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Multi-variable optimization of diesel engine fuelled with biodiesel using grey-Taguchi method

Mustabshirha Gul · Asad Naeem Shah · Younis Jamal · Imran Masood

Abstract The current work is aimed at the correlated multiple criteria optimization of various parameters of a turbocharged, direct injection, compression ignition engine alternatively fuelled with neat biodiesel and its 20 % blend with commercial diesel (B20) using grey–Taguchi method (GTM). The GTM converts multiple objectives of a problem into a single-objective function by an optimization technique. The process environment consisting of three input variables such as type of fuel, engine speed, and load was considered in this study. An orthogonal array was used for the design of experiments on the basis of L_9 (3^3). The optimal parameters were determined by the grey relational grade based on GTM. The consequent optimal combination of input parameters was used to maximize the output parameters including engine torque, brake power, heat release, and injection pressure with the possible diminution of brake specific fuel consumption of the engine. During the study, it was found that B20 as a fuel, 1,800 rpm as a speed, and 100 % as a load offer an optimal parametric combination at which the desired output results are achieved. Moreover, analysis of variance approach based on statistical software of Minitab 16 was used to investigate the comparative impacts of input variables on the output responses. It was known that load is the predominant factor with an influence of 92.42 % on the output parameters. Finally, a confirmatory test was performed to validate the results using artificial neural network in MATLAB.

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Abbreviations
CI	Compression ignition
DI	Direct injection
H.R	Heat release
IP	Injection pressure
BSFC	Brake specific fuel consumption
DOE	Design of experiments
OA	Orthogonal array
GRA	Grey relational analysis
GRG	Grey relational grade
OGRG	Overall grey relational grade
GRC	Grey relational coefficient
QLF	Quality loss function
ANOVA	Analysis of variance
DOF	Degree of freedom
ANN	Artificial neural network

1 Introduction

Pakistan is currently facing the crises of rising prices of fossil fuel and serious environmental threats. Being an agricultural country, it has a great potential of producing biodiesel. Nowadays biodiesel is gaining considerable attentions as a substitute fuel owing to its renewable, biodegradable, environmentally acceptable, readily available, miscible, and clean burning characteristics [1]. It has the potential to reduce both regulated and unregulated emissions without much disturbance to the engine performance by virtue of its better combustion in the combustion chamber [2–4].

Diesel engines are widely used to power the agricultural pumps and other machinery, heavy-duty transport vehicles,

construction machinery, and even to generate electricity. The energy crisis caused by the ever increasing demand of fossil fuels and the progressive tightening of emission standards have converged the attentions of the researchers of automotive industry to explore the alternative fuels for the compression ignition (CI) engines. Consequently, many efforts have been made in this field during the last couple of decades to decrease not only the exhaust emissions but also improve the thermal efficiency of the engines [5, 6]. It has been reported in the literature that a CI engine can perform adequately with biodiesels without any modification in the engine hardware because performance parameters are almost similar to that with fossil diesel [7–10].

The increasing demands of higher efficiency with reduced exhaust emissions have, therefore, led to recognize the parameters which may affect the performance and combustion phenomena of the engine. Fortunately, some optimization techniques are available in the literature which may be used to predict the engine behavior and thus to improve its efficiency. The most widespread optimization approach used for engine analysis is Taguchi method [11].

Taguchi method is widely used in the engineering domain to get the desired performance characteristics by optimizing the controlling factors. In this method, three stages such as system design, parameter design, and tolerance design are employed. System design uses engineering and scientific information necessary for producing a part. Tolerance design determines and analyzes the tolerances of optimum combinations suggested by parameter design. Parameter design is used to get the optimum levels of process parameters for determining the product parameter values. Taguchi approach improves the quality of plastic products and turning processes and decreases the cost without relying on physical structure or parts [12, 13].

Earlier, Taguchi approach was used to determine and analyze the optimal process parameters of a single quality response [14]. However, some processes have more than one quality responses, which are required to be considered. Traditional Taguchi approach cannot solve complicated interrelationships among multi-objective optimization problems into a single-objective function [15, 16].

Consequently, it was attempted to couple the grey relational analysis based on the grey system theory with Taguchi method to solve multi-performance characteristics [17, 18].

The newly developed method known as grey–Taguchi method (GTM) has a wide range of applications in many fields. Grey relational analysis is adopted to optimize machining parameters of the wire electric discharge machining process for improving multiple performance characteristics like maximum metal removal rate and minimum surface roughness [19, 20, 37]. GTM is also applied

to different laser cutting process to achieve better cut qualities within existing resources [22, 23, 38].

Yang et al. [39] designed light guide rod (LGR) that is used in automobile lighting. They optimized its experimental parameters by grey-Taguchi approach to get positive responses for illuminance flux and uniformity. Similarly GTM applications have also been reported in end milling process [40], CNC turning process [41] casting process [42] and submerged arc welding [43].

Through this method, it is possible to develop a correlation between desired and actual experimental data and then transform multi-quality characteristics into single grey relational grades. By comparing the computed grey relational grades, an optimal combination of process parameters is determined. Moreover, some efforts have been made by the researchers to develop the design of experiments for optimization in grey–Taguchi method on the basis of orthogonal array [21–24].

Furthermore, Roy et al. [25] attempted to determine an optimal combination of operating parameters of an engine that reduced the BSFC, NHC and PM emissions of a CRDI-assisted diesel engine under CNG–diesel dual-fuel mode. A positive correlation may be developed between operating parameters using the GTM. Karnwal et al. [26] have used the grey-Taguchi technique for improving diesel engine brake thermal efficiency with low emissions.

In automotive industry, some manufacturers and the researchers are in the pursuance of evaluation of performance of the CI engines at various compression ratios for various proportions of blends. This requirement needs a comprehensive experimental testing study of engine operation. Testing of engine under all possible operating conditions with different fuels is not only time consuming but also expensive. On the other hand, development of an accurate model of CI engine operating on biodiesel and its blends is very difficult due to the complicated processes involved. Contrary to conventional methods, GTM and artificial neural network (ANN) can be used to predict the engine performance and combustion more conveniently and effectively. This is the main goal of the current study. An ANN modeling technique can prove to be useful to determine the desired output parameters when sufficient experimental data are available [27].

It is a non-linear function, which develops a complex relationship between inputs and targeted outputs parameters [28] and thus may predict the output responses accurately. The ANN technique has also been used to predict performance and emission parameters of diesel engine using different injection pressure and engine speed [29]. Thus, the said ANN technique is deemed to play a decisive role in the validation of the already developed optimal results.

In the literature, efforts are made to reduce emissions in IC engines, there are currently no reports addressing the simultaneous optimization of multiple performance, combustion and injection parameters of multi-cylinder diesel engines fuelled with biodiesels without any modification in the engine hardware to best of authors' information. This work presents an experimental study to find an optimal combination of load, speed and type of fuel for improving performance, combustion and injection characteristics simultaneously using GTM.

2 Materials and methods

2.1 Experimental setup

A turbocharged, inter-cooled, four-cylinder DI, CI engine was engaged on a test bench as shown in schematic diagram Fig. 1. The other specifications of the engine are as follows: bore and stroke are 110 and 125 mm, respectively, while the displacement volume and compression ratio of the engine are 4,752 cm^3 and 16.8:1, respectively. The number of nozzle holes in the injector is 6, each with a diameter of 0.23 mm. The rated power (kW/rpm) and
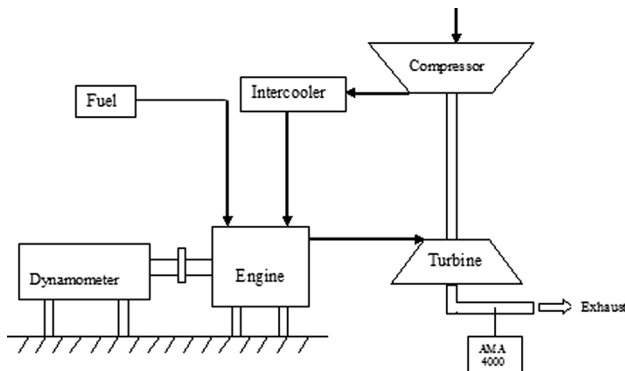

Fig. 1 Schematic diagram of test bench

Table 1 Properties of fuels

Properties	B100	B20	D	Standards[a]
Oxygen content (wt%)	11.33	n/a	0	Element analysis
Hydrogen content (wt%)	11.91	n/a	13.08	SH/T 0656-98
Carbon content (wt%)	76.83	n/a	86.92	SH/T 0656-98
Sulfur content (mg/L)	25	n/a	264	SH/T 0253-92
Lower heating value (MJ/kg)	37.3	41.57	42.8	GB/T 384
Viscosity (mm^2/s) at 20 °C	8.067	4.020	3.393	GB/T 265
Density (kg/m^3)	886.4	845.1	834.8	SH/T 0604
Cetane number	60.1	n/a	51.1	GB/T 386-91

[a] Chinese standard

maximum torque (N.m/rpm) are 117/2,300 and 580/1,400, respectively. No alteration or modification was made in the engine.

Three different fuels were used during the studies, which are recognized as petroleum diesel (D), neat biodiesel (B100), a blend of 20 % biodiesel and 80 % diesel (B20). The main properties of the test fuels are listed in Table 1. The fuel consumption and airflow rates of the engine were measured with the help of PLU-4000 (Pier Berg) and sensyflow-P (ABB Inc.), respectively, while the engine oil and cooling temperatures were measured through PT-100 sensors. Moreover, the engine exhaust temperature was monitored by employing a thermocouple (k-series). With the engagement of torque flange, the engine torque, speed and throttle positions were read directly in the control room through software "Automation System STARS Rev. 1.5". A Piezoelectric transducer (Kistler type 6125B) in conjunction with a charge amplifier was used to get the dynamic variations of engine cylinder pressure, while the sensor 2613A (Kistler) was used to receive the top dead center (TDC) signal. A combustion analyzer Dewetron (DEWE-5000) was employed to receive the output signal from amplifier, while TDC pulse was monitored through crankshaft optical encoder. Finally, the data was analyzed through FlexPro^{TM} spreadsheet software. In short, following important parameters were measured:

- Engine load, speed and torque (electrical dynamometer SCHENCK HT 350)
- Crankshaft crank angle (Kistler corporation 2613A sensor)
- HR in the cylinders and IP (DEWE-5000)
- Fuel flow rate (PLU-4000, Pier Berg)
- Airflow rates (Sensyflow-P, ABB Inc.)

2.2 Methodology used in grey-Taguchi method

The GTM is applied to design and perform the experiments for the assessment of output responses. The output parameters depend on several input factors without running the process at all possible combinations of given input values. It is possible to separate the individual responses by the systematic choose of some specific combinations of input variables. The GTM determines the correlations among actual and desired experimental data [19–24].

The design parameters affecting the engine performance are determined and then are controlled easily. The number of levels of the input parameters to be varied is to be specified. Increase in number of levels also increases the number of experiments to be performed.

In the current study, three input parameters such as type of fuel, speed, and load have been considered, each with three levels as shown in Table 2.

Table 2 Experimental factor and factor levels

Control variables	Code	Level		
		1	2	3
Type of fuel	A	B20	B100	D
Speed (rpm)	B	1,400	1,800	2,300
Load (%)	C	10	50	100

Table 3 Orthogonal array design L_9 (3^3)

Run number	Type of fuel	Speed	Load
1	1	1	1
2	1	2	2
3	1	3	3
4	2	1	2
5	2	2	3
6	2	3	1
7	3	1	3
8	3	2	1
9	3	3	2

The DOE is performed on the basis of OA. The design and selection of OA are dependent on the number of input parameters and levels of variation of each input parameter. Maximum number of OA depends on the number of tests performed for each level of each input parameter with the consequent OA as L_9 (3^3). Table 3 presents the OA design for the each run and its corresponding combination of fuel, speed, and load.

The next step is to conduct the experiments in accordance with OA design to collect the data. Then, the grey relational generation normalizes the data, and thus converts the original sequence (actual experimental data) into a comparable sequence in the following way [30].

Let the original sequence and comparable sequence are denoted by Y_0 (k) and Y_j (k), while $j = 1, 2, 3,…, m$ and $k = 1, 2, 3,…, n$, respectively; where m is the total runs of experiments to be conducted, and n is the total number of observations of given data.

If the desired objective is to maximize the outputs then the normalization of original sequence is completed using "the-larger-the-better" criterion, given as follows:

$$\left[Y_j^*(k) = \frac{Y_j(k) - \min Y_j(k)}{\max Y_j(k) - \min Y_j(k)} \right] \tag{1}$$

If the target is to minimize then the normalization of original sequence is completed using "the-smaller-the-better" criterion, given as follows.

$$\left[Y_j^*(k) = \frac{\max Y_j(k) - Y_j(k)}{\max Y_j(k) - \min Y_j(k)} \right] \tag{2}$$

A simple methodology can also normalize the original sequence as follows:

$$\left[Y_j^*(k) = \frac{Y_j(k)}{Y_j(1)} \right] \tag{3}$$

where $[Y_j^*(k)]$ is the value obtained after the grey relational generation, $\min Y_j(k)$ is the minimum value of $Y_j(k)$ for the kth response, and $\max Y_j(k)$ is the maximum value of $Y_j(k)$ for the kth response and $Y_j(1)$ is the first value of the sequence.

Moreover, the grey relational coefficient (GRC) is used to approximate the degree of correlation between the original and comparable sequences [$Y_0(k)$ and $Y_j(k)$, $j = 1, 2, 3….$]. If the two sequences are alike, then the value of the GRC equals to one. The GRC is given as:

$$\xi_j = \frac{\Delta_{\min} - \gamma \times \Delta_{\max}}{\Delta_{oj(k)} - \gamma \times \Delta_{\max}} \quad 0 \le \gamma \le 1$$

Here, $\Delta_{\min}$ and $\Delta_{\max}$ are the minimum and maximum values of $\Delta_{oj(k)}$ sequences. $\Delta_{oj(k)}$ is the quality loss function measured by the difference between the original values and the estimated normalized values of data. The quality loss function is used to investigate whether a certain characteristic is falling between a given particular limits or not. It helps in minimizing the cost by reducing the variations without affecting the quality.

$$\Delta_{oj(k)} = (\text{Quality loss}) = \left[Y_0^*(k) - Y_j^*(k) \right]$$
$$\therefore Y_0^*(k) = 1.00 \tag{4}$$

Then, the overall grey relational grade (OGRG) is the average of GRC corresponding to the given responses. The overall multiple response characteristic of a process depends on the calculated OGRG, given as follows:

$$\left[\psi = \frac{1}{n} \sum_{k=1}^{n} \beta_k \xi_j \right] \tag{5}$$
$$\text{Here,} \left[\sum_{k=1}^{n} \beta_k = 1 \right]$$

2.3 Analysis of variance (ANOVA)

ANOVA is carried out to estimate that input parameters, which affect the performance characteristics more significantly. It is calculated by the sum of the squared deviations from the total mean of the OGRG. In addition to this, the input parameter with larger F value has a significant effect on multiple output responses [16].

Where degree of freedom = DOF = $N-1$; N = number of levels = 3.

Sum of square of each process parameter SS_p is calculated as

J Braz. Soc. Mech. Sci. Eng. (2016) 38:621–632

625

Table 4 Experimental results of turbocharged CI engine

Run number	OA			Output responses				
	A	B	C	T (N. m)	P_b (kW)	HR (% H.R/°CA)	IP (bar)	BSFC g/(kW h)
1	B20	1,400	10	57.53 ± 18.86	8.66	2.98 ± 2.49	265.46 ± 18.11	410.65 ± 26.44
2	B20	1,800	50	270.06 ± 23.40	50.79	1.38 ± 3.20	443.16 ± 27.22	252.72 ± 23.15
3	B20	2,300	100	430.78 ± 34.45	103.24	0.81 ± 5.42	799.63 ± 45.25	281.14 ± 30.56
4	B100	1,400	50	290.14 ± 25.35	42.52	1.35 ± 2.12	394.94 ± 24.89	262.61 ± 23.29
5	B100	1,800	100	518.65 ± 38.78	97.71	0.85 ± 1.01	747.80 ± 26.98	268.15 ± 19.67
6	B100	2,300	10	39.79 ± 19.55	9.58	1.24 ± 3.12	355.91 ± 34.50	943.41 ± 38.12
7	D	1,400	100	577.77 ± 17.22	84.58	0.93 ± 5.22	514.35 ± 23.72	219.13 ± 22.22
8	D	1,800	10	51.68 ± 25.99	10.95	2.66 ± 2.15	266.60 ± 22.89	479.82 ± 33.12
9	D	2,300	50	242.90 ± 36.22	59.00	1.22 ± 3.88	492.07 ± 14.81	242.90 ± 25.86

$$\left[\mathrm{SS_p} = \sum_{i=1}^{3} N(\eta_i - \widehat{\eta})^2 \right]$$

η_i = avg OGRG of each parameter at ith level and $[\widehat{\eta}]$ = mean of avg OGRG of each parameter

Error sum of square = $\mathrm{SS_e} = \mathrm{SS_T} - \mathrm{SS_A} - \mathrm{SS_B} - \mathrm{SS_C}$

Mean sum of square = MSS = (individual sum of square)/DOF

F value = $\mathrm{MSS/MSS_e}$; % contribution = $(\mathrm{SS_p/SS_T}) \times 100$

3 Results and discussion

3.1 Experimental results based on OA

Table 4 presents the experimental data and results obtained on the basis of OA design. It is obvious that three input parameters including type of fuel, speed, and load were considered, each with three levels of variation. The DOE performed on the basis of L_9 (3^3) OA leads to experimental data of output parameters including T, P_b, HR, IP, and BSFC.

The experimental results given as output responses reveal that both T and P_b slightly decrease with biodiesel content in the fuels (B20 and B100) because of low heating value of biodiesel. These parameters steadily increase with the increase in engine speed and load. The HR is slightly higher for B20 and B100 as compared to neat diesel at all engine speeds and loads owing to better physicochemical properties of biodiesel [1]. Furthermore, IP and BSFC both were higher for both B20 and B100 as compared with their counterpart diesel. This was expected because of higher density and lower heating value of biodiesel relative to diesel as injection of biodiesel started earlier. So, more mass of biodiesel was injected as compared to the mass of neat

diesel [31], with the consequent rise in BSFC particularly at higher loads.

3.2 Grey-Taguchi method

3.2.1 Grey relational generation

Experimentally measured quantities of output parameters (in original sequence), listed in Table 4, cannot be compared as they have different units and hence it becomes necessary to convert them into normalized dimensionless values (in comparable sequence). In grey relational generation, each run of experimental data was normalized by maximizing T, P_b, HR and IP, while minimizing the BSFC. For this purpose, range was set from 0 to 1 using Eqs. (1) and (2). The larger the value of a normalized result, the better would be the performance. Thus, a value equal to 1 means the best result [30]. The results shown in Table 5 are presenting the linear normalization of output parameters taken in terms of grey relational generation, which distribute the data uniformly and scale it within the acceptable ranges for the subsequent analysis.

3.2.2 Evaluation of GRC and overall GRG

A GRC has the potential to develop a correlation between the original sequence and comparable sequence of the output responses. An output parameter which has the value of GRC closer to 1 indicates the good correlation. GRC is calculated from quality loss function (QLF).

Table 6 shows the Taguchi QLF of each response using Eq. (4). It is the direct measure of the level of variation between the original sequences and comparable sequences. Smaller values imply that the given characteristic is at its nominal value with a negligible small loss. So, Taguchi QLF gives a good way to analyze the costs associated with variability even within the limits, and thus leads to the

626

J Braz. Soc. Mech. Sci. Eng. (2016) 38:621–632

Table 5 Grey relational generation

Run number	Grey relational generation (larger-the-better)				Grey relational generation (smaller-the-better)
	T (N.m)	P_b (kW)	HR (% H.R/°CA)	IP (bar)	BSFC g/(kW h)
1	0.03298	0.00000	1.00000	0.00000	0.73557
2	0.42802	0.44543	0.26142	0.33267	0.95363
3	0.72678	1.00000	0.00000	1.00000	0.91439
4	0.46535	0.35795	0.25234	0.24239	0.93997
5	0.89011	0.94153	0.01905	0.90298	0.93232
6	0.00000	0.00973	0.20046	0.16932	0.00000
7	1.00000	0.80266	0.05861	0.46595	1.00000
8	0.02209	0.02424	0.85319	0.00213	0.64007
9	0.37754	0.53223	0.19162	0.42424	0.96718

Table 6 Taguchi QLF (Δ_{oj}) of each response

Run number	T (N.m)	P_b (kW)	HR (% H.R/°CA)	IP (bar)	BSFC g/(kW h)
1	0.96702	1.00000	0.00000	1.00000	0.26443
2	0.57198	0.55457	0.73858	0.66733	0.04637
3	0.27322	0.00000	1.00000	0.00000	0.08561
4	0.53465	0.64205	0.74766	0.75761	0.06003
5	0.10989	0.05847	0.98095	0.09702	0.06768
6	1.00000	0.99027	0.79954	0.83068	1.00000
7	0.00000	0.19734	0.94139	0.53405	0.00000
8	0.97791	0.97576	0.14681	0.99787	0.35993
9	0.62246	0.97576	0.80838	0.57576	0.03282

reduction of variability of engine output characteristics to a specific target value.

Table 7 presents the simultaneously generated single-valued overall GRG based on GRC and L_9 OA design, and is abbreviated as OGRG. An OGRG is required to give a combination which would be acceptable for all the output parameters to be at their optimum level. Although experiment No. 1 in Table 7 shows the maximum HR but does not give the

desired result for T, P_b and IP and BSFC with this particular OA combination. So, an OGRG was developed to get all the desired output responses simultaneously using Eq. (5).

A higher OGRG corresponds to a parametric combination closer to the optimal values, and thus leads to a better performance level [32]. It indicates that the experimental result is closer to the ideally normalized value. Here, Experiment No. 3 (B20, 2,300 rpm, 100 %) has the best multiple performance characteristics among the nine experiments because it has the highest OGRG. In other words, the optimized complex multiple performance characteristics are now converted into a single optimization in the form of OGRG. It is noteworthy from the above analysis that desired outputs can be obtained at the maximum engine speed and load along with B20 as a fuel.

3.2.3 Calculation of average OGRG

The effect of input parameters on OGRG at different levels is independent of the others because the experimental design is orthogonal. An average OGRG deals with the various types of parametric combinations to find out the best one, which will give the desired output results simultaneously.

Table 7 The generation of GRC and OGRG for various combinations

Run number	OA			Grey relational coefficients (distinguishing coefficient ɣ = 0.5)					OGRG
	A	B	C	T (N.m)	P_b (kW)	HR (% H.R/°CA)	IP (bar)	BSFC g/(kW h)	
1	1	1	1	0.34083	0.33333	1.00000	0.33333	0.65408	0.53231
2	1	2	2	0.46643	0.47413	0.40369	0.42833	0.91512	0.53754
3	1	3	3	0.64665	1.00000	0.33333	1.00000	0.85381	0.76676
4	2	1	2	0.48326	0.43781	0.40075	0.39758	0.89281	0.52244
5	2	2	3	0.81981	0.89530	0.33762	0.83750	0.88078	0.75420
6	2	3	1	0.33333	0.33551	0.38475	0.37575	0.33333	0.35254
7	3	1	3	1.00000	0.71701	0.34689	0.48354	1.00000	0.70949
8	3	2	1	0.33832	0.33881	0.77302	0.33381	0.58144	0.47308
9	3	3	2	0.44545	0.33881	0.38215	0.46479	0.93840	0.51392

Table 8 The generation of average OGRG

Levels	Factors		
	A (type of fuel)	*B* (speed)	*C* (load)
1	**0.6122**	0.58808	0.45264
2	0.54306	**0.58827**	0.52463
3	0.5655	0.5444	**0.74348**
Delta	0.06914	0.04387	0.29084
Rank	2	3	1

Bold values indicate the rank (maximum value of the average OGRG) of each input factor
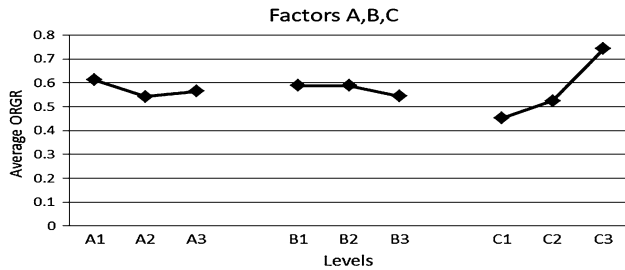
Fig. 2 Graph between average OGRG and level of factor

This average OGRG calculated for each level of input parameter gives the most significant level in accordance with multiple responses as summarized in Table 8.

In GTM, the statistic delta is defined as the difference between the higher and lower effects of each input factor. This classification also supports in determining the most influencing factor.

The maximum value of the average OGRG leads to the maximum possible effects of that particular factor known as rank. The results presented in Table 8 reveal that load has the predominant effect on the multiple performance characteristics of diesel engine. Moreover, the type of fuel is second, while the speed is the third ranked parameter in this study.

A response graph of the average OGRG of each input parameter at three different levels is also given in Fig. 2. This graph is used primarily for the selection of a level (among various factors) of the best performance.

Figure 2 depicts that the higher influence of the input parameters on the output results occurs at level 1 as far as the type of fuel is concerned, but at level 2 and level 3 for the speed and load, respectively. The difference between end points of load graph is greater than those of type of fuel and speed graphs. This leads to the fact that load is more sensitive parameter of the performance, and thus is ranked at position 1 in Table 8. Consequently, the optimal parametric combination at which the desired output results can be obtained is given as: (A1, B2, C3) = B20 as a fuel, 1,800 rpm as a speed, and 100 % as a load level.

Thus, when engine is operated with fuel B20 at 1,800 rpm speed and 100 % load then T, P_b, HR and IP

will be at their maximum or peak values, however, BSFC will remain at its minimum value and their values obtained experimentally are shown in Fig. 7.

3.3 ANOVA-based analysis of the input parameters

ANOVA technique is performed using the statistical software of Minitab 16, which indicates the relative percentage of influence of factors to the variation of output results and interprets the most significant input parameter of optimal combination [33, 34]. Table 9 shows that the load, i.e., factor C is the most significant factor with a contribution up to 92.42 %, when the maximization of T, P_b, HR and IP and minimization of BSFC are considered simultaneously. On the other hand, type of fuel and engine speed, i.e., factors A and B are the second and third contributors with their respective contributions of 5.01 and 2.57 %.

3.4 ANN-based validation of results

ANN approach is used to revalidate the output responses at optimum combination of input parameters (A1 B2 C3 in this case), obtained from GTM [29, 35, 36]. If the predicted and experimental values at optimal combination are close to each other, then the effectiveness of the optimal combination can be ensured. This will lead to the investigation of performance of diesel engine experimentally at optimum combination of input parameters.

3.4.1 ANN modeling

The experimentally collected data, based on OA design, is used to develop and to train the artificial neural network (ANN) using graphical user interface (GUI) in MATLAB with 'nntool' command. Three process parameters including type of fuel, speed and load and five output parameters of torque, power, heat release, injection pressure and B.S.F.C are used to model ANN as shown in Fig. 3. Here 3 neurons are used in input layer, 20 neurons (determined by trial and error to minimize the mean squared error between actual and predicted outputs) in hidden layer and 5 neurons in the output layer and proposed neural network architecture is shown in Fig. 4.

In the present study, feedforward backpropagation network algorithm with three layers of neurons (input, one hidden and output layers) is constructed. This specified ANN model forwards the information from input layer to output layer through hidden layer in one direction only. MSE (Mean Squared Error) is chosen as performance function of network. Number of neurons in input and output layers depends on the number of independent input parameters and dependent output parameters, respectively.

628

J Braz. Soc. Mech. Sci. Eng. (2016) 38:621–632

Table 9 Application of ANOVA technique for the output parameters

Factors	Levels			DOF	Sum of square (SS)	Mean square (MSS)	*F* value	Contribution (%)
	1	2	3					
A	0.61220	0.54306	0.56550	2	0.007466	0.003733	0.98	5.01
B	0.58808	0.58827	0.54440	2	0.003832	0.001916	0.51	2.57
C	0.45264	0.52463	0.74348	2	0.137665	0.068833	18.14	92.42
Error				2	0.007587	0.003794		
Total				8	0.148963			
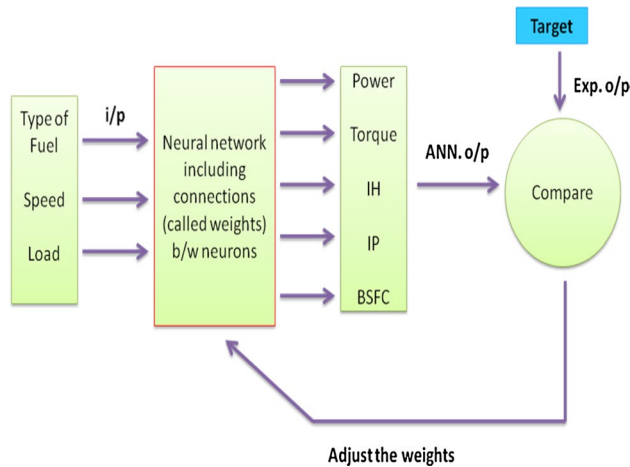
Fig. 3 Schematic model of ANN
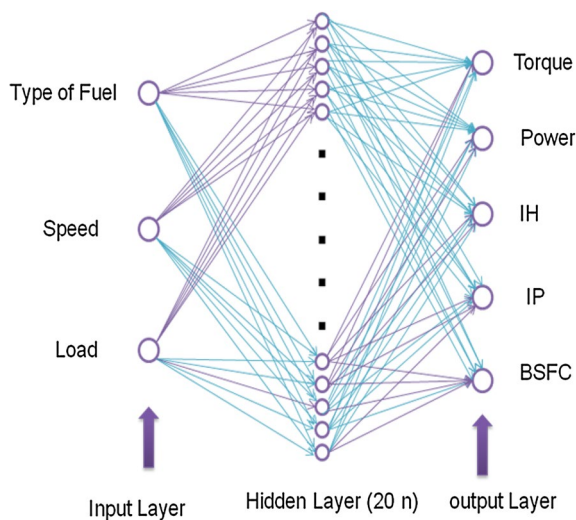
Fig. 4 Proposed ANN architecture

3.4.2 ANN training

Feedforward ANN is trained by applying the input parameters to the input layer having network-processing element. During this training, the network learns to predict new outputs through a repetitive method. The outputs generated by ANN are compared with the target (experimental output responses presented in Table 4) to adjust the network by adjusting the weights and biases, until the network output matches the target and MSE gets minimized. Activation function of the hidden layer is chosen as "tansig" and in the output layer as "purelin". For the training of the network, "trainlm" function is used, which updates the values of weight and bias according to the Levenberg–Marquardt optimization. The maximum training epochs are 300 and the MSE is 0.0001. The other training parameters of neural network were taken as defaults of neural network toolbox, MATLAB.

3.4.3 ANN simulation

At the end, the trained network is used to simulate (predict) the output responses (torque, brake power, heat release, injection pressure and brake specific fuel consumption) at optimum combination of input parameters (A1 B2 C3), obtained from GTM. Screen shots of ANN model development, ANN training and simulation are shown in Figs. 5 and 6.

3.5 Simulated ANN and experimental results

The simulated and experimental results of output responses at optimum combination of input parameters (A1 B2 C3), obtained from GTM, are presented in Table 10.

It is clear from Fig. 7 that results obtained from both methods (i.e., the ANN predicted values and experimental values taken at optimal combination) were closer to each other. This ensures the effectiveness of the GTM approach to find an optimal combination of input parameters.

4 Conclusion

In current study, grey-Taguchi method was used for the optimization of three input parameters of a turbocharged diesel engine such as type of fuel, speed and load to get the maximum possible values of T, P_b, HR and IP, but
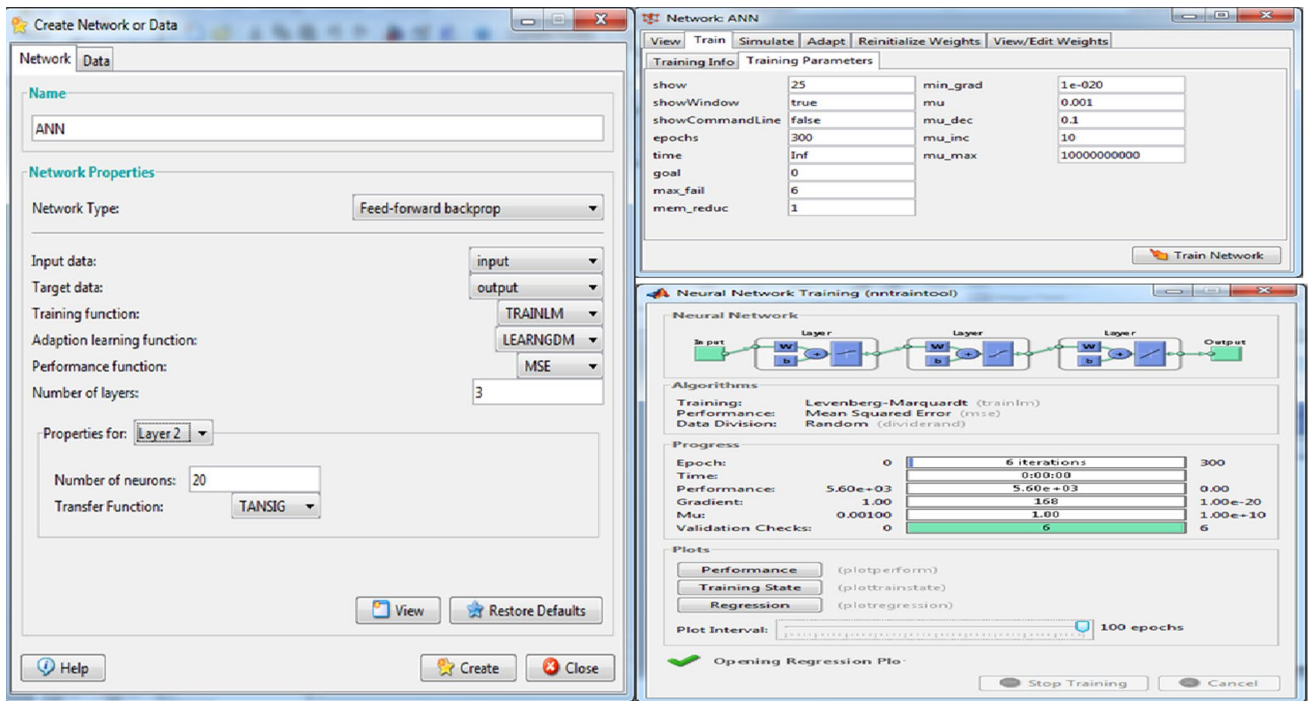
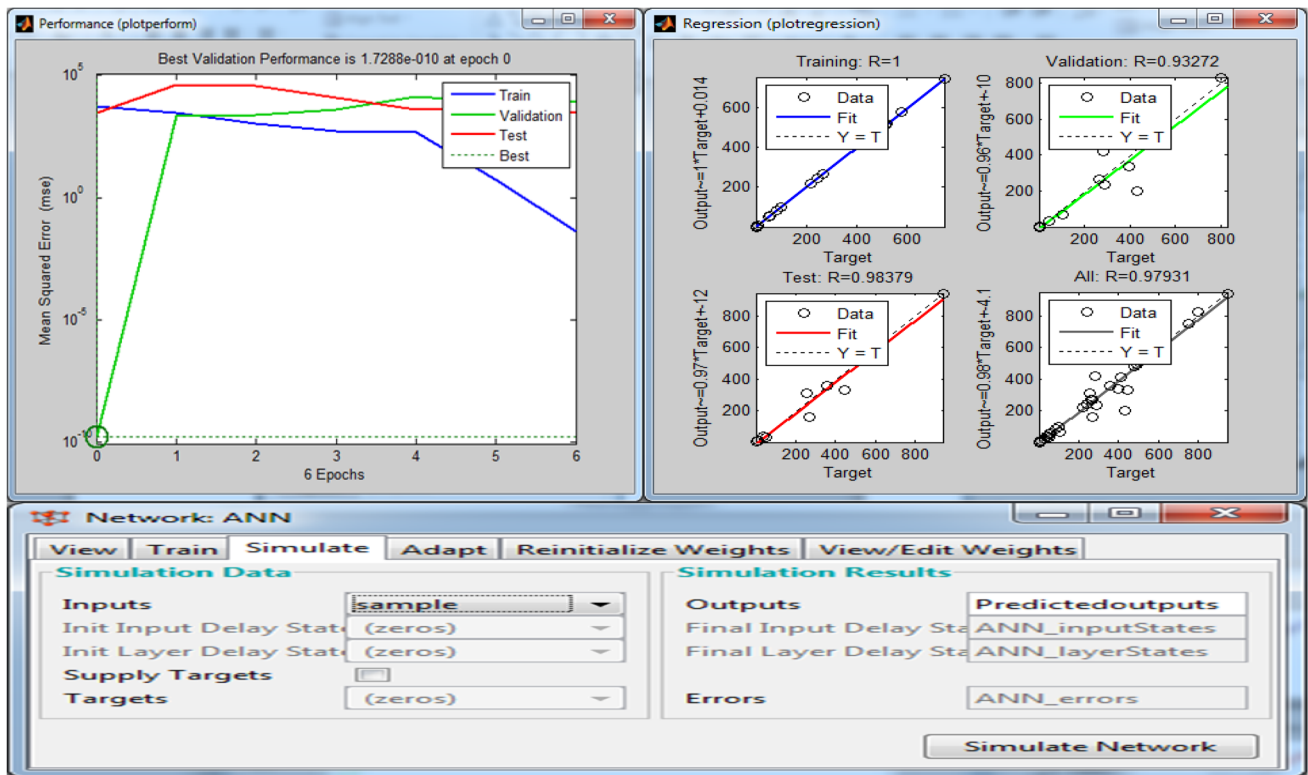**Fig. 5** Development of ANN model by using GUI in MATLAB


Fig. 6 Training and simulation of ANN

Table 10 Simulated ANN and experimental results

Predicted output by ANN at (A1 B2 C3)		Output by experiments at (A1 B2 C3)	
Torque (N.m)	493.22	Torque (N.m)	533.454
Power (K w)	100.37	Power (K w)	99.788
Injection pressure (bar)	740.36	Injection pressure (bar)	700.16
Heat release (% H. R/°CA)	0.8915	Heat release (% H.R/°CA)	0.8611
BSFC [g/(kW h)]	263.278	BSFC [g/(Kw h)]	238.002

minimum possible value of BSFC. To decrease the experimental efforts, Taguchi's L_9 OA was selected for design of experiments then combination of GRA with Taguchi was also proposed for the optimization of diesel engine. Following are the key findings of the study:

- Out put responses (e.g., T, P_b, HR, IP and BSFC) based on L_9 (3^3) OA experimental design were found. The results revealed that both T and P_b were slightly lower, while HR, IP and BSFC were higher with B20 and B100, relative to diesel.
- Under the GTM approach, each run of experimental data was normalized by maximizing T, P_b, HR and IP, while minimizing the BSFC. This simplified the analysis by converting the multi-objective performance characteristics into a single OGRG.

- Subsequently, a single-valued OGRG based on GRC and L9 OA design was generated to obtain an acceptable combination for all the output parameters so that an optimum level might be reached.
- An average OGRG was found for each level of input parameter to get the most suitable level of the multiple responses. Thus, B20, 1,800 rpm, and 100 % load were the outcome of average OGRG indicating the corresponding maximum values. So, it was concluded that the diesel engine working on B20 biodiesel–diesel blend at 1,800 rpm speed and 100 % load achieves the optimum engine performance as defined by maximum T, P_b, HR and IP, and the minimum BSFC.
- B20 was found to be an effective substitute fuel for diesel engine.
- Based on ANOVA technique, engine load was found a predominant input parameter with an influence of 92.42 % on the engine output parameters. While speed was found an insignificant parameter, because it has low % contribution (2.57 %) and smaller F value.
- The load and type of fuel (biodiesel) are primary factors that affect the performance of diesel engine, while speed is considered a secondary factor.
- The ANN-based confirmatory results revealed that the predicted optimal combination of input parameters under the GTM approach is suitable for the better performance of the diesel engine.
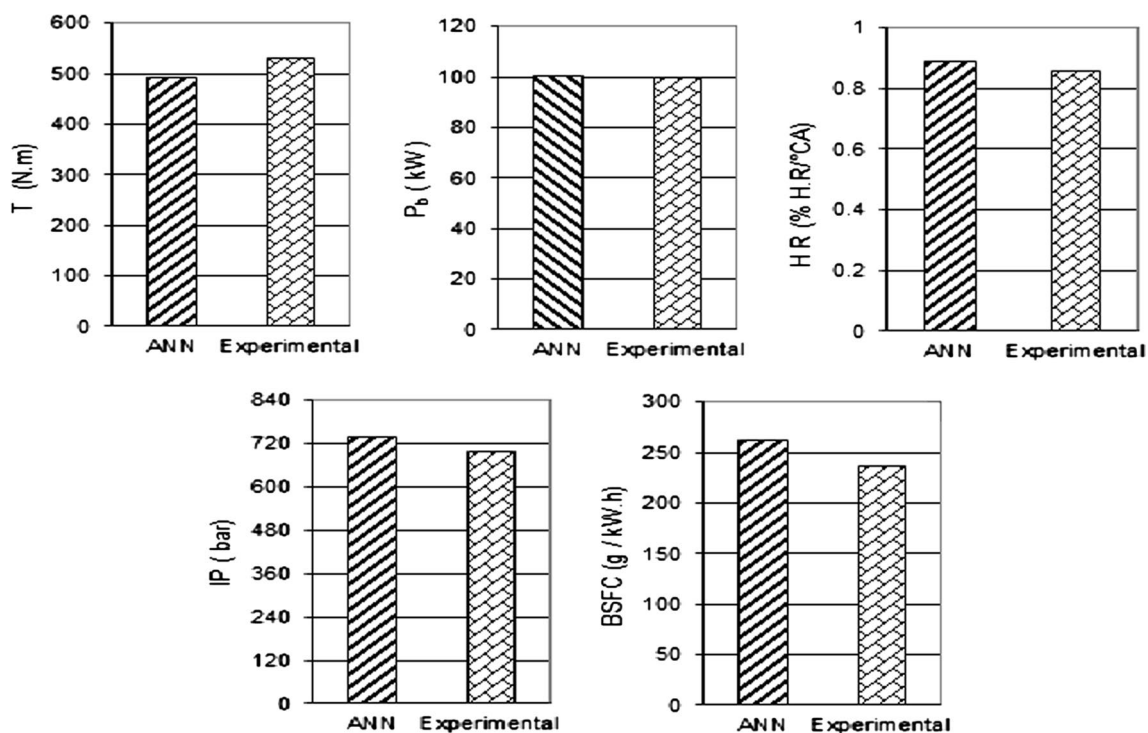
Fig. 7 A comparison of ANN and experimental results

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632

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