBF network trained using centers selected using fuzzy c means algorithm considering variable width. The network was also trained using constant width values. The variation of MSE with the values of width is shown in Fig. 4 which shows that for a width of 0.07, the MSE was found to be minimum. The network was trained and the performance of the network is shown in Table VI for both training and test data.

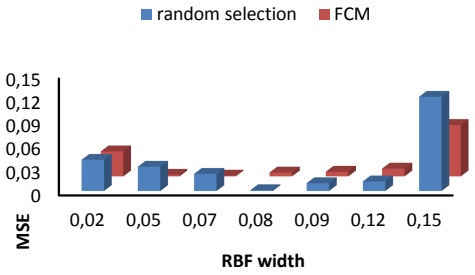

Fig. 4 Variation of MSE with RBF width for random initialization and using FCM methods

TABLE VI
PERFORMANCE OF RBF MODEL (CENTERS SELECTED BY FCM, FIXED WIDTH)

S.No	Variable	Training MRE (%)	Test MRE (%)	Training Accuracy (%)	Test Accuracy (%)
1	BTE	2.60	2.92	100	100
2	BSEC	2.45	2.72	100	98
3	T_{exh}	3.15	3.82	97	96
4	NOx	8.21	8.99	90	85
5	Smoke	9.04	9.21	85	82
6	CO	11.02	11.35	76	74
7	UBHC	10.41	11.04	76	76

On comparing the results predicted by using FCM methods with random selection method, MRE for the parameters predicted by FCM methods is lower with a marginal increase in prediction accuracy. In case of FCM the algorithm helped in fixing and locating the optimum number of centers for desirable performance and hence the overall prediction performance has improved. The average MRE for the test data related to performance parameters has decreased by 14% and for emission parameters by 11.3%. On comparing the prediction accuracy for the above two methods FCM methods showed an improvement of 4.2 % for performance parameters and 5.7% for emission parameters. Hence prediction by using

FCM methods has outperformed the prediction by random selection methods.

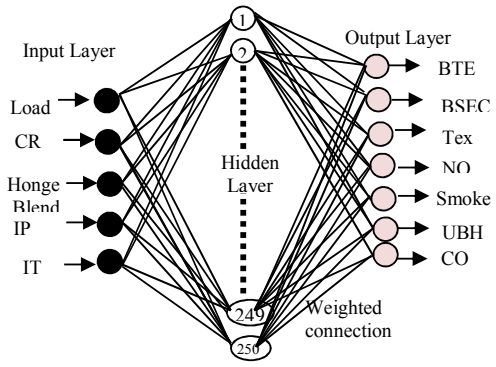

Fig. 5 RBF model showing inputs and outputs

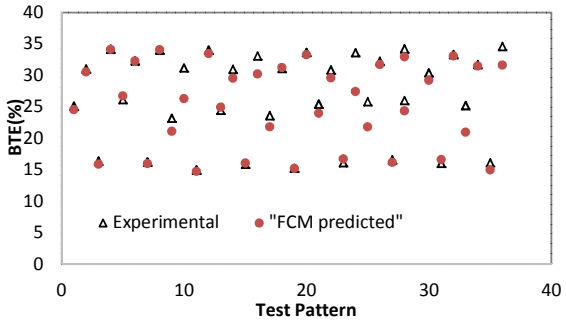

Fig. 6 Variation of BTE for experimental and FCM predicted values for the test data

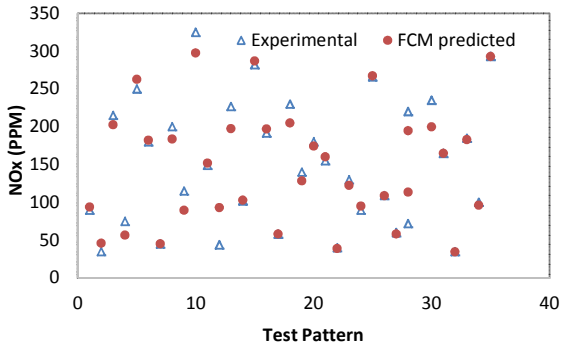

Fig. 7 Variation of NOx for experimental and FCM predicted values for the test data

Further results obtained using fixed values of widths for the RBF centers were better than variable values of widths determined using P- nearest neighborhood heuristic. Fig. 5 shows the optimized RBF model with the input layer with number of inputs, output layer with the number of out puts and the hidden layer. Figs. 6 & 7 show the typical plot of experimental and FCM predicted values for 36 test patterns for performance (BTE) and emission parameters (NOx). It again reveals that ANN predicted results and experimental values are very close to each other.

IV. Conclusions

In the present study applicability of Radial Basis Neural Networks which is a relatively new class of feed forward networks has been studied for the prediction of performance and emission parameters from a diesel engine fuelled with honge methyl ester. Experimental results under different operating conditions were used for ANN modeling.

Two different learning strategies were used for the initialization of centers of the RBF units. In the random initialization method, the centers were randomly selected and the network was trained by using fixed and varying widths for the RBF units. In the second method, centers were selected using clustering algorithms like fuzzy c means (FCM). ANN results were found to be very close to the experimental values. Results predicted by FCM were better than predicted by random selection method both in terms of lower MRE and higher prediction accuracy.

Hence it can be concluded that RBFNN can be effectively used to predict the performance and emission parameters of a CI engine fuelled with blends of vegetable oils. This helps in reducing the experimental efforts and cost, and improves the accuracy of prediction.

Nomenclature

ANN	Artificial Neural Networks
BSEC	Brake Specific Energy Consumption
BTE	Brake Thermal Efficiency
CO	Carbon Monoxide
CR	Compression Ratio
FCM	Fuzzy C Means
IP	Injection Pressure
IT	Injection Timing
LMS	Least Mean Square
MRE	Mean Relative Error
RBF	Radial Basis Function
Tex	Exhaust Gas Temperature
UBHC	Unburnt Hydrocarbon
WCO	Waste Cooking Oil

References

[1] A. K. Hossain & P. A. Davies, "Plant oils as fuels for CI engines- A technical review and life cycle analysis", *Renewable Energy*, Vol 35, 2010, pp. 1-13.
[2] A. K. Babu and G. Devaradjane, "Vegetable oils and their derivatives as fuels for CI engines", *SAE paper*, 2003-01- 0767, pp.406-418.
[3] A. K Agarwal & L. M. Das, "Biodiesel development and characterization for use as a fuel in CI engines", *ASME Journal of Engineering for Gas Turbines and Power*, Vol 123, 2001, pp. 440- 447.
[4] Narayan Reddy & A. Ramesh, "Parametric studies for improving the performance of a jathropa oil fuelled compression ignition engine", *Renewable Energy*, Vol 31, 2006, pp.-1194-2016.
[5] Baiju, M. K Naik & L. M. Das, "A comparative evaluation of compression ignition characteristics using methyl and ethyl esters of karanja oil", *Renewable Energy*, Vol 34, 2009, pp.1616-1621.
[6] Heywood, J. *Internal Combustion Engine fundamentals*, McGraw Hill, Inc. New York, 1988.
[7] Cenk Sayin, H. Metin Ertunc & Mustafa Canakci, "Performance and exhaust emissions from a gasoline engine using ANN", *Applied Thermal Engineering,* Vol 27, 2007, pp. 46-54.

[8] Mustafa Canakci, Ahmet Erdil & Erol Arcakliglu, "Performance and exhaust emissions of a biodiesel engine", *Applied Energy*, Vol 83, 2006, pp.594-604.
[9] Gholamhassn Najafi, Barat Ghobadian & Talal Y. Yusafand Hadi Rahim, "Combustion analysis of a CI engine performance using waste cooking oil with artificial neural network", *American Journal of Applied Science*, Vol 4, No 10, 2007, pp. 756- 764.
[10] Erol Arcaklioglu & E. Celikten, "A diesel engine performance and exhaust emissions using ANN", *Applied Energy*, Vol 80, 2005, pp. 11-22.
[11] Jose M. D Esantes, Jose J. Lopez & Jose M. Garcia, "Application of neural networks for prediction and optimization of exhaust emissions in a H.D diesel engine", *SAE paper* 1144, 2002, pp. 1993-2001.
[12] Simon Haykin, 1999, *Neural Networks- A Comprehensive Foundation*, Pearson Education Publishing.
[13] T. N. Nagabhushana, Course material- Advances in Neural Computing, Short Term Training Program, sponsored by AICTE-ISTE- New Delhi, India, 1999.
[14] Srinivasa Pai. P, Acoustic Emission based Tool Wear Monitoring using some improved neural network methodologies, Ph.D Thesis, S.J. College of Engineering, University of Mysore, Mysore, 2004.