Alexandria Engineering Journal (2016) 55, 1201–1209

HOSTED BY

ELSEVIER

Alexandria University

Alexandria Engineering Journal

www.elsevier.com/locate/aej
www.sciencedirect.com

ORIGINAL ARTICLE

Improvement of biodiesel methanol blends performance in a variable compression ratio engine using response surface methodology

Y. Datta Bharadwaz *, B. Govinda Rao, V. Dharma Rao, C. Anusha

Department of Mechanical Engineering, Gayatri Vidya Parishad College of Engineering, Visakhapatnam, India

Received 21 January 2016; revised 20 March 2016; accepted 4 April 2016
Available online 23 April 2016

KEYWORDS

Bio-diesel;
VCR engine;
Response surface methodology;
Compression ratio;
Methanol blends

Abstract The main objective of this work was to improve the performance of biodiesel–methanol blends in a VCR engine by using optimized engine parameters. For optimization of the engine, operational parameters such as compression ratio, fuel blend, and load are taken as factors, whereas performance parameters such as brake thermal efficiency (Bth) and brake specific fuel consumption (Bsfc) and emission parameters such as carbon monoxide (CO), unburnt hydrocarbons (HC), Nitric oxides (NOx) and smoke are taken as responses. Experimentation is carried out as per the design of experiments of the response surface methodology. Optimization of engine operational parameters is carried out using Derringers Desirability approach. From the results obtained it is inferred that the VCR engine has maximum performance and minimum emissions at 18 compression ratio, 5% fuel blend and at 9.03 kg of load. At this optimized operating conditions of the engine the responses such as brake thermal efficiency, brake specific fuel consumption, carbon monoxide, unburnt hydrocarbons, nitric oxide, and smoke are found to be 31.95%, 0.37 kg/kW h, 0.036%, 5 ppm, 531.23 ppm and 15.35% respectively. It is finally observed from the mathematical models and experimental data that biodiesel methanol blends have maximum efficiency and minimum emissions at optimized engine parameters.

1. Introduction

In light of the recent events such as decreasing fossil fuel resources, hiking crude oil price and pollution has made many researchers check the viability of biodiesels as potential alternative fuels. At this juncture a lot of research has been done on improving the efficiency of the engine by using different blends of biodiesels, using additives, advancing the injection timing, etc. All these methods have proved helpful up to some extent but the problems of low performance and emissions from biodiesels are unanswered. In this scenario, some researchers have tried to improve the performance of the engine fueled with biodiesels and their blends by using different optimization techniques. In this regard Kesign [1] investigated on the effects of operational and design parameters on

* Corresponding author. Tel.: +91 9581456166.
E-mail addresses: ydattabharadwaz@yahoo.com (Y. Datta Bharadwaz), govind_budda@rediffmail.com (B. Govinda Rao), vdharmarao@gvpce.ac.in (V. Dharma Rao), anusha.chalumuri@gmail.com (C. Anusha).
Peer review under responsibility of Faculty of Engineering, Alexandria University.

http://dx.doi.org/10.1016/j.aej.2016.04.006
1110-0168 © 2016 Faculty of Engineering, Alexandria University. Production and hosting by Elsevier B.V.

efficiency and NOx emissions of a natural gas engine using Genetic Algorithm and neural network analysis. The results showed an increase in efficiency as well as the amount of NOx emissions being kept under the constraint value of 250 mg/Nm3 for stationary engines. Win et al. [2] studied the conflicting effects of the operating parameters (speed, load) and the injection parameter (injection timing) by varying as per $4 \times 4 \times 3$ full factorial design array on the performance like Radiated engine smoke and smoke level. The authors made some conclusions that RSM is found to be effective in obtaining objective functions between the input parameters and output parameters showing good predictions except for HC, which has a poor fit. Alonso et al. [3] studied the feasibility of using artificial neural networks (ANNs) along with genetic algorithms (GAs) to optimize the diesel engine settings to decrease fuel consumption and to regulate emissions. The authors made a conclusion that the engine emissions and consumption improvement were reached without the incorporation of any new technological device, but by just combining the operating parameters better in a way. Sayin et al. [4] studied the artificial neural network (ANN) modeling of gasoline engine to predict the brake specific fuel consumption, brake thermal efficiency, exhaust gas temperature and exhaust gas emissions of a four-cylinder, four stroke test engine fueled with gasoline having various octane numbers (91, 93, 95, and 95.3) and operated at different engine speeds and torques. During their study the authors observed that the ANN model can predict the engine performance, exhaust emissions and exhaust gas temperature better with correlation coefficients in the range of 0.983–0.996, mean relative errors in the range of 1.41–6.66% and very low root mean square errors.

Sahoo and Das [5] in their study on optimization for biodiesel production from Jatropha, Karanja, and Polanga oils stated that the addition of biodiesel to diesel fuel changes the physico chemical properties of blends. Ganapathy et al. [6] proposed a methodology for thermodynamic model based on two-zone Weibe's heat release function to simulate Jatropha biodiesel engine performance using Taguchi's optimization approach. Using this approach, the authors concluded that the compression ratio, Weibe's heat release constants, and combustion zone duration are the critical parameters that affect the performance of the engine compared to other parameters. Najafi et al. [7] studied the performance and exhaust emissions of a gasoline engine with ethanol blended gasoline fuels using artificial neural networks (ANNs) and observed that the ANN model can predict engine performance and exhaust emissions with correlation coefficient (R) in the range of 0.97–1. Mean relative errors were in the range of 0.43–5.57%, while root mean square errors were found to be very low. Ghobadian et al. [8] studied the modeling of a two cylinder, four-stroke diesel engine fueled with waste vegetable cooking biodiesel and diesel blends and operated at different engine speeds using artificial neural networks (ANNs). Authors found the ANN model can predict the engine performance and exhaust emission quite well with correlation coefficients of (R) 0.9847, 0.999, 0.929 and 0.999 for engine torque, SFC, CO, HC, emissions. The prediction mean square error (MSE) was between the desired outputs as measured values and the simulated values were obtained as 0.0004 by the model. Jindal et al. [9] conducted experiments on the effects of the engine design parameters viz. compression ratio (CR) and fuel injection pressure.

For agricultural applications (3.5 kW), the optimum combination was found as CR of 18 with IP of 250 bar. Pandian et al. [10] investigated the effect of injection system parameters on performance and emission characteristics of a twin cylinder compression ignition direct injection fueled with pongamia biodiesel-diesel blend using response surface methodology and found that at injection pressure of 225 bar, injection timing of 21° BTDC and 2.5 mm nozzle tip protrusion were found to be optimal values for pongamia biodiesel blended diesel fuel operation in the test engine of 7.5 kW at 1500 rpm. Karnwal et al. [11] in their study on multi-response optimization of diesel engine performance parameters on Thumba biodiesel–diesel blends using Taguchi method and gray relational analysis stated that the combination of a blend consisting of 30% Thumba biodiesel (B30), a compression ratio of 14, a nozzle opening pressure of 250 bar and an injection timing of 20° produces maximum performance and minimum emissions. Costa et al. [12] in their study of CFD optimization for GDI spray model tuning and enhancement of engine performance reported that optimal choice of both the start of single injection strategy and the time of spark advance is realized by means of the simplex algorithm to maximize engine power output. Jose et al. [13] in their study of modeling and multi-objective optimization of a gasoline engine using networks and evolutionary algorithms, concluded that the non-dominated sorting genetic algorithm-II achieved reductions of at least 9.84%, 82.44%, 13.78% for CO, HC, and NOX. Molina et al. [14] experimented on the fuel consumption and NOX emissions in a diesel engine by developing a control-oriented model using Response surface methodology and found that the mean errors of predicted NOX and BSFC are 6% and 2% with a calculation time of 5.5 ms. Sivaramakrishnan and Ravikumar [15] investigated the influence of compression ratio on the performance and emissions of the diesel engine using biodiesel (10%, 20%, 30% and 50%) blended diesel fuel at compression ratios of 17.5, 17.7, 17.9 and 18.1 and the experiments were designed using the design of experiments using response surface methodology. They concluded that Desirability approach of the RSM is the simplest and most efficient optimization technique. A high desirability of 0.97 was obtained at the optimum engine parameters of CR of 17.9, fuel blend B10 and 3.18 kW power, where the values of BTHE, BSFC, CO, HC, NOX were found to be 33.65%, 0.2718 $kg/kW^{-1} h^{-1}$, 0.109%, 158, and 938 ppm. Hirakude and Padalkar [16] worked on the optimization of the direct injection single cylinder, diesel engine with respect to brake power, fuel economy and smoke emissions through experimental investigation and response surface methodology. Using desirability approach of the RSM, Optimization was carried out for superior performance and lesser smoke emissions and they found that a CR of 17.99, IP of 250 bar and 27° BTDC were optimal values for the Waste Fried oil Methyl Esters blended with diesel. Beatrice et al. [17] studied on the injection parameter optimization using Design of experiment on a light-duty diesel engine fueled with Bio-ethanol, rapeseed methyl ester, and diesel blend. They said that the robustness and the efficiency are enhanced by this optimization technique, and the longer ignition delay time and the lower heat content of the ethanol blend are well compensated by the closed loop combustion control. Lee and Reitz [18] studied the emission reduction capability of exhaust gas recycler and other performance parameters on a high-speed direct-injection diesel engine equipped with a common rail injection system using a response surface methodology (RSM) technique at a speed of 1757 rpm and 45% load and concluded that RSM optimization is an effective and powerful tool for realizing the full advantages of the combined effects of combustion control techniques by optimizing their parameters. Dhingra et al. [19] optimized performance, emission and combustion characteristics of a jatropha biodiesel blend using CCD designs of RSM and NSGA-II. They concluded that the optimal solutions thus obtained are in good agreement with confirmatory experiments. Anand et al. [20] conducted experiments on biodiesel methanol blends and found higher ignition delay, lower peak cylinder pressures, and peak heat release rates. Lower combustion durations are also noted for biodiesel methanol blends. A hike in thermal efficiency, Low CO, moderate HC, low NOx and smoke are observed for biodiesel methanol blends when compared with pure biodiesel. Yilmaz et al. [21] conducted a detailed analysis on biodiesel–ethanol and biodiesel–methanol blends. It is observed from the results that biodiesel–alcohol blends are good at reducing the NO emissions while increasing CO and HC emissions at below 70% load conditions. Results also show that biodiesel–ethanol blends are more effective than biodiesel–methanol blends. Yilmaz et al. [22] found the effects biodiesel–butanol blends on diesel engine performance and found an increase in brake specific fuel consumption, CO and HC emissions whereas NOx and smoke decreased considerably.

From the above literature review, it can be inferred that operational parameter optimization of the engine can be done effectively by using Response Surface Methodology. It can also be noted that biodiesel–methanol blends are good at reducing the emissions and improving the performance of the engine. From the literature survey, it can also be concluded that optimization of biodiesel–methanol fueled VCR engine has not been done so far. So the present work is an effort to optimize the biodiesel–methanol blend fueled VCR engine for maximum brake thermal efficiency and minimum brake specific fuel consumption, CO, HC, NOx and Smoke emissions.

2. Experimental setup

The experimental setup consists of a single cylinder, direct injection variable compression ratio engine as shown in Fig. 1. The specifications of the engine test setup are shown in Table 1. For this investigation three different test fuels are prepared like pure palm oil biodiesel, BM5 (95% biodiesel + 5% methanol), BM10 (90% biodiesel + 10% methanol) and BM15 (85% biodiesel + 15% methanol). The properties of pure palm oil biodiesel and Methanol are shown in Table 2, whereas the properties of biodiesel–methanol blends are shown in Table 3. The engine operational parameters such as brake power, brake thermal efficiency (Bth) and brake specific fuel consumption (Bsfc) are obtained through online analysis of the Variable Compression Ratio (VCR) engine using a Lab view based software "IC Engine Soft". The emission parameters such as CO, HC, NOx and Smoke are obtained from INDUS Five Gas Analyzer and INDUS Smoke meter. The specifications accuracy and range of the INDUS Gas Analyzer and Smoke meter are shown in Table 3a. The Percentage uncertainties for each measured and calculated parameter are computed and shown in Table 3b.

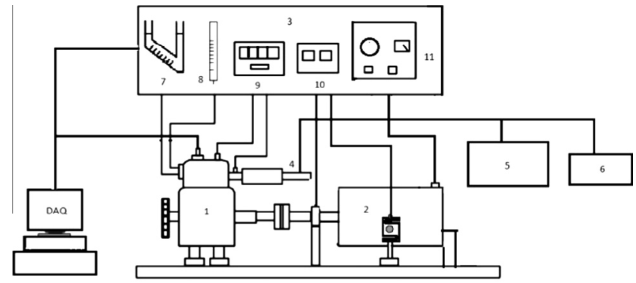

Figure 1 Schematic layout of the engine test setup.

Table 1 Engine specifications.

Engine model	Kirloskar, TV1
Engine details	Four stroke, Compression ignition, Constant speed, Vertical, Water cooled, Computerized diesel engine
No. of cylinders	One
Bore	87.5 mm
Stroke	110 mm
Swept volume	661 cc
Compression ratio	17.5:1
Rated output	5.2 KW at 1500 rpm

Table 2 Properties of test fuels.

SL.No	Property	Biodiesel	Methanol
1.	Calorific value (kJ/kg)	38,420	22,700
2.	Density (kg/m^3)	890.3	787
3.	Flash point (°C)	> 160	11–12
6.	Viscosity (mm^2/s)	4.52	1.01

Table 3 Properties biodiesel methanol blends.

SL.No	Blend	Calorific value (kJ/kg)	Density (kg/m^3)
1	BM5	33,100	851
2	BM10	32,140	846
3	BM15	29,760	843

3. Response surface methodology

In this study, the Compression ratio, fuel blends, and load were considered as the input factors which potentially affect output responses such as brake thermal efficiency (Bth), brake

Table 3a Five gas analyzer and smoke meter specifications.

SL. No	Instrument	Measurement	Range	Resolution	Accuracy
1.	Five gas Analyzer	CO	0–15%	0.001%	±0.006%
		HC	0–30,000 ppm	1 ppm	±12 ppm
		NOx	0–5000 ppm	1 ppm	±20 ppm
		CO_2	0–20%	0.01%	±0.5%
		O_2	0–25%	0.01%	±0.1%
2.	Smoke meter	HSU	0–99.9	0.1%	±0.1%
		K	0-α	0.01 m^{-1}	±0.1 m^{-1}

Table 3b Uncertainty of measured and calculated engine parameters.

SL. No	Measured		SL. No	Calculated	
	Parameters	% uncertainty		Parameters	% uncertainty
1.	Engine speed (rpm)	±0.5	1.	Power	±2.1
2.	Temperatures (°C)	±0.5	2.	Brake thermal efficiency	±3.4
3.	Carbon monoxide (%)	±0.7	3.	Brake specific fuel consumption	±4.3
4.	Hydro carbons (ppm)	±3.0			
5.	Nitrogen oxides (ppm)	±0.1			
6.	Crank angle (°)	±0.2			
7.	Load (kg)	±0.5			

specific fuel consumption (Bsfc) and emission parameters such as CO, HC, NOx and smoke. Full factorial designs of Design of Experiments (DOEs) are considered for the experimentation where each factor is varied in levels of 3 × 3 × 5 respectively. The design matrix was generated based on the full factorial design obtained from the software "Design Expert" trail version 9 which contained 45 runs .The experiments are carried out as per the run order of the Design matrix for a different combination of the factors as shown in Table 4, and the corresponding response values are noted. The model is analyzed by using Analysis of variance (ANOVA). Optimization is carried out by using Derringer's Desirability approach of RSM, where the solution with highest desirability is considered as the optimum one. The corresponding factor combination for the optimum solution is considered to be the best parameters for engine operation.

4. Results and discussions

4.1. Analysis of the model

Analysis is based on analysis of variance (ANOVA) which provides the numerical information about *p*-value. *p*-value is defined as the alternative to rejection points to provide the smallest level of significance at which the null hypothesis would be rejected. The maximum value of p is considered to be 0.05 and the model terms for which *p*-value is more than 0.05 are considered to be insignificant. The models for various responses are found to be significant as the p-values are less than 0.05. The regression equations developed for different responses are shown below.

$$\begin{aligned} \mathrm{Bth} = {} & +34.70 + 1.18 \times \mathrm{A} + 2.15 \times \mathrm{B} + 8.31 \times \mathrm{C} + 1.17 \\ & \times \mathrm{AB} + 0.90 \times \mathrm{AC} + 1.58 \times \mathrm{BC} - 0.40 \times \mathrm{A}^2 \\ & + 4.09 \times \mathrm{B}^2 - 9.89 \times \mathrm{C}^2 \end{aligned} \tag{1}$$

$$\begin{aligned} \mathrm{Bsfc} = {} & +0.31 - 0.017 \times \mathrm{A} + 0.017 \times \mathrm{B} - 0.13 \times \mathrm{C} \\ & - 0.019 \times \mathrm{AB} + 7.00\mathrm{E} - 0.03 \times \mathrm{AC} - 0.026 \\ & \times \mathrm{BC} + 8.667\mathrm{E} - 0.03 \times \mathrm{A}^2 - 0.019 \times \mathrm{B}^2 + 0.17 \times \mathrm{C}^2 \end{aligned} \tag{2}$$

$$\begin{aligned} \mathrm{CO} = {} & -2.51 - 0.83 \times \mathrm{A} + 0.046 \times \mathrm{B} + 0.26 \times \mathrm{C} + 0.074 \\ & \times \mathrm{AB} - 0.19 \times \mathrm{AC} - 0.15 \times \mathrm{BC} - 0.24\mathrm{A}^2 - 0.25 \\ & \times \mathrm{B}^2 + 0.91 \times \mathrm{C}^2 \end{aligned} \tag{3}$$

$$\begin{aligned} \mathrm{HC} = {} & +38.17 - 8.30 \times \mathrm{A} + 25.30 \times \mathrm{B} + 1.40 \times \mathrm{C} - 2.45 \\ & \times \mathrm{AB} + 0.77 \times \mathrm{AC} - 6.53 \times \mathrm{A}^2 + 1.27 \times \mathrm{B}^2 \\ & + 10.10 \times \mathrm{C}^2 - 10.95 \times \mathrm{A}^2\mathrm{B} + 9.17 \times \mathrm{A}^2\mathrm{C} - 4.45 \\ & \times \mathrm{AB}^2 \end{aligned} \tag{4}$$

$$\begin{aligned} \mathrm{NOx} = {} & +471.53 + 108.20 \times \mathrm{A} - 39.27 \times \mathrm{B} + 389.80 \times \mathrm{C} \\ & - 15.20 \times \mathrm{AB} + 60.0 \times \mathrm{AC} - 28.00 \times \mathrm{BC} \\ & + 33.93 \times \mathrm{A}^2 + 48.53 \times \mathrm{B}^2 - 74.57 \times \mathrm{C}^2 \end{aligned} \tag{5}$$

$$\begin{aligned} \mathrm{Smoke} = {} & +36.06 - 4.44 \times \mathrm{A} + 3.70 \times \mathrm{B} + 2.91 \times \mathrm{C} \\ & + 2.78 \times \mathrm{AB} - 5.95 \times \mathrm{B}^2 \end{aligned} \tag{6}$$

where A- CR, B - Fuel Blend (%), C - Load in kg

4.2. Evaluation of the model

The stability of the model is analyzed using ANOVA presented in Table 5. From the table, the model is found to be stable with *P*-values less than 0.0001. Regression statistics such as the goodness of fit (R^2) and the goodness of predictions (adj. R^2) shown in the table are in good accordance with each other as the difference between them is less than 0.2. Here R^2 value

Table 4 Design matrix.

Run order	Compression Ratio	Fuel Blend (%)	Load (kg)	Bth (%)	Bsfc (kg/kW)	CO (%)	HC (ppm)	NOx (ppm)	Smoke (%)
1	16	10	12	33.55	0.32	0.88	35	408	35.1
2	17	5	12	35.59	0.31	0.057	11	582	26.8
3	16	15	16	43.13	0.30	0.094	82	582	32.1
4	17	15	8	32.39	0.40	0.122	68	303	37
5	18	5	20	36.46	0.30	0.064	24	1208	25.1
6	16	10	4	15.15	0.79	0.201	39	20	34.2
7	17	15	12	42.85	0.30	0.073	58	568	29.6
8	16	10	8	28.35	0.38	0.132	38	152	45.5
9	18	5	12	34.04	0.32	0.027	8	722	17.6
10	16	15	20	34.72	0.37	0.392	80	630	46.4
11	17	5	8	32.29	0.34	0.074	16	309	24.8
12	17	10	8	29.78	0.37	0.096	37	212	35
13	16	15	12	40.39	0.32	0.081	60	421	34.4
14	16	15	8	30.9	0.42	0.114	53	205	35.2
15	16	5	8	28.29	0.38	0.11	28	193	31.6
16	17	5	20	32.7	0.33	0.293	29	804	30.3
17	17	15	4	20.88	0.62	0.187	89	42	27.4
18	18	15	4	16.49	0.72	0.189	62	30	35.9
19	17	10	4	17.29	0.63	0.149	43	46	32.3
20	18	10	4	17.2	0.63	0.04	24	143	29.6
21	18	10	16	39.06	0.28	0.027	29	816	32
22	18	5	4	20.63	0.53	0.03	9	192	13.6
23	17	10	20	32.5	0.33	0.336	51	766	35
24	16	5	12	37.11	0.29	0.073	31	567	30.4
25	18	15	12	43.24	0.3	0.037	36	575	33.3
26	18	15	8	34.88	0.37	0.038	24	345	30.6
27	17	15	20	38.55	0.34	0.263	75	767	36.4
28	17	5	4	20.08	0.54	0.105	16	90	25
29	16	5	20	31.4	0.35	0.746	42	717	47.1
30	16	5	16	37.23	0.29	0.128	35	703	29.3
31	17	10	12	31.02	0.35	0.066	40	461	33.6
32	18	15	4	23.26	0.56	0.048	27	124	30.1
33	17	5	16	38.9	0.28	0.05	25	737	24.7
34	18	5	8	28.02	0.39	0.039	4	366	14.6
35	18	15	20	44.89	0.29	0.048	58	973	34.5
36	17	15	16	45.41	0.29	0.064	60	660	30.6
37	18	5	16	37.34	0.29	0.024	21	946	22.6
38	17	5	4	21.32	0.51	0.183	33	34	32.6
39	16	10	16	36.94	0.29	0.06	43	652	39.7
40	16	10	20	29.78	0.37	0.873	59	615	41.3
41	16	10	16	35.75	0.3	0.134	55	608	43.4
42	18	10	12	31.91	0.34	0.03	25	612	31.8
43	18	15	16	43.86	0.3	0.03	40	767	33.6
44	18	10	20	35.9	0.3	0.065	43	993	32.9
45	18	10	8	28.16	0.39	0.036	22	349	39.5

indicates the total variability of the response after significant factors are considered and adj. R^2 indicates a number of predictors in the model. From the values of R^2 and adj. R^2 it can be concluded that the model fits the data very well.

4.3. Optimization

The optimization criteria followed in this study is shown in Table 6. Here for all the responses except Brake thermal efficiency, the goal is given as minimize. An equal weight of 0.1 is added for each of the responses as shown in Table 6. In desirability approach in addition to weights, importance can be assigned to each response starting from 1 to a value of 5. The highest importance of 5 is given for all the emission responses whereas an importance of 3 and 4 is assigned for Brake thermal efficiency and brake specific fuel consumption respectively. Desirability approach has many optimal solutions. The solution with high desirability was preferred. The maximum desirability of 0.978 was obtained at the following engine parameters such as 18 compression ratio, 5% of fuel blend, and 9.03 kg of load which is 45% of full load. The value of factor at which there is highest desirability is considered as the optimal solution.

4.4. Validation experiments

In order to evaluate the numerical model, validating experiments are conducted at the optimized parameters of 18 compression

Table 5 Model evaluation.

Model	BTH	BSFC	CO	HC	NOx	Smoke
Mean	15.15	0.28	0.024	4	20	13.6
SD	8.0769	0.126556	0.202662	20.5334	303.392	7.2151
R-squared	0.9575	0.9227	0.8072	0.9446	0.9791	0.7423
Model degree	Quadratic	Quadratic	Quadratic	RCubic	Quadratic	RQuadratic
Adj. R^2	0.9466	0.9028	0.7576	0.9261	0.9739	0.7093
Pred. R^2	0.9267	0.8542	0.7106	0.8910	0.9646	0.6462

Table 6 Optimization criteria.

Source	Lower limits	Upper limits	Weight		Importance	Goal	Desirability
			Upper	Lower			
Compression ratio	16	18	1	1	3	In range	1
Fuel blend	5	15	1	1	3	In range	1
Load	4.00	20	1	1	3	In range	1
Bth	15.15	45.41	1	0.1	3	Maximize	0.943565
Bsfc	0.28	0.79	0.1	1	4	Minimize	0.986675
CO	0.024	0.88	0.1	1	5	Minimize	1
HC	4.00	89	0.1	1	5	Minimize	0.998279
NOx	20.00	1208	0.1	1	5	Minimize	0.945491
Smoke	13.60	47.1	0.1	1	5	Minimize	0.985615

Table 7 Validation experiments.

Optimized parameters			Value	Bth (%)	Bsfc (kg/kW h)	CO (%)	HC (ppm)	NOx (ppm)	Smoke (%)
CR	Blend (%)	Load (kg)							
18	5	9.03	Predicted	32.07	0.34	0.02	5.44	529.42	18.11
			Actual	31.95	0.37	0.03	5	531.23	15.35
			Error	−0.12	0.03	0.01	−0.45	1.47	−2.76

ratio, 5% biodiesel–methanol blend and a load of 9.03 kg. A triplicate experimentation criterion is used to evaluate the predicted response values. The experimental values proved that the models are correct as there is good agreement between predicted values and experimental values as can be seen from Table 7.

5. Interaction effects

5.1. Brake thermal efficiency

Brake thermal efficiency is plotted against blend and compression ratio as shown in Fig. 2 to depict the effect of methanol-blend and compression ratio on it. From the plot it is observed that brake thermal efficiency of the blends seems to be increasing with the increase in methanol content and compression ratio. This may be due to the increase in oxygen content of the fuel with methanol and due to the wider flammable characteristics of methanol in the fuel [20,21]. The increase of thermal efficiency with compression ratio can be attributed to the rise in cylinder pressures and temperatures inside the combustion chamber. High cylinder pressures and temperatures are a much desired phenomena in thermal efficiency perspective as it ensures clean combustion, increasing the efficiency of the

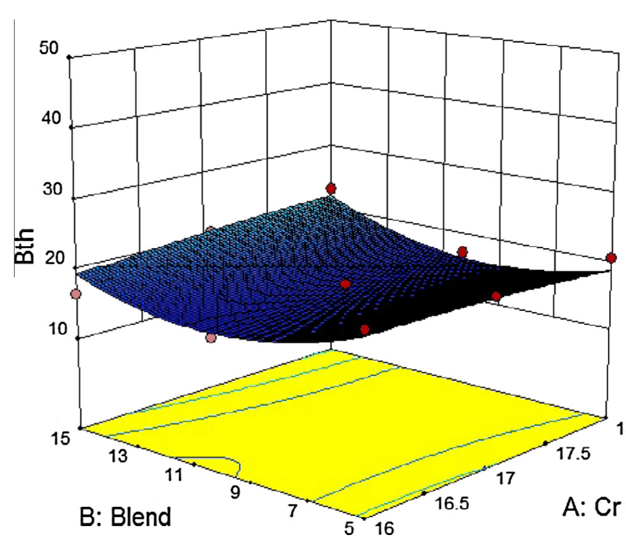

Figure 2 Variation of brake thermal efficiency against blend and compression ratio.

engine [19]. The highest value and lowest value of brake thermal efficiencies are shown in Table 4. The highest value of BTH is found to be 44.89% at 18 compression ratio, 15% of

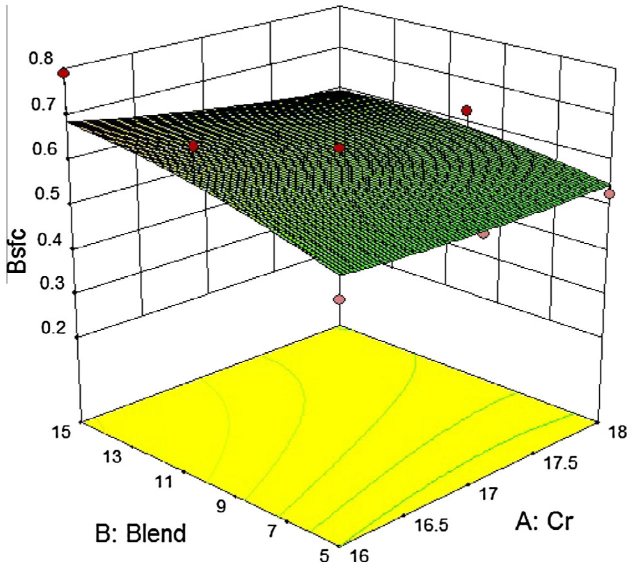

Figure 3 Variation of brake specific fuel consumption against blend and compression ratio.

methanol blend and 20 kg of load. The least value of 15.15% is found to be at 16 compression ratio, 10% of methanol blend and 4 kg of load. The above are reasonable as the brake thermal efficiency is highest at the high compression ratio and least at the low compression ratio. It is also observed from the results that the Bth values are high at high load and least at low load. This can be due to the increase in brake power and decrease in specific fuel consumption with increase in load of the engine. However this increase in Bth trend with load can be observed only up to only 80% of full load on the engine. If the load is increased beyond that limit there will be a drastic rise in fuel consumption leading to decrease the thermal efficiency of the engine.

5.2. Brake specific fuel consumption

Brake specific fuel consumption is the other important parameter which will decide the efficiency of the engine. Fig. 3 shows the interaction effect of blend percentage and compression ratio on the brake specific fuel consumption. It is observed from the response surface plot that there is an increase in specific fuel consumption with rise in methanol blend and a decrease in specific fuel consumption with compression ratio. The increase of fuel consumption with the increase of methanol content in the blend is mainly because of the high latent heat of methanol and its fast burning characteristics. The decrease of fuel consumption with compression ratio is due to high cylinder pressures which prevail at high compression ratios. The highest value for Bsfc is found to be 0.79 kg/kW h at 16 compression ratio, 10% of fuel blend and 4 kg of load. The lowest value of Bsfc is found to be 0.28 kg/kW h at 18 compression ratio, 10% fuel blend and 16 kg of load. Form the above results it is inferred that compression ratio and load play a key role in fuel consumption. The decrease of fuel consumption with load is because of the increase in temperatures and pressures which will improve the combustion efficiency and reduce the fuel consumption.

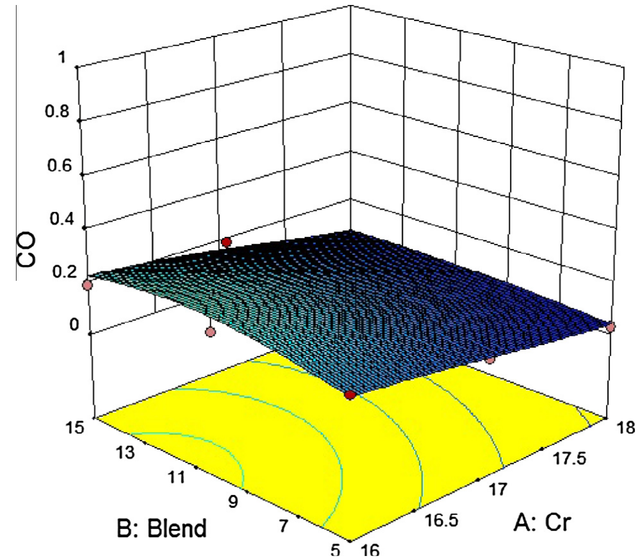

Figure 4 Variation of CO emissions against blend and compression ratio.

5.3. CO emissions

In Fig. 4 the effect of blend and compression ratio on CO emissions is shown as a response plot. From the figure, it is noted that CO emissions are increasing with increase in blend percentage whereas they are decreasing with the rise in compression ratio. The decrease of CO emissions with a rise in compression ratio is due to the increase in temperature and pressures with compression ratio. The main reason for CO emissions is due to the lack of sufficient oxidization temperatures at the latter part of combustion. High compression ratio and high loads will provide oxidation temperatures and reduced emissions. In this study high CO emissions of 0.392\% are found to be at 16 compression ratio, 15% of blend and 20 kg of load and a low CO emissions of 0.024% is found at 18 compression ratio, 5% of blend and 16 kg of load. It is noted from the above results that there is an increase in CO emissions with blend percentage as shown in Fig. 4. This rise in CO emission with methanol blend percentage is mainly because of the increase in ignition delay with addition of methanol. As the ignition delay increases, the time of combustion reduces resulting in incomplete combustion [20].

5.4. HC emissions

Fig. 5 portrays the effect of blend percentage and compression ratio on HC emissions. From the plot it is noted that there is a rise in HC emissions with increase in blend percentage and decrease in HC emissions with compression ratio. The results in Table 4 show highest HC emissions of 80 ppm at 16 compression ratio, 15% blend, 20 kg of load and lowest of 4 ppm at 18 compression ratio, 5% blend and 8 kg of load. Both CO and HC emissions depend on the availability of oxygen. Biodiesel is a highly oxygenated fuel and addition of another highly oxygen fuel like methanol to it should reduce the HC emissions. But conversely there is a rise in HC emissions with blend because of the increase in ignition delay with addition of methanol and formation of rich zones at high load

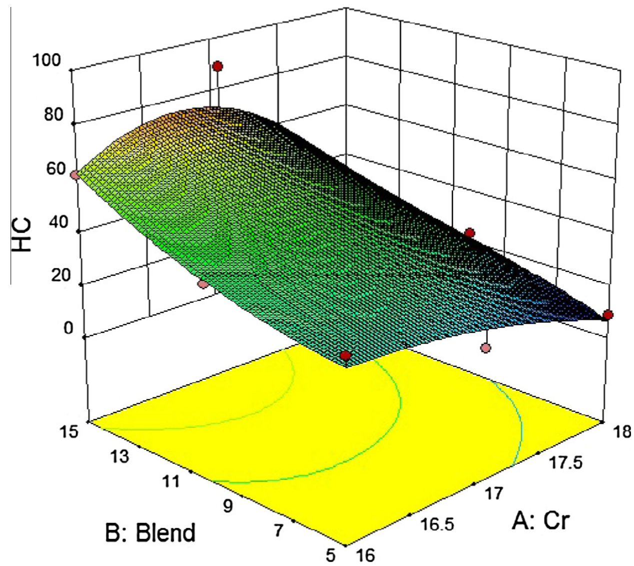

Figure 5 Variation of HC emissions against blend and compression ratio.

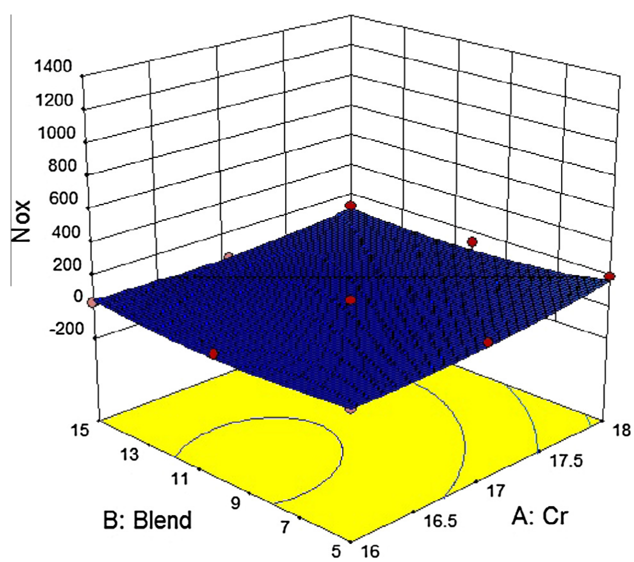

Figure 6 Variation of Nox emissions against blend and compression ratio.

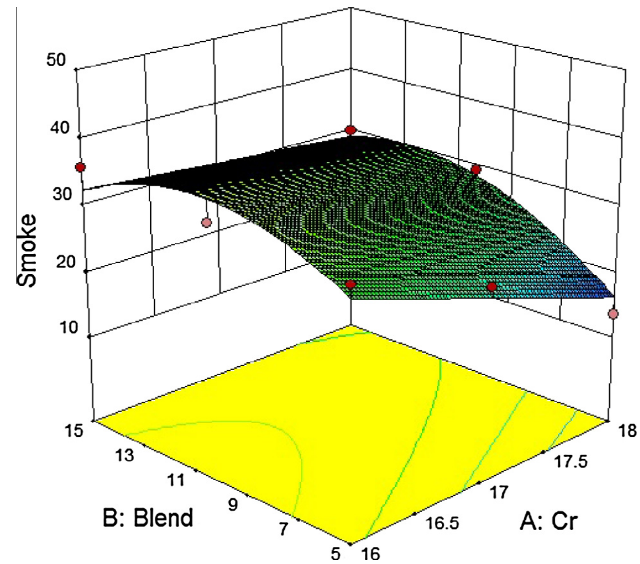

Figure 7 Variation of smoke emissions against blend and compression ratio.

conditions. High ignition delays leave a very small time for combustion and results in high HC emissions. Formation of rich zones inside the cylinder at high loads will demand high oxygen for oxidation of HC. The combined effect of these two (less time for combustion and high oxygen requirement) results in high HC emissions for biodiesel methanol blends especially at high loads.

5.5. NOx emissions

NOx emissions are a direct function of temperatures. Fig. 6 shows the variation of NOx emissions against blend and compression ratio. It is noted from the graph that unlike CO and HC emissions NOx emissions are decreasing with increase in blend percentage. From Table 4 it is observed that highest NOx emissions of 1208 ppm are observed at 18 compression ratio, 5% of blend and 20 kg of load whereas there is low NOx emissions of 20 ppm at 16 compression ratio, 10% of blend and 4 kg of load. The formation of NOx inside the combustion chamber requires high temperatures and pressures which are available at high loads and compression ratio. In diesel engines NOx emissions are very high because of the high compression ratio. There is a decrease in NOx emissions with the increase of methanol content in the blend. This is due to the high latent heat of methanol which will reduce the combustion temperatures resulting in low NOx.

5.6. Smoke emissions

Fig. 7 shows the variation of smoke emissions against blend and compression ratio. Smoke formation depends completely on the local air fuel ratios [20]. It is observed from the figure that smoke emissions are increasing with the increase of blend percentage up to some extent and then decrease. It is noted from the results in Table 4 that highest value of smoke density is found to be 46% at 16 compression ratio, 15% of blend and 20 kg of load and lowest value is found to be 22.6% at 18 compression ratio, 5% of blend and 16 kg of load. This can be due to high volatility of methanol which results in better mixing and lean combustion thus reducing the smoke [20]. The decrease of smoke emissions with a rise in compression ratio can be attributed to the better combustion and mixing which can be cited at higher compression ratios.

6. Conclusions

Optimization is carried out to find the optimal parameters for Biodiesel–methanol blends and the following conclusion can be made:

1. The experiments designed by the software helped to predict the accurate Reponses.
2. By using Desirability approach of RSM highest desirability of 0.978 is obtained.
3. The optimum operating conditions of the engine to get high performance and least emissions from methanol blends are found to be at 9.03 kg of load, 18 compression ratio and methanol blend of 5%.
4. Responses such as Bth, Bsfc, CO, HC, NOx and smoke at optimized parameters are found to be 31.95%, 0.375 kg/kW h, 0.036%, 5 ppm, 531.23 ppm and 15.35% respectively.
5. Brake thermal efficiency and brake specific fuel consumption are found to be increasing with increase of methanol content in the blend.
6. It is also noted that with use of methanol blends CO and HC emissions are increasing whereas NOx and Smoke are reducing.

The response surface methodology (RSM) is demonstrated to find the process variables so as to achieve the desired objectives for any IC engine. In the present study the compression ratio, the percentage of blend and load are found to obtain the maximum thermal efficiency and minimum emissions. Thus RSM is found to be an effective method for multi-objective optimization of IC Engines.

Acknowledgments

The authors would like to thank Prof. D. Varadaraju for his support and timely suggestion in perfecting this work.

References

[1] Ugur Kesign, Genetic algorithm and artificial neural network for engine optimisation efficiency and NOx emission, Fuel 83 (2004) 885–895.

[2] Z. Win, R.P. Gakkhar, S.C. Jain, M. Bhattacharya, Parameter optimization of a diesel engine to reduce noise, fuel consumption and exhaust emissions using response surface methodology, J. Automobile Eng. 219 (2005) 1181–1192.

[3] Jose M. Alonso, Fernando Alvarruiz, Jose M. Desantes, Leonor Hernandez, Vicente Hernandez, German Molto, Combining neural networks and genetic logrithms to predict and reduce diesel engine emissions, IEEE transactions on evolutionary computation, 2009.

[4] Cenk Sayin, H. Metin Ertunc, Murat Hosoz, Ibrahim Kilicaslan, Mustafa, Canakci, Performance and exhaust emissions of a gasoline engine using artificial neural network, Appl. Therm. Eng. 27 (2007) 46–54.

[5] P.K. Sahoo, L.M. Das, Process optimization for biodiesel production from Jatropha Karanja and Polanga oils, Fuel 88 (2009) 1588–1594.

[6] T. Ganapathy, K. Murugesan, R.P. Gakkhar, Performance optimization of Jatropha biodiesel engine model using Taguchi approach, Appl. Energy 86 (2009) 2476–2486.

[7] G. Najafi, B. Ghobadian, T. Tavakoli, D.R. Butts worth, T.F. Yusaf, M. Faizo Ilahnezad, Performance and exhaust emissions of a gasoline engine with ethanol blended gasoline fuels using artificial neural network, Appl. Energy 86 (2009) 630–639.

[8] B. Ghobadhian, H. Rahimi, A.M. Nikbakht, G. Najafi, T.F. Yusaf, Diesel engine performance and exhaust emission analysis using waste cooking biodiesel with an artificial neural network, Renew. Energy 34 (2009) 976–982.

[9] S. Jindal, B.P. Nandwana, N.S. Rathore, V. Vashistha, Experimental investigation of compression ratio and injection pressure in a direct injection diesel engine running on Jatropha methyl ester, Appl. Therm. Eng. 30 (2010) 442–448.

[10] M. Pandian, S.P. Sivapirakasam, M. Udaykumar, Investigation on the effect of injection system parameters on performance and emission characteristics of a twin cylinder compression ignition direct injection engine fueled with Pngamia biodiesel–diesel blend using response surface methodology, Appl. Energy 88 (2011) 2663–2676.

[11] A. Karnwal, M.M. Hasan, N. Kumar, A.N. Soddiquee, Z.A. Khan, Multi response optimization of diesel engine performance parameters using Thumba biodiesel–diesel blends by applying the Taguchi method and Grey relational techniques, Int. J. Automot. Technol. 12 (2011) 599–610.

[12] M. Costa, U. Sorge, L. Alocca, CFD optimization for GDI spray model tuning and enhancement of engine performance, Adv. Eng. Softw. 49 (2012) 43–53.

[13] Jose D. Martinez-Morales, Elvia R. Palacios-Hernandez, Gerardo A. Velazquez-Carillo, Modeling and multi objective optimization of a gasoline engine using neural networks and evolutionary algorithms, Appl. Phys. Eng. 14 (2013) 557–570.

[14] S. Molina, C. Guardiola, J. Martin, D. Garcia-Sarmiento, Development of a control-oriented model to optimize fuel consumption and Nox emissions in a DI Diesel engine, Appl. Energy 119 (2014) 405–416.

[15] K. SivaRamakrishnan, P. Ravikumar, Optimization of operational parameters on performance and emissions of a diesel engine using biodiesel, Int. J. Environ. Sci. Technol. 11 (2014) 949–958.

[16] Jagannath B. Hirakude, Atul S. Padalkar, Performance optimization of CI engine fuelled with waste fried oil methyl ester-diesel blend using response surface methodology, Fuel 119 (2014) 266–273.

[17] Carlo Beatrice, Pierpapolo Napolitano, Chiara Gudio, Injection parameter optimization by DOE of a light-duty diesel engine fed by Bio-ethanol/RME/diesel blend, Appl. Energy 113 (2014) 373–384.

[18] T. Lee, R.D. Reitz, Response surface method optimization of a high speed direct-injection diesel engine equipped with a common rail injection system, J. Eng. Gas Turb. Power 125 (2003) 541–546.

[19] Sunil Dhingra, Gian Bhushan, Kashyap Kumar Dubey, Multi-objective optimization of combustion, performance and emission parameters in a jatropha biodiesel engine using non-dominated sorting genetic algorithm-II, Front. Mech. Eng. 9 (2014) 81–94.

[20] K. Anand, R.P. Sharma, Pramod S. Mehta, Experimental investigation on combustion, performance and emission characteristics of neat karanji biodiesel and its methanol blend in a diesel engine, Biomass Bioenergy 35 (2011) 533–541.

[21] Nadir Yilmaz, Tomas M. Sanchez, Analysis of operating a diesel engine on biodiesel–ethanol and biodiesel–methanol blends, Energy 46 (2012) 126–129.

[22] Nadir Yilmaz, Francisco M. Vigil, Kyle Benalil, Stephen M. Davis, Antonio Calva, Effect of biodiesel-butanol fuel blends on emission and performance characteristics of a diesel engine, Fuel 135 (2014) 46–50.