Optimization of CI Engine Performance Parameters for Jatropha Biodiesel Blending Fuel by Using ANN Software

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Abstract ***In this paper the applicability of artificial neural networks (ANN) has been presented for a Jatropha biodiesel (JBD) fueled internal combustion engine. Jatropha biodiesel significantly affect the performance parameters of CI engine. This work investigates optimization of CI engine performance parameters of Jatropha biodiesel blending of fuel for engine operating conditions. Experiments were performed on single cylinder four stroke CI engines operating at different load conditions. For optimization purpose selected input parameters were fuel consumption, percentage of blending, percentage of load and output parameters like Brake power, Brake thermal efficiency, Brake Specific fuel consumption, and smoke intensity. ANN model based on the standard back propagation algorithm was developed for this purpose. Finally the best blending of fuel for selected CI engine to the selected engine has been proposed for better performance.***

Key Words: *JBD Fuel: Artificial Neural Network: Optimization Result:*

1. Introduction

The requirement of energy increases due to industrialization and continuously growing population in the world. Therefore, developing and newly developing countries tend to the new energy sources to compensate their energy necessity. Currently, the main energy source of the motor vehicles is petroleum products. It is expected that the petroleum reserves will be consumed away in the near future. In addition, one of the main causes of air pollution in the cities is harmful emissions of the motor vehicles which are operated with petroleum products. As a result, a lot of researchers have started to search for cheap, renewable and environmentally friendly alternative fuels such as different type of biodiesel. Jatopha biodiesel is a best alternative solution of fuel in CI engine. As far as the internal combustion engines are concerned the thermal efficiency and emission is the important parameters of the engine. For this purpose the operating performance parameters have to be optimized when using the biodiesel as fuel for compression ignition engine, because of the estimation of biodiesel performance of engine is non linear complex problem due to variations in chemical and thermodynamic properties of biodiesel fuels that affects the combustion process. Many researchers have carried out experiments to evaluate diesel engine for various biodiesel blends. As the experimental investigation is time consuming, tedious and costly these necessitates the most common ANN optimization techniques is used for to analysis of different engineering problems. This proposed study presents an alternative methodology for optimization of CI engine performance parameters by employing ANN virtual models.

Artificial neural networks (ANN) are used to solve a wide variety of problems in science and engineering, particularly in complex domains where conventional techniques fail. A well developed ANN can be used as predictive models which can minimize processing time and costs. Also, ANN has the ability to learn when new data becomes available in the future. These gradually improve its performance and predictability. An ANN model can accommodate multiple input variables to predict multiple outputs. This can be achieved without prior knowledge on the process relationships, as opposed to conventional mathematical techniques.

In recent years, numerous studies had been undertaken to predict the performance and exhaust emission characteristics of internal combustion engines employing ANN methodologies [5-8]. ANN has been found to be the domain for numerous successful applications of prediction tasks. In addition, this study employs an iterative control methodology in optimizing the following engine performance parameters such as fuel consumption, percentage of blending, percentage of load and out parameters such as Brake power, Brake thermal efficiency, Brake Specific fuel consumption, and smoke intensity, to control the within a suite of pre-defined limits. The four mentioned engine parameters were chosen due to their ease of control when adopted at the time of testing. This paper has been divided into three main sections.

1.1 Experimental Procedure

The first part of this paper highlights some background information, past work and discusses the experimental procedures to obtain an accurate experimental dataset. We study the basic procedure for testing of selected parameters and find out the experimental data for the prediction and optimization purpose. An accurate experimental dataset will lead to more accurate predictive models.

1.2 Construction of ANN Model

ANN is an approach inspired by brain structure and tries to simulate the brain processing capabilities. Haykin defines a neural network as a massively parallel distributed processor [13]. It has an inherent tendency for storing experimental knowledge and making it available for use. It resembles the human brain in two respects: the knowledge is acquired by the network through a learning process, and inter-neuron connection strengths known as synaptic weights are used to store the knowledge. The optimization layer-by-layer network is used for this study based on the back propagation algorithm.

1.3 Artificial neural network optimization

This section discusses the optimization process, the iterative control algorithm, where the desired target (goal) is defined. The uses of neural network for engine predictions make it possible to perform optimization studies over the entire operating conditions. The optimized output is obtained by using Backward Feed Propagation method in Artificial Neural Network. The optimized output is obtained by using Artificial Neural Network with MATLAB software.

2. Experimental Investigation

The Performance test were conducted on a computerized single cylinder, four stroke, direct injection, water cooled diesel engine test rig. The engine was directly connected to eddy current dynamometer for variable loading conditions.

Fig - 1: Computerized Single Cylinder Diesel Engine Test Set Up

Table 1: Specification of Single Cylinder Diesel Engine Test Rig

Parameter	Description
Manufacturer	Kirlosker Oil Engins Ltd .,Pune
Engine Type	Single Cylinder, 4 Stroke, Water Cooled, Diesel Engine.
Cylinder	Single
Stroke	110mm
Cubic capacity	661 cc (0.661 ltr.)
Bore	87.5 mm
Net Power	7 HP @ 1500 rpm
Compression Ratio	17.5 :1

The engine was run using different jatropha biodiesel blending (JBD10%, JBD20%, JBD30%, JBD40%, JBD50%, JBD60%, JBD70%, JBD80% JBD90%, and JBD100%) and required data are collected to optimization of the engine performance parameters. The performance of Jatropha Biodiesel - diesel blends at different loading conditions namely o% , 20% , 40%, 60%, 80% and 100% load conditions were evaluated. Engine was run for 15-20 minutes for one test and data available is stored by log key at the end of time interval. The test result obtained in the experimental was used to train and test the ANN. Table 2 below shows the observation made by performance parameters of engine by using diesel and jatropha biodiesel blending conditions.

Table - 2: Observation Table

Sr. No.	Load (%)	Jatropha Blending (%)	F. C. (kg/hr)	B.P. (kW)	n_{th}	B.S.F.C. (kg/kWhr)	BSU
1	0	5	0.4	0.46	0.85	10.06	2
2	0	10	0.36	0.48	9.34	0.92	1
3	0	20	0.37	0.46	11.7	0.74	2
4	0	30	0.4	0.48	9.01	0.97	2
5	0	40	0.41	0.47	10.23	0.85	3
6	0	50	0.37	0.45	11	0.81	2
7	0	60	0.45	0.46	9.18	0.98	3
8	0	70	0.41	0.45	10.33	0.87	3
9	0	80	0.45	0.48	10.69	0.84	2
10	0	90	0.48	0.49	9.89	0.97	3
11	0	100	0.49	0.44	8.42	1.11	3
12	20	5	0.48	1.04	18.22	0.46	1

13	20	10	0.53	1.04	16.88	0.51	1	41	60	70	1.03	3.11	27.24	0.33	3
14	20	20	0.48	1.04	18.7	0.46	2	42	60	80	0.98	3.11	28.26	0.31	4
15	20	30	0.51	0.99	16.86	0.52	2	43	60	90	1.08	3.11	26.17	0.34	6
16	20	40	0.54	1.05	21.65	0.41	2	44	60	100	1.14	3.14	25.76	0.35	5
17	20	50	0.4	1.03	23.08	0.39	2	45	80	5	0.94	3.11	28.45	0.26	3
18	20	60	0.61	1.06	15.69	0.57	2	46	80	10	1.12	3.99	30.57	0.28	3
19	20	70	0.49	1.02	18.74	0.48	2	47	80	20	1.11	3.89	30.55	0.28	4
20	20	80	0.52	1.05	18.07	0.5	2	48	80	30	1.18	4.02	29.8	0.29	3
21	20	90	0.7	0.99	12.85	0.7	4	49	80	40	1.05	3.86	30.22	0.27	3
22	20	100	0.7	1.15	15.09	60	3	50	80	50	1.21	4.05	29.67	0.3	4
23	40	5	0.59	2.01	29.36	0.29	2	51	80	60	1.27	4.03	28.61	0.31	4
24	40	10	0.77	2.08	25.7	0.33	2	52	80	70	1.13	3.93	31.14	0.29	5
25	40	20	0.62	2.1	29.34	0.3	3	53	80	80	1.23	4	29.24	0.31	4
26	40	30	0.75	2.05	23.98	0.36	3	54	80	90	1.35	3.96	26.65	0.34	6
27	40	40	0.68	2.03	26.34	0.33	2	55	80	100	1.52	3.94	23.82	0.38	5
28	40	50	0.65	2.07	28.13	0.32	3	56	100	5	1.53	5.07	28.26	0.3	3
29	40	60	0.69	2.08	27.27	0.32	3	57	100	10	1.45	4.81	28.46	0.3	4
30	40	70	0.74	2.04	24.91	0.36	3	58	100	20	1.41	4.89	30.01	0.29	3
31	40	80	0.7	2.12	27.32	0.33	3	59	100	30	1.5	4.92	28.79	0.3	3
32	40	90	0.88	2.09	21.58	0.42	4	60	100	40	1.46	4.98	30.06	0.29	4
33	40	100	0.9	2.17	22.15	0.41	4	61	100	50	1.46	4.9	35.7	0.3	4
34	60	5	1.08	4.01	32.25	0.27	2	62	100	60	1.54	4.88	26.75	0.31	4
35	60	10	0.87	3.03	30	0.29	3	63	100	70	1.51	4.79	28.65	0.31	5
36	60	20	0.83	3.14	32.89	0.26	3	64	100	80	1.45	4.92	30.6	0.29	5
37	60	30	0.94	3.05	28.29	0.31	2	65	100	90	1.4	4.89	31.52	0.28	6
38	60	40	0.87	3.01	30.29	0.29	3	66	100	100	1.86	4.89	24.88	0.37	6
39	60	50	0.96	3.15	29.3	0.3	3	67	120	5	1.62	5.32	26.21	0.33	4
40	60	60	0.96	3.02	28.25	0.32	2	68	120	10	1.59	5.11	27.89	0.31	4

69	120	20	1.65	5.34	26.47	0.31	3
70	120	30	1.8	5.41	26.33	0.33	3
71	120	40	1.7	5.38	28.11	0.31	5
72	120	50	1.68	5.21	27.58	0.32	4
73	120	60	1.83	5.27	24.51	0.37	4
74	120	70	1.89	5.28	28.65	0.31	5
75	120	80	1.93	5.38	25.1	0.36	6
76	120	90	1.96	5.42	25.13	0.36	7
77	120	100	1.97	5.12	23.89	0.36	6

3. Construction of ANN model

An artificial neural network (ANN) is a mathematical model or computational model that is inspired by the structure and/or functional aspects of biological neural networks. A neural network consists of an interconnected group of artificial neurons, and it processes information using a connectionist approach to computation. ANN has three main layers, namely, input, hidden and output layers. Neurons (processing elements) at input layer transfer data from external world to hidden layer. The data in input layer do not process as the data in the other layers. In the hidden layer, outputs are produced using data from neurons in input layer and bias, and summation and activation functions. Each hidden layer sends outputs to the following layer. In the output layer, the output of network is produced by processing data from hidden layer and sent to external world. The summation function calculates net input coming to a cell. For this reason, different functions are used. The most common one is to calculate the weighted sum. Inputs (load, %blending and fuel consumption) and outputs (brake power, Brake specific fuel consumption, brake thermal efficiency and smoke intensity.) are the knowledge from other cells or external world to the input cells. These are determined by examples that network wants to learn. Weights (w_1, w_2, wn) are the values which determine the effect of input set or another processing element in previous layer on the processing element. Each input value is multiplied by weight value which connects it to the processing element and then, it is combined by summation function. Signals flow into the input layer, pass through the hidden layer(s), and arrive at the output layer. With the exception of the input layer, each neuron receives signals from the neurons of the previous layer. The incoming signals or input (w_{ij}) are multiplied by the weights (x_j) and summed up with the bias (wb_i) contribution. Thus, net input of the network can be found [1]. Summation function is given in Eq. (1).

$$NETi = \sum_{j=1}^{n} w_{ij}x_j + wb_i \qquad 1$$

Logistic sigmoid transfer function has been commonly used as an activation function in multilayer perception model, because it is a differentiable, continuous and non-linear function. For this reason, the logistic sigmoid transfer function was used as the activation function in this study. This function produces a value between 0 and 1 for each value of net input. The formula of the logistic sigmoid function is as follows:

$$f(NET_i) = \frac{1}{1 + e^{-NET_i}} \qquad 2$$

The relationship between the various inputs and output parameters can be easily brought about by optimization. The uses of neural network for engine predictions make it possible to perform optimization studies over the entire operating conditions. The optimized output is obtained by using Backward Feed Propagation method in Artificial Neural Network. Finally, a set of outputs is produced as the actual response of the network. During the forward pass the synaptic weights of network are all fixed. During the backward pass, on the other hand, the synaptic weights are all adjusted in accordance with the error-correction rule. The actual response of the network is subtracted from a desired target response to produce an error signal. This error signal is then propagated backward through the network, against direction of synaptic connections - hence the name “error back-propagation”. The synaptic weights are adjusted so as to make the actual response of the network move closer the desired response [14].

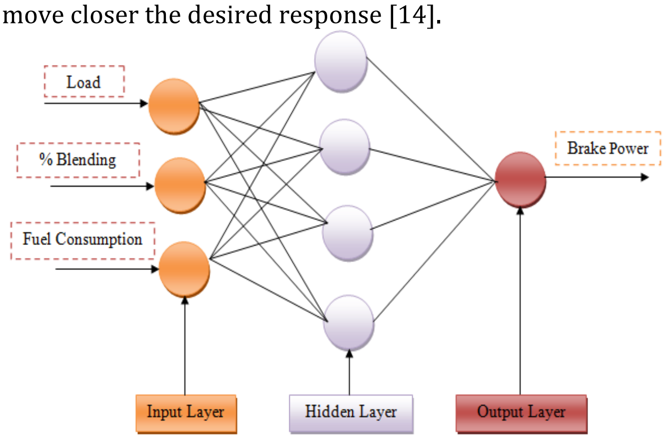

Fig. – 2: ANN architecture with multiple hidden layers

4. Artificial Neural Networks Optimization

Once good correlations between measured and predicted engine performance have been obtained they were employed to optimize independent control variables. The set points of independent control variables were optimized at any given combination of engine load, blending of fuel and fuel consumption. When the optimizer calls ANN surrogate models to obtain engine responses, the responses were then used to evaluate the objective function and constraints. If the convergence criteria were not satisfied, the optimizer will update the values of independent control variables and the ANN surrogate models will be called again. The process iterates until the optimization objective is achieved and all constraints are satisfied. The target of the optimization values for selected parameters is as follows.

Table – 3: Target of the optimization for selected Parameters

Parameters	Brake Power (kW)	BTHE (%)	BSFC (kg/kW-hr)	Smoke Intensity (BSU)
Target Values	5.2	35	0.23	3

The main target of optimization process is to be maximizing the brake power, brake thermal efficiency and to minimize the brake specific fuel consumption, smoke intensity. The objective function for the operating parameter constraint and the output parameters, the objective function is defined as follows equation for maximization and minimization purpose.

$$F(X)_{max} = \sum_{n=1}^{2} max(n) - predicted\ (i) \qquad 3$$

$$F(X)_{min} = \sum_{n=1}^{2} min(n) - predicted\ (i) \qquad 4$$

$$F\ (T)_{opt.} = sort\ F(X) \qquad 5$$

The optimization is focused by the above two equation 6.1and equation 6.2 for the maximization and minimization of the selected output parameters and optimized it to be sort by eqn. 6.3. But in order to average weight in different constraint parameter was indicated by weight factor, for final value of selection purpose weight factor is used. The final 10 result obtained through the optimization process of performance parameters it can seen in table no.6.3, parameters optimized result was obtained out of 77 results obtained through the neural network training. Final most optimization result can be found by overall weighted values of constraint, If the reduction in overall weighted values in objective function is less then these result obtained is most optimized, it means overall weighted value is less then these result obtained is most optimized. In this study most optimized result is JBD50 blending of fuel with fuel consumption in 1.46kg/hr for 100% load condition.

Table – 4: Optimized Parameters Value

Sr. No.	% Load	Blending	F. C. (kg/hr)	Weight
1	100	50	1.46	0.6379
2	100	70	1.51	0.7499
3	100	90	1.40	1.7595
4	60	5	1.08	1.8926
5	100	10	1.34	3.0348
6	80	70	1.13	4.1000
7	100	40	1.46	4.1295
8	100	80	1.45	4.1899
9	100	20	1.41	4.2697
10	80	10	1.12	5.6001

5. Conclusions

The aim of this paper is to show the optimization of C.I. engine performance parameters using the neural networks technique. In this investigation, assessed using ANN modeling has been found most suitable software for optimization purpose of CI engine performance parameters. Back propagation algorithm is a suitable technique for prediction and optimization purpose because it gives more accurate result as comparative to another algorithm. The performance of the ANN prediction were measured by comparing the predictions with experimental results, it is found to be very close to the Mean Square Error which are used for training the network. After training the network it was observed it is very close to one, these results within the acceptable limit. Through the optimization process, the optimized result found to be JBD50 at 100% load, at the output condition of selected parameters as Brake Power is 4.90 kW, BSFC is 0.29 kg/kW-hr, BTHE is 29.74%, and Smoke Intensity is 3. So JBD50 is most suitable blending of fuel for selected C.I. engine.

The result of this study shows that ANN has ability to learn and generalize a wide range of experimental conditions. Therefore, the usage of ANNs may be highly recommended to predict and optimization of the engine performance parameters, instead of having to undertake complex and time-consuming experimental studies.

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