Research Article

Optimization of Performance Parameters of a Diesel Engine fuelled with Biofuels

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Abstract

This paper aims to study the optimization of performance parameters to improve diesel engine efficiency . An attempt has been made to solve the correlated multiple criteria optimization problem of performance parameters of diesel engine. The process environment has been assumed consisting of four variables load, time taken for 10cc fuel consumption, type of fuel, valve opening position. Taguchi method has been adopted to convert multiple objectives of the optimization problem into a single objective function. Taguchi's technique has been applied to determine the optimal setting, which can maximize The output parameters B.P , Break thermal Efficiency,co2%,and can minimize F.C.H,B.S.F.C, CO%,HC,O2%.The result of this optimization technique has been imported to that of grey – Taguchi technique, another approach which is widely used for solving multi criteria optimization problems. A confirmatory test showed satisfactory result by Artificial neural network in MATLAB.

Keywords: Biodiesels, optimization, Taguchi method, Artificial neural network.

1. Introduction

The present day energy crisis and the ever increasing demand for the fuels in addition with the global pollution scenario has led to the search of newer, renewable, bio-degradable fuels which are safe for usage in engines. Biodiesel(technical name- mono alkyl ester) which is meant to be used in standard diesel engines refers to a vegetable oil or animal fat based diesel fuel consisting of long chain alkyl esters, typically made by chemically reacting liquids with an alcohol producing fatty acid esters. It can be used alone or can be blended with petro diesel.

Table 1. Compares some of the physical and chemical properties of diesel and various methyl easters. Vegetable oils have higher density than diesel, but lower energy content. Vegetable oil have lower carbon content than diesel, which means lower CO_2 emissions per liter of fuel burnt, however CO_2 emissions per km travelled may not be lower due to the lower energy content of vegetable oil and a higher portion of multi bonded carbon compound.

Tangavelu.*et.al* conducted experiments on diesel engine fuelled with jathropa and diesel oil blends at various loads and concluded that the emissions are about 20% lower than the diesel oil. Asad Naeem shah.*et al*(2009*)* made carbonylisis emission comparison of a turbocharged diesel engine fuelled with diesel, biodiesel and biodiesel-diesel blends and the results show that formaldehyde and total carbonylisis from the test fuels

exhibit maximum BSE at low load., which decreases with the increase in load.

Table 1.Comparision of typical properties of diesel and various methyl easters

S.No	Characteristics	diesel	Mahua Methyl Ester	Cotton Seed Methyl Ester	Jathropa Methyl Ester
1	Density (kg.m^3)	0.83	0.869	0.871	0.868
2	Calorific value (KJ/kg)	43,000	38,800	36,300	36,100
3	Viscosity (cst)	2.75	4.38	5.17	5.33
4	Cetane number	45	50		55
5	Acid number (mg.KOH/gm)	0.2 max	<0.2	0.018	0.011
6	Flash point(ºC)	0	168	174	162

Taguchi method is a technique for designing and performing experiments to investigate processes where the output depends on many factors (variables, inputs) without

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having to tediously and uneconomically run the process using all possible combinations of values of those variables. By systematically choosing certain combinations of variables it is possible to separate their individual effects.

Traditional Taguchi methods cannot solve multi objective optimization problem. To overcome this Taguchi method is coupled with grey relational analysis which has a wide application. Calculated to repeat the correlation between desired and actual experimental data. Then overall grey relational grade is determined by averaging the grey relational coefficient corresponding to selected responses. The overall performance characteristic of the multiple response process depends on the calculated Grey Relational Grade.

Sanjit Moshat *et al*.(2010) adopted the Taguchi method for optimization of CNC end milling process parameters. This method is adopted to get good surface finish as well as high MRR. Datta *et al*(2009) applied the Taguchi method for correlated multi-correction of submerged arc weld. There are several bead parameters like bead height, penetration depth, bead width, percentage dilution etc, which indicate quality of submerged arc weldmet. Hydein *et al* (2010) applied Grey Taguchi method for friction stir welding to improve tensile strength, & elongation of welded Al-alloy. Rotating speed, welding speed and shoulder are input process parameters.

Siba Shankar Mahapatra *et al*(2010) adopted Taguchi method for simultaneous optimization of correlated multiple surface quality characteristics of MS turned product. In this study spindle speed, feed and depth of cut are taken as process variables. In the literature review, it has been observed that Taguchi method has been adopted in the fields of arc welding, straight turning operation and in CNC end milling operation. In the present study, the foresaid method has been used to optimize the performance parameters and emission parameters of a diesel engine fuelled with biofuel.

2. Design of the experiment

Table 2 Process control parameters and their limits.

S.No.	Trail	Load	Time for 10cc	Type of fuel	Valve opening position
1	1	1	1	1	1
2	2	1	2	2	2
3	3	1	3	3	3
4	4	2	1	2	3
5	5	2	2	3	1
6	6	2	3	1	2
7	7	3	1	3	2
8	8	3	2	1	3
9	9	3	3	2	1

The objective of Taguchi's efforts is process and product design improvement to the identification of easily controllable factors and their settings, which minimize the variation in product response while keeping the mean response on target. Change the experimental procedures from varying one factor at a time to varying many factors at a time through statistical experimental techniques.

Table 3 Process control parameters for OA design.

S. No.	Trail	Load	Time for 10cc	Type of fuel	Valve opening position
1	1	2	61	Diesel	1/8
2	2	2	64	Bio-diesel	3/32
3	3	2	60	Methanol additive	1/16
4	4	4	61	Bio-diesel	1/16
5	5	4	64	Methanol additive	1/8
6	6	4	60	Diesel	3/32
7	7	6	61	Methanol additive	3/32
8	8	6	64	Diesel	1/16
9	9	6	60	Bio-diesel	1/8

Table 4 Output response table for performance parameters.

S.No	FCH	BHP	BSFC	$\eta_{B.m}$
1	0.491	0.92	0.169	24.79
2	0.469	0.92	0.178	29.69
3	0.474	0.92	0.167	32.48
4	0.492	1.84	0.169	59.38
5	0.445	1.84	0.177	64.96
6	0.499	1.84	0.166	49.58
7	0.467	2.77	0.169	67.78
8	0.468	2.77	0.169	65.45
9	0.501	2.77	0.177	66.89

Table 5 Output response table for emission parameters.

S.No	CO	CO2	HC	O2
1	0.15	4.55	22	14.32
2	0.12	4.87	16	14.86
3	0.16	4.84	21	14.79
4	0.21	6.22	25	11.92
5	0.28	5.74	48	11.99
6	0.29	6.41	28	11.89
7	0.52	8.1	58	9.7
8	0.46	7.95	47	8.98
9	0.45	8.22	42	9.03

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│     GETTING EXPERIMENTAL DATA        │
└─────────────────────────────────────┘
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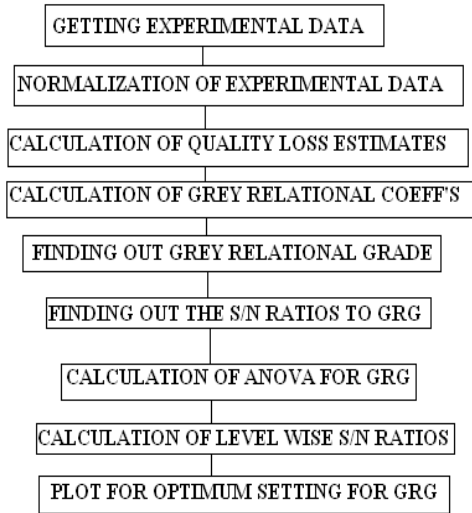
Fig.1 Block diagram of GRA:

3. Methodology used in Grey Relational Analysis:

Getting experimental data:

The experimental values for the four output responses are tabulated and are taken to optimization.

Normalization of experimental data:

As the desired objective is to maximize Tensile Strength, Elongation, Flexural Strength and Impact Strength, hence the experimental data is normalized by using the higher-the-better (HB) criterion. Higher-the-better (HB) criterion, the normalized data can be expressed as:

$$x_i(k) = \frac{y_i(k) - \min\, y_i(k)}{\max\, y_i(k) - \min\, y_i(k)} \qquad (1)$$

Here $x_i(k)$ is the value after the grey relational generation, $\min\, y_i(k)$ is the smallest value of $y_i(k)$ for the kth response, and $\max\, y_i(k)$ is the largest value of $y_i(k)$ for the kth response.

Calculation of quality loss estimates:

An ideal sequence is $x_0(k)$ for the responses. The quality loss for each ith trial is estimated as $x_0(k) - x_i(k)$.

Calculation of Grey Relational Coefficients:

The purpose of grey relational grade is to reveal the degrees of relation between the sequences say, [$x_0(k)$ and $x_i(k)$, i =1, 2, 3......., 16]. The grey relational coefficient $\xi_i(k)$ can be calculated as

$$\xi_i(k) = \frac{\Delta_{min} + \psi \Delta_{max}}{\Delta_{0i}(k) + \psi \Delta_{max}} \qquad (2)$$

Here $\Delta_{0i} = \|x_0(k) - x_i(k)\|$ = difference of the absolute value $x_0(k)$ and $x_i(k)$; ψ is the distinguishing coefficient

$0 \leq \psi \leq 1;$ $\Delta_{min} = \forall j^{min} \in i \forall k^{min} \|x_0(k) - xj(k)\| =$ the smallest value of Δ_{0i} .

Finding out the Grey Relational Grade:

By averaging the grey relational coefficients, the grey relational grade can be computed.The grey relational grade γ_i can be computed as:

$$\gamma_i = \frac{1}{n} \sum_{k=1}^{n} \xi_i(k) \qquad (3)$$

Here n = number of process responses.

Finding out the S/N ratios to GRG:

There are three types of S/N ratios Normal – the – best, Higher- the- better , and Lower-the-better criterion. By taking HB criterion the S/N ratios are calculated.

The formula for calculating S/N Ratios:

$$SN\left(\text{Higher-the-Better}\right) = -10 \log\left(\frac{1}{t}\sum_{i=1}^{t}\frac{1}{y_i^2}\right)$$

Here t is the number of measurements, and y_i is the measured i^{th} characteristic value, i.e., i^{th} quality indicator.

Calculation of ANOVA for GRG:

ANOVA   OF GRG Formulae:

DOF= Degrees of Freedom=n-1;   n=number of levels
For example for temperature n=3; so DOF=3-1=2
Total sum of squares= $SS_T = .\sum y_i^2 - (\sum y_i)^2 /N$ =0.252071
Correction Factor= C.F. = $(\sum y_i)^2 /N$

Sum of squares of factor A= $SS_A = (A_1^2 + A_2^2 + A_3^2 + A_4^2)/4$ -C .F=0.212581
Similarly SS_B, SS_C and SS_D are calculated as 0.004506, 0.034137, 0.00081.

$SS_e = SS_T - SS_A - SS_B - SS_C - SS_D$
Error sum of squares=$SS_e = SS_T - SS_A - SS_B - SS_C - SS_D$ = 0.0004

Mean Sum of Squares = (Individual sum of squares)/ D.O.F.

M SS_A = 0.18993/ 2 = 0.094965
F-Ratio= M SS_A/ M SS_e 0.094965/ 0.00628 = 2.6182
% Contribution = SS_A/ SS_T = 0.049369/ 0.0004= 237.4125
 According to % contribution Ranks have been given.

Calculation of Level wise S/N ratios:

The S/N ratios of GRGs are as shown below:
-13.2715,-12.1486,-8.56932.-7.97167,-4.72937,-6.44299,-2.90797,-3.50241,-4.72116.
The first output response Temperature is at first level for first four trials. So for level 1 of Temperature will be the average of first four S/N ratio values.

S/N ratio of level 1=sum of -13.2715,-12.1486,-8.56932)/3= -11.02261.

Plot for optimum setting for GRG:

Plot has been drawn for the level wise GRG values.

3.1 Tabular calculations as per methodology:

Table 6 Data preprocessing of each performance characteristics

S.No	FCH	BP	BSFC	$\eta_{B.th}$
1	0.17	0	0.181818182	0.014884
2	0.57	0	0	0.113953
3	0.48	0	0.909090909	0.178837
4	0.16	0.49	0.727272727	0.804419
5	1	0.49	0	0.934186
6	0.03	0.49	1	0.576512
7	0.6	1	0.727272727	0.999767
8	0.58	1	0.727272727	0.945581
9	0	1	0	0.97907

Table 7 Calculation of quality loss estimates

S.No	FCH	BP	BSFC	$\eta_{B.\tau\eta}$
1	0.83	1	0.818182	0.985116
2	0.43	1	1	0.886047
3	0.52	1	0.090909	0.821163
4	0.84	0.51	0.272727	0.195581
5	0	0.51	1	0.065814
6	0.97	0.51	0	0.423488
7	0.4	0	0.272727	0.000233
8	0.42	0	0.272727	0.054419
9	1	0	1	0.02093

Table 8 Individual grey relational coefficients of individual responses and overall grey relational grade

S.No	FCH	BP	BSFC	$\eta_{B.\tau\eta}$
1	0.83	1	0.818182	0.985116
2	0.43	1	1	0.886047
3	0.52	1	0.090909	0.821163
4	0.84	0.51	0.272727	0.195581
5	0	0.51	1	0.065814
6	0.97	0.51	0	0.423488
7	0.4	0	0.272727	0.000233
8	0.42	0	0.272727	0.054419
9	1	0	1	0.02093

Table 9 GRG & S/N Ratios

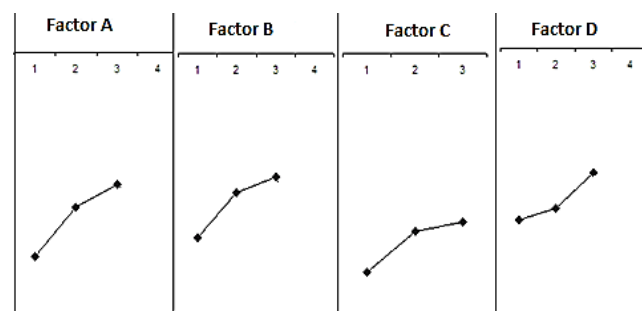| S.No	GRG	S/N RATIO
1	0.216984	-13.2715
2	0.246927	-12.1486
3	0.37285	-8.56932
4	0.399408	-7.97167
5	0.580138	-4.72937
6	0.476267	-6.44299
7	0.715487	-2.90797
8	0.668158	-3.50241
9	0.5687	-4.72116

Fig 2 S/N ratio plot for overall grey relational grade

3.2 Optimum levels of each process parameter using GRG

Table 10 Calculation of quality loss estimates

S. No	Performance parameters	Optimum levels	Optimum values
1	LOAD	3	6
2	TIME FOR 10 CC FC	3	60
3	TYPE OF FUEL	3	METHONAL ADDITIVE
4	VALVE OPENING POSITION	3	1/16

4. Artificial neural network modeling:

The experimentally obtained data is used to train the network and to develop the model. ANN model is developed in the MATLAB Neural network toolbox. The model can be developed by graphical user interface or by writing code. 12 datasets are used to train the neural network. The input and output combined data is called as dataset. Neural networks are trained using training data set and their generalization capacity is examined by using test sets. The training data never used in the test data. Number of neurons to be used in the hidden layer of neural network is critical in order to avoid over fitting problem, which hinders the generalization capability of the neural network.

Number of hidden layer neurons is usually found with trial and error approach. In all the cases of the present work, multilayer feed-forward artificial neural networks are used. In the present work, the following steps are developed:

- Database collection
- Analysis and pre-processing of the data
- Training of the neural network
- Test of trained network
- Post processing of the data
- Use of trained NN for simulation and prediction.

4.1 Schematic model of ANN for prediction of process parameters

The input parameters and the output parameters are needed to develop the artificial neural network model. The following figure represents the input and output parameters have been used in the present work.
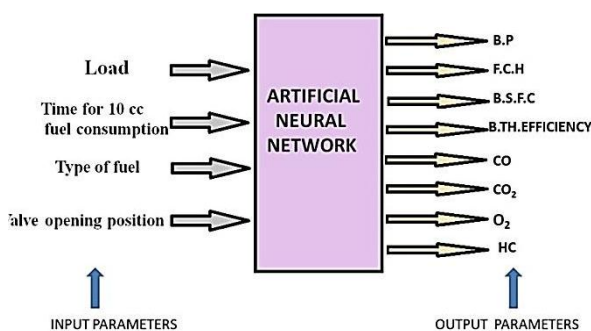
Fig 3 Schematic model of ANN for prediction of process parameters

In the present work load, time for 10cc fuel consumption, type of fuel, valve opening position are taken as input parameters;B.P,BSFC,FCH,BTH,EFFICIENCY,CO,CO_2, HC and O_2 are taken as output parameters.

4.2 Proposed neural network architecture
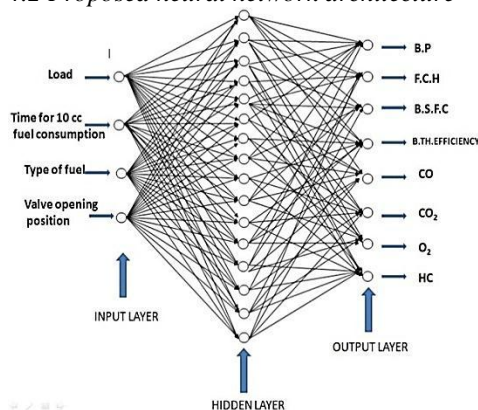
Fig 4 Proposed neural network architecture

Figure 4 represents the proposed neural network architecture with four inputs and eight outputs. From the different architectures, this network is chosen as the best

network architecture to out experimental data and has the good generalization capability. One hidden layer is used in this network architecture. The hidden layer contains sixteen hidden neurons.

No. of layers used
- 1 input layer with four input neurons
- 1 hidden layers
- 16 neurons in the hidden layer
- 1 output layer with eight output neurons

Transfer function

The transfer function (Activation function) is used to calculate the output response of a neuron. The sum of the weighted input signal is applied with an activation to obtain the response. For neurons in the same layer, same activation functions are used.

Training function

The training algorithm of back propagation involves four stages,
- Initialization of weights
- Feed forward
- Back propagation of errors
- Updating the weights and biases.

Performance function

MSE – Mean Squared Error performance function.
MSE is a network performance function. It measures the network's performance according to the mean of squared errors.

The function **mapstd** normalizes the inputs and targets. So that, they will have zero mean and unity standard deviation.

Steps to improve generalization

Do not train forever: Overtraining can actually degrade performance on the test set. If you can, set aside part of your training data for cross validation, and stop the training when the performance on the cross validation set deteriorates. If our data is too small to afford cross validation and then stop the training when the learning curve (error vs. epoch) just begins flatten out.

Repeat the training several times: Neural networks are highly non-linear and can have many local minima in the weight space. Repeating the training increases your chance of finding or getting closer to the global minimum.

Principle component analysis to the input data: For high dimensional input data, use a principle component analysis layer at the input to project the input onto a smaller dimension. The smaller dimensional input reduces the no of free weights in the layers that follow, which can improve generalization and orthogonalization of the input can speed up training.

Selection of hidden neurons: The problem of selecting the no of neurons in the hidden layers of multilayer

networks is an important issue that remains open research. The no of nodes must be large enough to form a decision region as complex as that required by the problem. And yet, the number must not be excessively large, so that, the weights cannot be reliably estimated by available training data.

4.2 Neural Network Simulation

The following figure.4 represents the program development in the MATLAB editor by using the above commands.

Fig 4 Program developed in the MATLAB editor

Development of ANN model using Graphical User Interface

The artificial neural network model can also be developed by using graphical user interface (GUI) in the form of screen shots. The command used to develop the ANN model using the GUI is '**nntool'**. The following figure 5.4 represents the loading of input data (load, time for 10cc fuel consumption, type of fuel, Valve opening position) into the MATLAB workspace. The input data is represented by the variable 'p'.
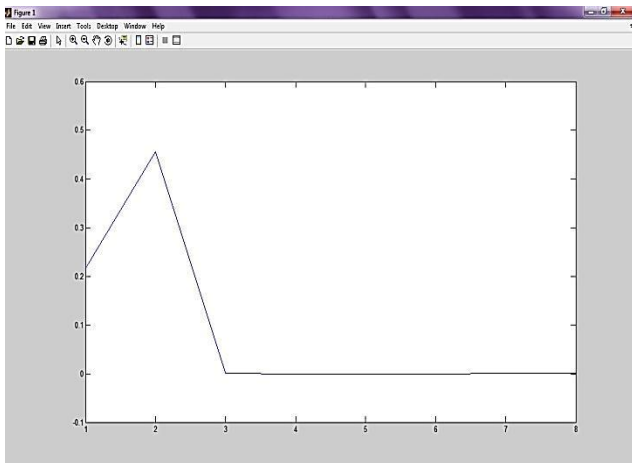
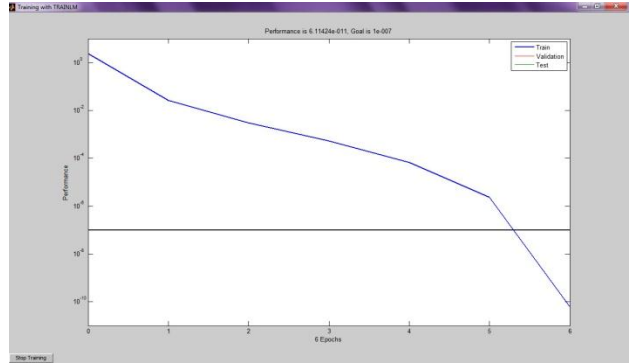

Fig 6 Performance of the training network

Fig 7 Simulation of the network

4.3 ANN Results

The results of artificial neural networks are displayed in the MATLAB and are compared with the experimental results. The error percentage between ANN and experimental values are also displayed. The figure 5.21 represents the testing input data given to the trained network. There are four sets of testing data used to check the generalization capability of the network.

Fig 8 Error percentage between the ANN and Experimental results

From the above results we can observe the following things.

- Comparison of predicted cutting forces, tool temperatures and surface roughness with experimental results in all tested cases indicate that the error is less than 4% for ANN model.
- The average error percentage for all the predicted values in the ANN model is 1.897%.

Table 11 Optimum levels of each process parameter using GRG (ANNOVA) as per performance:

S. No	Performance parameters	Optimum levels	Optimum values
1	Load	3	6
2	Time for 10 cc fc	3	60
3	Type of fuel	3	Methanol additive
4	Valve opening position	3	1/16

Table 12 GRG & S/N Ratios for emission

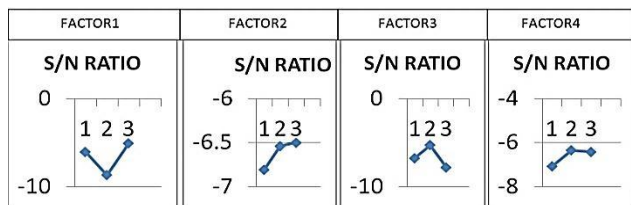| GRG	S/N Ratio
0.0.45536	-6.83284
0.60375	-4.38287
0.45178	-6.90144
0.42185	-7.36812
0.30746	-10.2442
0.37726	-8.46717
0.48889	-6.21573
0.56323	-4.9863
0.62183	-4.12652

Fig 8 S/N ratio plot for overall grey relational grade as per emission

Fig.8 shows that for factor A(load) the optimum level is 3, for factor B(time for 10 cc fuel consumption) optimum level is 3, for factor C(type of fuel) the optimum level is 2 and for factor D(valve opening position) the optimum level is 2.

Table 13 Optimum levels of each process parameter using GRG (**ANNOVA**) as per emissions

S. No	Performance parameters	Optimum levels	Optimum values
1	Load	3	6
2	Time for 10 cc fc	3	60
3	Type of fuel	2	Biodiesel
4	Valve opening position	2	3/32

5. Conclusions

- Similar to grey based Taguchi technique, the proposed method has been found efficient for solving multi-attribute decision - making problem, i.e., for multi objective product as well as process optimization, for continuous quality improvement.

- It can be recommended that the Taguchi method is good in the case of process (chemical and pharmaceutical) industries when there are hundreds of response variables.
- The disadvantage of Taguchi approach is the selection of composite quality indicator which depends on the type of problem and trial and error solution.
- As obtained by the ANOVA for overall grey relational grade, the load is more significant factor. Therefore, optimal setting is supposed to be affected due to the change in the level of load.
- Found out optimum levels and optimum values for load, time for 10cc.fuel consumption, type of fuel, valve opening position by taguchi, grey taguchi.
- Comparison of predicted FCH, BP, BSFC, BTH Efficiency, CO, CO_2, HC, O_2 with experimental results in all tested cases indicated that error is less than e^{-7} for ANN model.
- The average error percentage for all the predicted values in the ANN model is 1.897%.

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