Artificial Neural Networks Methodologies to Optimize Engine Performance Parameters Using MATLAB

N. Balaji Ganesh and P. V. Srihari

Abstract This work is concerned with the use of artificial neural network as a simulation tool for optimizing the performance of four-stroke single-cylinder diesel engine, operating at various conditions for this performance, test on a four-stroke diesel engines is conducted and the performance parameters are calculated with standard formulae. The output values obtained from the conventional method are used as input for training artificial neural networks in combination with backpropagation algorithm has been performed using MATLAB. The results obtained from the practical networks are compared with the conventional values and the errors are estimated for each parameter. The error deviation obtained against each parameter indicates the net variation of engine output, and accordingly the corrective actions may be initiated with the engine for the improvement of performance parameters.

Keywords Artificial neural network · Backpropagation algorithm · MATLAB · CI Engine

1 Introduction

ANN is an efficient approach amid the black-box design approach that is extensively used in different engineering applications in recent years [1]. This craft aims to greatly decrease dynamometer analysis, thereby developing scientific models of the engine outputs using a smaller subset of experimental data. Once the scientific models have been refined, the errors can be minimized using techniques such as gradient procedures [2], different approaches are included for using ANN to boost up modeling and graduate of engines [3]. The capability of ANN as a system testimony tool is pre-owned to represent the nonlinear performance of engine operations. Many analysts used ANN for predicting twisting moment, brake power, total fuel consumption, and

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smoke formation including engine speed and diesel injection pressure [1, 4, 5, 6 7, 8] found the ANN adds accuracy and ease in the inquiry of the engine performance. GISCA and WU described how effectively ANN is used for deciding the operating parameters of the compression ignition engine, being internal pressure in cylinders or the fuel–air ratio [9, 10]. But in ANN design draft of network topology, the trigger function, learning rule, and the permissible error for stopping the training phase is crucial and done by the engineer. So, it is tough to frame the size of the network as there is no fixed method to do it. Even though the neural networks based results is very dynamic in terms of evolution, time, and resources. By practicing and being employed on different planning, weights, and designs, we can afford actual solutions. By conducting accurate research by using various innovations and selected the best one that gives efficient output by considering input details. Depending upon the experimental data, ANN correlates various engine operating parameters with the input data. Garg explained a broad literature review and different utilizations of ANN [11]. Thus, actual-time activity and averaging of complex, nonlinear, and dynamic patterns in engine operations are challenges to be met in today's engine advancement. Neural networks architectures, combinations of networks, and different algorithms play an important role in the execution. There is a need to use ANN as an execution critical tool that optimizes cost and time in advancing new models and techniques for overall engine performance. Further, it will support in achieving which algorithm is perfect for the appropriate situation.

2 Experimental Setup and Engine Specifications

The below line diagram represents the engine along with various parts incorporated in it (Fig. 1).

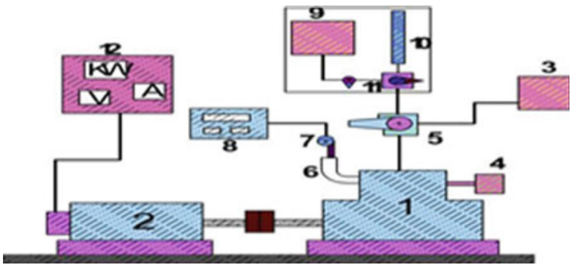


Fig. 1 Experimental setup of engine. 1. Alamgir engine, 2. T alternators, 3. Diesel tank, 4. Air filter, 5. Three-way valve, 6. Exhaust pipe, 7. Probe, 8. Exhaust gas analyzer, 9. Fuel tank, 10. Burette, 11. Three-way valve, 12. Control panel

2.1 Engine Specifications

See Table 1.

Table 1 Specifications of engine

Make	Alamgir Industries Ltd.
Ignition system	Compression ignition
Arrangement of cylinder	Vertical
Cooling	Air cooled
Bore	0.102 m
Stroke	0.116 m
Compression ratio	19.5
Speed	1500 rpm
Rated power	9 HP
Fuel	Diesel
Lubricant	SAE 20/SAE 40

Table 2 Standard formulae to calculate performance parameters

1. Brake power (B.P)	VI COS Ø/ηtran × ηgen × 1000 (units kW)
Where V	Voltage, volts
I	Current, amp
ηtran	Transmission Efficiency = 0.8
ηgen	Generator Efficiency = 0.9
COS Ø	Power factor = 1
2. Total fuel consumption (TFC)	20*0.85*3600/t*1000 (units kg/h)
3. Brake-specific fuel consumption	TFC/BP (units kg/kW-h)
4. Heat input	TFC* calorific value of fuel (units kJ/kg)
5. Frictional power (F.P)	From Williams line method
6. Indicated power (I.P)	B.P + F.P (units kW)
7. Mechanical efficiency (η_{mech})	B.P/I.P
8. Indicated thermal efficiency ($\eta_{I.Th}$)	I.P/Heat input
9. Brake thermal efficiency ($\eta_{B.Th}$)	B.P/Heat Input
10. Brake mean effective pressure (BMEP)	B.P*60/LANK (units kN/m^2)
11. Indicated mean effective pressure (IMEP)	I.P*60/LANK (units kN/m^2)
12. Volumetric efficiency	Actual air intake/Theoretical air intake

Table 3 Experimental values for diesel

S. No.	Item	Units	Trail-1	Trail-2	Trail-3	Trail-4	Trail-5	Trail-6
1	Load	W	0	1000	2000	3000	4000	5000
2	Speed	Rpm	1500	1500	1500	1500	1500	1500
3	Voltage	Volts	270	260	250	230	215	200
4	Current	Amp	2.5	5.2	8.5	12	15.5	18
5	Time taken for 20 c.c fuel consumption	Sec	80	58	47	40	35	32
6	Exhaust gas temperature	°C	87	124	167	201	243	275
7	Air velocity	m/s	7.2	8.2	8.2	8.2	8.2	8.2
8	Brake power	kW	0.765	1.53	2.4	3.12	3.77	4.08
9	Total fuel consumption	Kg/h	0.76	1.05	1.3	1.53	1.74	1.91
10	BSFC	Kg/kW.h	0.993	0.686	0.5416	0.49	0.461	0.468
11	Heat input	kW	8.86	12.2	15.16	17.85	20.28	22.26
12	Friction power	kW	1.6	1.6	1.6	1.6	1.6	1.6
13	Indicated power	kW	2.365	3.13	4	4.72	5.37	5.68
14	Mechanical efficiency	%	32.34	48.88	60	66.1	70.2	71.8
15	Brake thermal efficiency ($\eta_{B.Th}$)	%	8.63	12.54	15.83	17.47	18.58	18.32
16	Indicated thermal efficiency ($\eta_{I.Th}$)	%	26.69	25.65	26.38	26.44	26.47	25.5
17	Volumetric efficiency	%	58.46	66.58	66.58	66.58	66.58	66.58
18	Brake mean effective pressure	kN/m^2	64.56	129.13	202.56	263.32	318.18	344.35
19	Indicated mean effective pressure	kN/m^2	199.6	264.17	337.6	398.36	453.22	479.39

2.2 Formulae

See Table 2.

2.3 Experimental Values for Diesel

See Table 3.

3 Working with MATLAB

MATLAB is widely used in scientific estimations. It integrates computation, perception, and programming in a simple manner in which questions and answers are revealed in simple mathematical notation.

3.1 Feeding Inputs and Outputs in MATLAB

The input values are entered in command window, which is scaled in between 0 and 1 for minimizing the error.

Speed	= [0.1500 0.1500 0.1500 0.1500 0.1500 0.1500]
Voltage	= [0.270 0.260 0.250 0.230 0.215 0.200]
Input	= [Speed; Voltage]
Bp	= [0.0765 0.153 0.240 0.312 0.377 0.408]
Tfc	= [0.076 0.105 0.13 0.153 0.174 0.191]

The output is entered in the same form of input data by varying the neurons according to the preference of the user.

For example, if the user prefers 2 neurons, then the output should be assigned as

Output1 = [Bp; Tfc]

Likewise, all other individual output parameters are grouped as 2 rows and initialized in the MATLAB command window. Similarly, for the same individual output variable, various neurons are selected and initialized in the same manner as shown above. As soon as they entered, they are recorded as a matrix in the workspace and it is saved with the file extension MAT.

3.2 *Working with Neural Network*

To invoke the neural network toolbox, a command, tool is entered in the command window. The following window pops up as shown in Fig. 2.

The input values are given by clicking the import button in this window. The following window pos up (Fig. 3).

All initialized data are automatically stored in the data manager scroll box and for giving the input the variable input1 is selected and is to be imported as inputs. Similarly, variables output 1 and output 2 are selected as target values which have to be optimized depending upon the neurons.

Now all the selected data are imported in neural network toolbox, next a network is to be formed. For this, new network icon in the neural network manager is clicked.

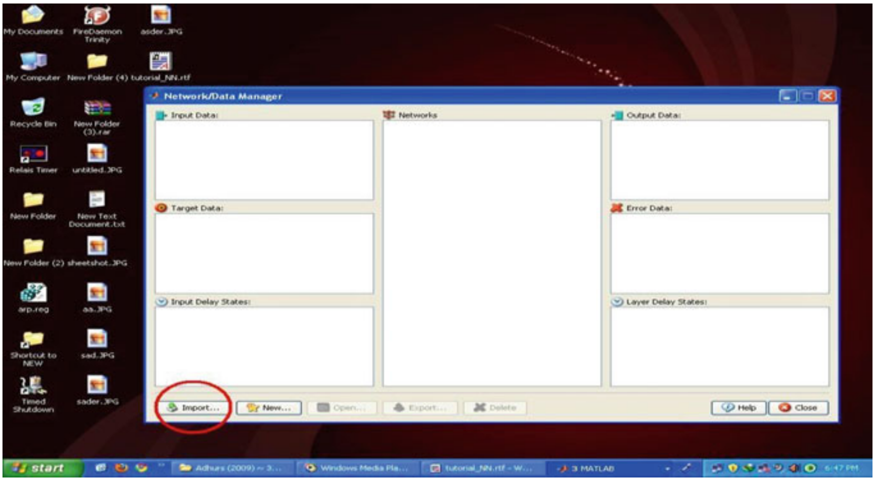


Fig. 2 Network data manager

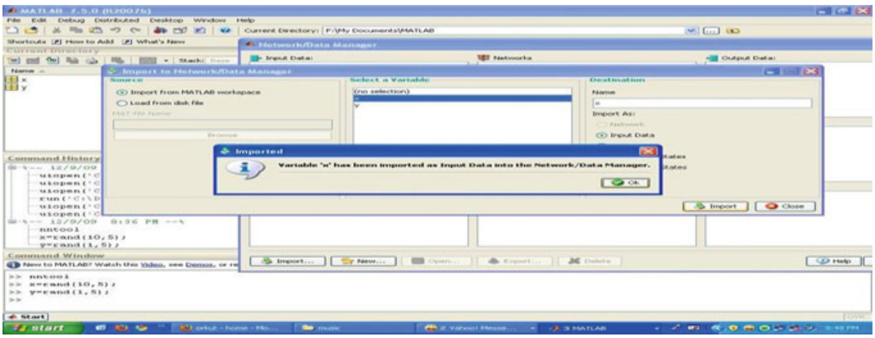


Fig. 3 Data manager

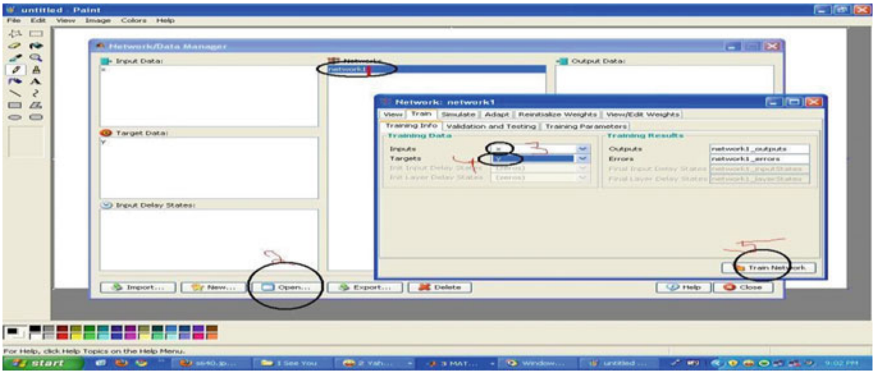


Fig. 4 Training a network

In that dialog box, various networks types are available in that we have selected "FEED FORWARD BACK PROPAGATION" network type with the training function as trained. The ranges for the input can be taken from the variable input1. The number of layers to be specified here is the total number of hidden layers and neurons for output data's. For each layer, the number of neurons is specified and the suitable transfer function of purelin is chosen and by clicking create button in the dialog box, new network is created, next, the network has to be trained. There is an icon available in the network manager. The following window pops up (Fig. 4).

The training data are taken from input 1 and output 1, by scrolling down the pull-down menu. The training parameters specify the numbers of epochs, goal, etc., are also given. The network is then trained. A window with the training graph appears. The training stops if the goal is reached or if the number of epochs exceeds or if one intentionally stops the training. Confirmatory values are simulated and it is displayed in the network output dialog box of network manager toolbox and similarly the trained error values are displayed in network error of network manager toolbox. The network error and output values are in scaled form.

3.3 Trained Values for Diesel with Network 2 Hidden Layers 2 Neurons

See Table 4.

3.4 Error Values for Diesel

See Table 5.

Table 4 Trained values for diesel

S. No.	Parameters	Trail 1	Trail 2	Trail 3	Trail 4	Trail 5	Trail 6
1	B.P	0.076755	0.153521	0.216788	0.312402	0.3771	0.397027
2	I.P	0.236848	0.313689	0.341977	0.472522	0.53712	0.559671
3	T.F.C	0.085204	0.123424	0.132431	0.149023	0.171052	0.181499
4	S.F.C	0.992878	0.741593	0.543347	0.503409	0.475381	0.469018
5	B.Th	0.0863	0.128712	0.154048	0.178341	0.183833	0.18525
6	I.Th	0.265759	0.255004	0.255005	0.255004	0.255003	0.255002
7	Vol Eff	0.604222	0.664712	0.665765	0.665796	0.6658	0.6658
8	Mech Eff	0.34087	0.499495	0.604254	0.645813	0.675763	0.685874
9	BMEP	0.008587	0.136874	0.207421	0.285753	0.321876	0.334208
10	IMEP	0.203629	0.252193	0.314663	0.421597	0.464949	0.475287

Table 5 Error values for diesel

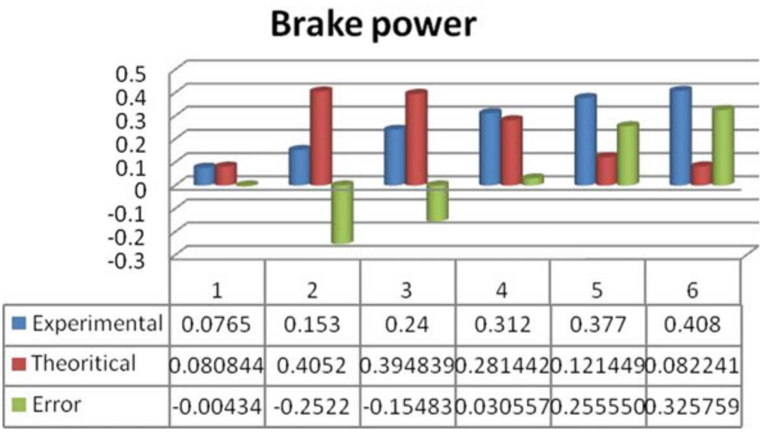
S. No.	Parameters	Trail 1	Trail 2	Trail 3	Trail 4	Trail 5	Trail 6
1	B.P	−2.55E-04	−5.21E-04	0.023212	−4.02E-04	−1.00E-04	0.010973
2	I.P	−3.48E-04	−6.89E-04	0.058023	−5.22E-04	−1.20E-04	0.008329
3	T.F.C	−9.20E-03	−0.01842	−0.00243	0.003977	0.002948	9.50E-03
4	S.F.C	1.22E-04	−0.05559	−0.00175	−0.01341	−1.44E-02	−0.00102
5	B.Th	−8.29E-09	−3.31E-03	0.004252	−0.00364	0.001967	−2.05E-03
6	I.Th	0.001141	1.50E-03	0.008795	0.009396	0.009697	−2.40E-06
7	Vol Eff	−0.01962	0.001088	3.49E-05	3.50E-06	3.48E-07	8.33E-08
8	Mech Eff	−1.75E-02	−0.0107	−0.00425	0.015187	0.026237	3.21E-02
9	BMEP	−0.00246	−0.00774	−0.00486	−0.02243	−0.0037	1.01E-02
10	IMEP	−4.02E-03	0.011979	0.022937	−0.02323	−0.01173	4.10E-03

4 Results and Discussion

Graph between Experimental Values and Theoretical values:

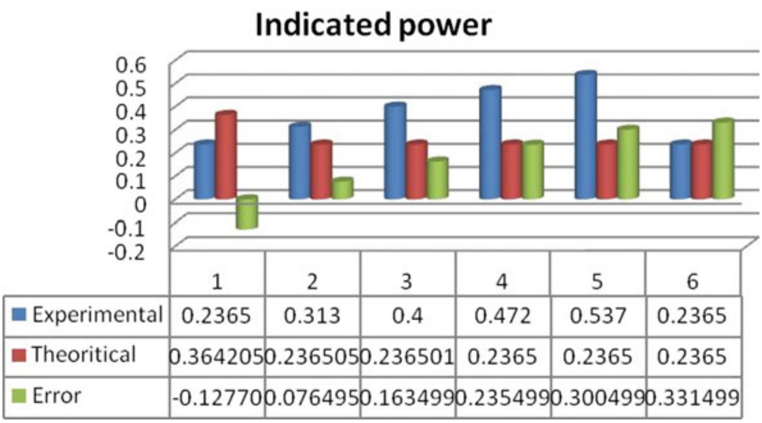
From Graph 1 brake power values obtained from experimental and theoretical results are compared, error is calculated, and the error is minimum for trail 4 and maximum for trail 6, the maximum value of brake power by theoretical method is 0.4052 for trail 2 and by experimental method is 0.408 for trail 6, so in order to reduce the error the number of hidden layers has to be increased.

From Graph 2 indicated power values obtained from experimental and theoretical results are compared, error is calculated and the error is minimum for trail 2 and maximum for trail 6, the maximum value of indicated power by theoretical method is 0.364 for trail 1 and by experimental method is 0.537 for trail 5, so in order to reduce the error the number of hidden layers has to be increased.



	1	2	3	4	5	6
Experimental	0.0765	0.153	0.24	0.312	0.377	0.408
Theoritical	0.080844	0.4052	0.394839	0.281442	0.121449	0.082241
Error	-0.00434	-0.2522	-0.15483	0.030557	0.255550	0.325759

Graph 1 Error for brake power

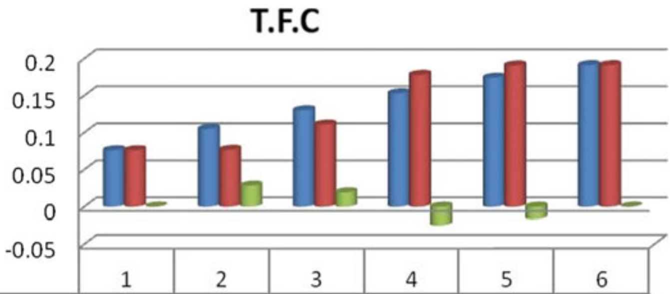


	1	2	3	4	5	6
Experimental	0.2365	0.313	0.4	0.472	0.537	0.2365
Theoritical	0.364205	0.236505	0.236501	0.2365	0.2365	0.2365
Error	-0.12770	0.076495	0.163499	0.235499	0.300499	0.331499

Graph 2 Error for indicated power

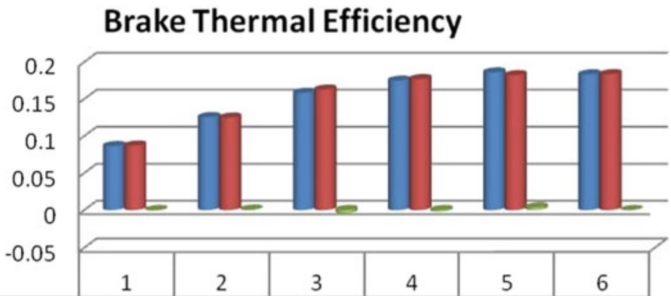
From Graph 3 total fuel consumption obtained from experimental and theoretical results are compared, error is calculated and the error is minimum for trail 1 and maximum for trail 2, the maximum fuel consumption by theoretical method is 0.1909 for trail 6 and by experimental method is 0.191 for trail 5, error is minimum in this case and no need to change the hidden layers.

From Graph 4, brake thermal efficiency values obtained from experimental and theoretical results are compared, the error is calculated and the error is minimum all the trails, the maximum efficiency is obtained for trail 6 in both the cases and no need to change the hidden layers.



	1	2	3	4	5	6
Experimental	0.076	0.105	0.13	0.153	0.174	0.191
Theoritical	0.076	0.076659	0.110721	0.17787	0.190508	0.190945
Error	-5.20E-0	0.028341	0.019279	-0.02487	-0.01650	5.50E-05

Graph 3 Error for total fuel consumption

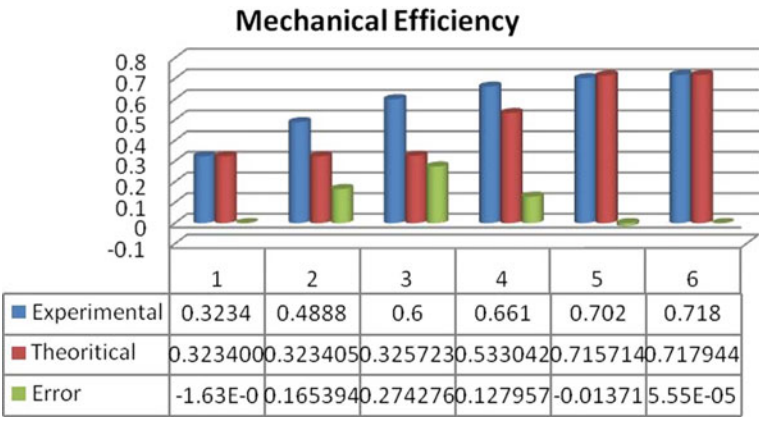


	1	2	3	4	5	6
Experimental	0.0863	0.1254	0.1583	0.1747	0.1858	0.1832
Theoritical	0.086962	0.124785	0.162603	0.176778	0.182111	0.183385
Error	-6.62E-0	6.15E-04	-0.00430	-0.00207	0.003688	-1.85E-0

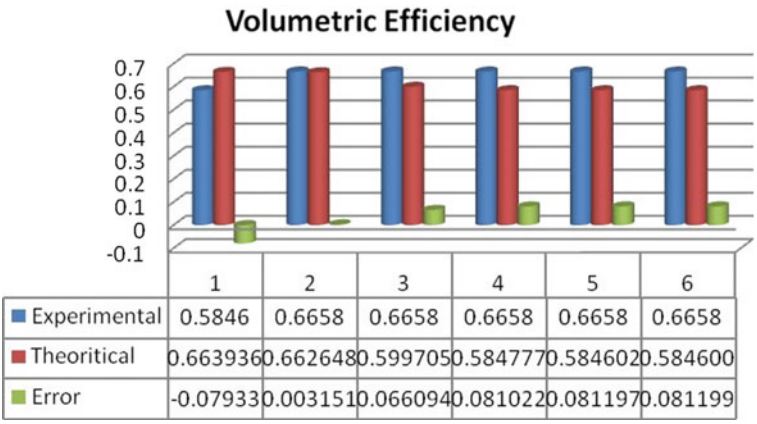
Graph 4 Error for brake thermal efficiency

From Graph 5, mechanical efficiency values obtained from experimental and theoretical results are compared, error is calculated, and the error is minimum for trail 1 and maximum for trail 3, the maximum value of mechanical efficiency by theoretical method is 0.717 for trail 6 and by experimental method is 0.718 for trail 6, so in order to reduce the error the number of hidden layers has to be increased.

From Graph 6, volumetric efficiency values obtained from experimental and theoretical results are compared, error is calculated and the error is minimum for trail 2 and maximum for trail 5, the maximum value of volumetric efficiency by theoretical method is 0.663 for trail 1 and by experimental method is 0.665 for trail 6, so in order to reduce the error the number of hidden layers has to be increased.



Graph 5 Error for mechanical efficiency



Graph 6 Error for volumetric efficiency

5 Conclusions

The experimental data is trained in MATLAB using neural networks by backpropagation algorithm and all the error values are measured. By measuring the error deviation between experimental values and trained values engine performance parameters are optimized and required changes are suggested in the experimental setup which can improve the performance of engine so that error values are minimized further. ANN will be a very good tool to optimize the engines in the future.

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