Research Article

Prediction of NO_x Emissions from a Direct Injection Diesel Engine Using Artificial Neural Network

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In the present study, artificial neural network is used to model the relationship between NO_x emissions and operating parameters of a direct injection diesel engine. To provide data for training and testing the network, a 6-inline-cylinder, four-stroke, diesel test engine is used and tested for various engine speeds, mass fuel injection rates, and intake air temperatures. 80% of a total of 144 obtained experimental data is employed for training process. In addition, 10% of the data (randomly selected) is used for network validation and the remaining data is employed for testing the accuracy of the network. The mean square error function is used for evaluating the performance of the network. The results show that the artificial neural network can efficiently be used to predict NO_x emissions from the tested engine with about 10% error.

1. Introduction

Direct injection diesel engines are used as propulsion systems with low fuel consumption and very high efficiency for automotive applications. Any attempts to use their privileges require considering emissions stringent disciplines which enforce engine manufacturers to tender their productions with lower emissions [1]. Recently, Lenz and Cozzarini [2] have presented statistics showing that the worldwide passenger car and commercial vehicle traffic contribute 20% of the total anthropogenic emissions of nitrogen oxides (NO_x). These emissions have damaging effects upon the environment and people. Therefore, how to control the exhaust emissions especially NO_x from diesel engines has become an essential subject for researchers of the automotive field in the world.

The diesel engine industry has undergone a great technical development in the last few years, creating a number of new strategies such as electronic control units (ECUs) and/or engineering management systems (EMSs) as well as new injection systems [3–7]. They all use some kinds of artificial intelligence (AI) techniques such as artificial neural network

(ANN) to process the engine operating conditions and prognosticate the fairly best values of the controlling parameters with the aim of optimizing the engine characteristics.

Digital computers have provided a rapid means of performing many calculations involving the ANN methods. Along with the development of high-speed digital computers, the application of the ANN approach could be outspread in a very impressive rate in several fields. One of the major applications of ANN is industrial pollutants control. Kalogirou [8] presented an elaborated review on the recent applications of AI in environmental pollutants control.

Neural networks are powerful modeling techniques with the ability of identifying cryptic nonlinear highly complex relationships between their input and output data [9]. ANN describes such relations by updating network weights using a trial-and-error-based arithmetic method and a training algorithm such as Levenberg-Marquardt (LM).

A number of studies have been conducted to predict the characteristics of internal combustion engines (ICE) by using ANN approach. This approach has been used by Xu et al. [10] to predict engine systems reliability. The injection

TABLE 1: Tehnical specifications of the test engine.

Engine type	OM355 Mercedes-Benz S. 355093
Number of injector holes	4
Injection pressure	195 bar
Max output power	240 hp
Intermediate power speed	1400 rpm
Number of cylinders and layout	6-inline
Compression ratio	16.1 : 1
Injection timing (Deg BTDC)	18
Displacement	11580 cc
Stroke	150 mm
Bore	128 mm

characteristics of direct injection (DI) diesel engines have been investigated by Yang et al. [11]. In [12], the effects of NO_x and soot level in the case of high-pressure fuel injection have been investigated in a single-cylinder DI diesel engine. ANN has been used to predict the exhaust emissions and performance of a diesel engine taking into account several operating conditions such as the percentage of throttle opening, injection time, engine speed, and fuel compositions as the network inputs [13–15]. However, there is no literature that reports the application of neural network to predict and model NO_x emissions in terms of engine speed, intake air temperature, and mass fuel injection (MFI) rate. In this study, NO_x emissions from a diesel engine are investigated using ANN. For this purpose, experimental tests have been conducted for 144 engine speeds ranging from 591 to 2308 rpm.

2. Experimental Setup

The test engine used to conduct the experiments is a heavy duty (HD) six-cylinder, direct-injection, four-stroke diesel engine. The technical specifications of the engine are given in Table 1. Standard laboratory procedures are used to measure the engine operating parameters and its tailpipe emissions (see Figure 1). The engine is connected to the data acquisition systems, so that several operating parameters could be simultaneously measured and precisely controlled. The ST10 fuel controller sensor is used to measure the mass fuel injection rate in the range of 0.39–10.31 g/sec. An electrical dynamometer is assembled on the engine and used to measure the speed, brake power, and torque of the engine. The engine speeds are recorded between 591 and 2308 rpm. Simultaneously, other engine properties such as exhaust emissions (NO_x , soot, HC, CO, CO_2), air-fuel ratio (AFR), and intake air temperature are measured by various connected instruments. The range of variations of the operating parameters and the corresponding values of NO_x emissions have been listed in Tables 2 and 3, respectively [16, 17].

TABLE 2: Range of variations of the operating parameters during the experimental study.

Operating parameter	Unit	Range of variations
N	rpm	[591, 2308]
M_f	g/sec	[0.39, 10.31]
T	$^{\circ}\text{C}$	[15.4, 28.3]

FIGURE 1: Schematic of the test engine: (a) fuel tank, (b) air tank, (c) test engine, (d) muffler, (e) emissions analyzer, (f) tachometer, (g) dynamometer, (h) air measuring container, (i) fuel measuring container, (j) transducer, (k) thermometer.

3. ANN Approach

The building unit of an ANN is a simplified model of the much more complex one known as organic neuron. This model was introduced by the neurophysiologist McCluch and the logician Pitts in 1943 [18], but its learning behavior was first treated extensively in a book by Rosenblatt in 1962 [19].

One of the main advantages of ANN is its ability to model complex nonlinear relationships between multiple input variables and the required outputs. Another important advantage of the ANN approach is its fast response, which allows one to use it in more complex procedures including optimization applications. Therefore, it offers the advantage of being fast, accurate, reliable, and powerful in dealing with multivariate problems as well as in the prediction or approximation affairs, especially when numerical and mathematical methods fail [20, 21].

To get the best prediction by the network, many parameters should be adjusted such as biases, weights, number of hidden layers, number of hidden layer neurons, and type of transfer function. The biases and weights must be modified in every epoch by using training algorithms such as LM algorithm. The performance of the network is evaluated by comparing the error obtained from converged neural network runs and the measured data. The error of the network is calculated at the end of training, validation, and testing processes based on the differences between the targeted and calculated outputs. The back propagation algorithm is used

TABLE 3: Measured NO_x emissions with respect to the three operating parameters.

OP* and NO _x	EN**																													
Engine speed (RPM)	591	592	601	601	602	602	603	604	604	605	606	606	608	611	612	612	615	616	616	617	618	621	623	626	627	628	628	631	631	632
Intake air temperature (°C)	25.5	25.1	23.4	28.3	27.6	17.3	16	20.5	17.3	20.4	15.9	28.1	23.8	21.5	22	24.7	25.3	20.8	20.9	22.5	20.8	27.1	23	22.8	15.9	15.9	26.1	26.6	26.5	23
Mass fuel (g/sec)	0.43	0.43	0.42	0.42	0.41	0.44	0.42	0.41	0.43	0.43	0.42	0.44	0.43	0.39	0.39	0.39	0.39	0.44	0.4	0.43	0.4	0.42	0.47	0.47	0.44	0.43	0.45	0.44	0.46	0.47
NO _x (g/kw·hr)	18.96	19.97	21.56	29.01	47.71	18.69	19.42	24.49	21.51	24.09	18.54	29	22.75	21.42	18.26	20.73	20.18	19.13	24.05	25.23	20.45	31.56	22.53	21.64	27.95	24.88	28.74	37.91	28.23	15.14
OP* and NO _x	EN**																													
Engine speed (RPM)	632	633	636	638	640	645	1389	1391	1396	1396	1397	1398	1398	1399	1399	1399	1399	1400	1401	1401	1401	1401	1402	1402	1402	1402	1402	1403	1403	1403
Intake air temperature (°C)	24.9	22.9	26.2	23.7	18.6	18.6	16	15.8	15.5	15.6	23.3	24.6	23.7	20.4	24.8	21.7	23.8	20	19.3	21.7	19.9	15.8	21.2	19.7	17.2	16.9	25.5	23.8	15.6	19.9
Mass fuel (g/sec)	0.4	0.46	0.44	0.41	0.48	0.49	1.53	1.54	1.48	1.48	2.24	2.34	3.65	6.7	2.33	2.19	2.24	6.72	2.21	2.3	5.03	1.5	6.51	5.02	4.88	491	6.63	0.82	2.2	3.54
NO _x (g/kw·hr)	26.7	14.09	39.32	27.04	24.21	23.31	10.21	10.67	11.02	11.25	13.1	13.01	11.98	8.905	12.89	12.7	13.13	8.753	11.6	12.28	11.08	12.6	9.398	11.2	12.63	12.79	10.55	4.43	9.242	9.963
OP* and NO _x	EN**																													
Engine speed (RPM)	1403	1403	1403	1404	1404	1404	1404	1404	1404	1404	1404	1404	1405	1405	1405	1406	1406	1406	1406	1406	1406	1407	1407	1407	1407	1407	1407	1408	1408	1411
Intake air temperature (°C)	18.9	20.1	25.5	19.6	21.1	15.6	18	15.4	15.4	24.6	17.7	16.7	24.3	15.8	18.3	24.2	15.7	17.5	15.7	16.5	21.6	24.6	15.4	26.9	21.7	17.7	18.6	21.2	18.1	21.4
Mass fuel (g/sec)	3.59	3.54	6.65	2.2	6.52	2.19	6.71	3.55	3.55	3.8	6.67	5.01	0.84	2.18	3.6	0.83	2.17	6.69	3.51	5.02	2.18	0.85	3.5	2.29	2.16	1.51	1.51	6.62	6.7	3.5
NO _x (g/kw·hr)	10.23	9.972	10.54	9.466	9.346	9.469	9.565	10.37	10.61	12.51	10.64	12.39	4.055	9.401	10.28	3.935	9.863	10.5	11.05	12.11	12.39	4.105	10.75	12.47	12.53	15.88	16.68	8.118	9.605	11.73

TABLE 3: Continued.

OP* and NO _x	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
OP* and NO _x	91	92	93	94	95	96	97	98	99	100	101	102	103	104	105	106	107	108	109	110	111	112	113	114	115	116	117	118	119	120
Engine speed (RPM)	1411	1412	1414	2001	2002	2005	2055	2104	2106	2148	2154	2194	2194	2195	2196	2198	2200	2200	2200	2200	2200	2200	2201	2201	2201	2201	2201	2201	2201	2203
Intake air temperature (°C)	17.2	21.2	17.5	20.4	17.7	17.9	16.8	17.4	17.6	17.2	17.4	21.3	19.5	25.5	21.9	21.5	24.5	18.3	21	20.5	21	24.2	20.1	19.7	21.2	20.8	19.6	20.2	20.7	21.8
Mass fuel (g/sec)	1.53	3.49	1.54	9.11	9.28	9.21	9.42	9.65	9.59	9.91	9.83	5.64	10	10.04	5.7	8.05	8.34	10.11	10.15	7.5	8.03	8.36	7.66	7.78	7.56	3.85	10.02	9.98	10.03	10.24
NO _x (g/kw·hr)	10	11.86	10.03	10.4	12.26	12.13	11.85	11.47	11.49	11.13	11.3	10.96	9.073	10.56	11.06	9.117	9.31	11.06	8.407	11.96	8.99	9.004	10.77	10.73	12.23	10.89	9.169	9.358	9.371	8.712
OP* and NO _x	121	122	123	124	125	126	127	128	129	130	131	132	133	134	135	136	137	138	139	140	141	142	143	144						
Engine speed (RPM)	2203	2204	2204	2205	2205	2205	2205	2206	2207	2207	2207	2207	2207	2208	2210	2210	2211	2215	2250	2254	2303	2304	2305	2308						
Intake air temperature (°C)	23.7	20.7	18.5	19.9	20.8	17.3	21.5	20.2	21.8	22.1	21.7	24	24.4	20.9	17.9	24.1	20.8	21.2	19.9	20.5	18.6	18.8	16.4	17.2						
Mass fuel (g/sec)	6.3	10.11	10.13	5.98	5.99	10.17	3.77	3.82	5.72	5.72	4.22	4.37	4.42	4.15	10.16	1	3.75	10.1	10.31	10.3	9.01	8.88	9.93	9.92						
NO _x (g/kw·hr)	8.91	11.64	11.12	9.21	9.354	10.32	12.94	10.67	11.54	11.15	11.55	9.57	9.538	11.11	10.8	5.885	11.83	11.9	11.06	11.41	8.095	7.305	9.631	10.19						

* Operating parameter, ** experiment number.

to minimize the error function, which relates the outputs of each neuron in the output layer and the corresponding desired output. The error function used here is the so-called mean square error (MSE) function given by

$$E = \frac{1}{Q} \sum_p \sum_k (y_{pk} - f_{pk})^2, \quad (1)$$

where Q represents training pairs of vectors, k is the index of elements in the output vector, y_{pk} is the k th element of the p th desired pattern (target value) vector, and f_{pk} is the k th element of the output vector when pattern p is introduced as input to the network. Investigations have proved the accuracy and rapid convergence of LM algorithm for training in engineering applications with limited number of experimental data [22, 23]. In the present work, the LM training algorithm is employed, which uses Hessian matrix approximation. In what follows, a detailed description of this algorithm is presented.

4. LM Algorithm

The LM algorithm is a virtual standard in nonlinear optimization which significantly outperforms gradient descent and conjugate gradient methods for medium-sized problems. It is a pseudo-second-order method which means that it works with only function evaluations and gradient information but it estimates the Hessian matrix using the sum of outer products of the gradients (for more details, see [23]). It also fits a curve on a given dataset by finding the optimum parameters β based on a user specified model f such that the final parameters can characterize the target function by minimizing the errors. This is analogous to solving the least squares problem, where we want to minimize the sum of squares between the target values y_i and the output of the user model f with the input values x_i and the estimated parameter vector β with m number of input data points [24]:

$$S(\beta) = \sum_{i=1}^m (y_i - f(x_i, \beta))^2. \quad (2)$$

Here, $S(\beta)$ is the function to be minimized. To start a minimization, the user has to provide an initial guess for the parameter vector, β , which may be critical in convergence if the user model f is high dimensional or nonlinear with a large number of parameters. In many cases, an uninformed standard guess like $\beta^T = (1, 1, \dots, 1)$ will work fine; in other cases, the algorithm converges only if the initial guess is already somewhat close to the final solution. At each step, the initial parameters are updated by a small amount in the optimum direction by adding the update delta values, δ , such that

$$\beta_{t+1} = \beta_t + \delta. \quad (3)$$

To find the update delta value, δ , we need to solve for the approximation of the sum of squares function by setting the gradient equal to zero as follows:

$$J^T [y - (f(x_i, \beta) + J_i \delta)] = 0. \quad (4)$$

FIGURE 2: Simple structure of used ANN.

This relation can readily be reduced to

$$J^T J_i \delta = J^T [y - f(x_i, \beta)], \quad (5)$$

where J is the Jacobian matrix or gradient of the function that describes the user model and the superscript T represents its transpose form. Equation (5) yields a set of linear equations in the form $Ax = b$, where A is a square matrix, x represents the vector of unknown delta values, and b is a known vector of the same length as x . At each step, the delta values can be obtained by solving this set of linear equations. However, the LM algorithm also adds a regularization parameter λ that helps as the dampening factor to produce the final LM equation:

$$[J^T J_i + \lambda \text{diag}(J^T J_i)] \delta = J^T [y - f(x_i, \beta)]. \quad (6)$$

Here, $\text{diag}(J^T J_i)$ stands for the principal diagonal elements of the matrix $J^T J_i$. This equation is still a system of linear equations of the form $Ax = b$ and one can use direct solvers to solve for delta values at each step.

5. Implementation of the ANN to Predict NO_x Emissions

The neural network toolbox of MATLAB 7.8 is used to form the ANN. Simple and detailed structures of the employed ANN have been shown in Figures 2 and 3, respectively. According to the Kolmogorov theory, multilayer perceptron algorithms can approximate any complex and nonlinear relation between input and output data, among which the three-layer algorithm is the simplest but efficient one. The three layers include the input layer, the hidden layer, and the output layer. Each layer involves some neurons which should be properly determined. The number of input and output parameters of the system determines the number of neurons in the input and output layers of the network, respectively. Thus, the input layer has three neurons while the output layer has only one neuron. It should be noted that in the present

FIGURE 3: Detailed structure of the used ANN.

work, nominal 19 neurons (determined by trial and error) are used in the hidden layer.

The number of data patterns required for training the network should be chosen in such a way that the network is properly trained and in the meantime adequate data is remained for testing the network. In addition, it is essential to set aside some data patterns for validating the network during the process. About 80% of the total 144 experimental data (i.e., 116 data) is used for training the network and 10% (i.e., 14 data) of the data is used for validation. The remainder data is left for testing the network. Neural network requires that the range of both the input and output values lies between 0 and 1. For this purpose the following formula is used to normalize these values [25]:

$$V_{\text{norm}} = \frac{V_a - V_{\min}}{V_{\max} - V_{\min}} \times (V_h - V_l) + V_l, \quad (7)$$

where V_{norm} is the normalized value and V_a is the actual value of the data. $V_{\min}$ and $V_{\max}$ are the minimum and maximum values of the experimental data, respectively. Also, the values of V_h and V_l are set to be 0 and 1, respectively.

There are various types of transfer functions such as logsig, tansig, purelin, among others. In the present work, the logsig transfer function is used in both the hidden and output layers. This function is defined as

$$\text{logsig}(n) = \frac{1}{1 + e^{-n}}, \quad (8)$$

where n is the weighted sum of the input.

6. Results and Discussions

The artificial neural network is used to predict the NO_x emissions from a direct injection diesel engine using LM training algorithm. Technical specifications of the test engine are given in Table 1. The input data of the network are the measured operating parameters of the engine such as mass fuel injection rate, intake air temperature, and speed of engine whose range of variations is given in Table 2.

A MATLAB program has been developed to first obtain the desired correlations for training, validation, and testing stages of the network. Then, the accuracy of the network is

FIGURE 4: Training outputs versus targets with correlation factor $R = 0.91972$.

evaluated through the comparison of the predicted values of NO_x emissions with the experimentally measured ones. The total 144 measured engine's operating parameters and the corresponding values of NO_x emissions are listed in Table 3.

Figures 2 and 3 show the simple and detailed structures of the ANN employed, respectively. These figures demonstrate the three layers of the network, namely, input layer, hidden layer, and output layer. The operating parameters of the engine are fed into the network as inputs and NO_x emissions leave the network as outputs. Note that W in Figure 3 represents the weight of the layer.

Figure 4 shows a regression analysis between the network response (outputs) and the corresponding targets. According

FIGURE 5: Validation outputs versus targets, with correlation factor $R = 0.98222$.

FIGURE 6: Testing outputs versus targets with correlation factor $R = 0.89123$.

to this figure, the training process has been properly performed, where the correlation factor between outputs and targets is 0.91972. Figures 5 and 6 show the validation and testing results of the network, respectively. It is observed from these figures that the ANN represents the best accuracy in modeling the NO_x emissions with correlation factors of 0.98222 and 0.89123, respectively, for the network validation and testing.

The results show that the ANN with LM training algorithm is an appropriate technique, which can accurately predict NO_x emissions for different engine operating parameters including engine speed, intake air temperature, and mass fuel rate. A comparison between the predicted and the measured values of NO_x emissions are depicted in Figure 7. There is a good agreement between the predicted values using the neural network model and the measured values obtained from experimental tests. It may be noted that, for medium engine speeds, the agreement is more considerable than that for the medium speeds. For medium speeds the MSE is less than 8%.

7. Conclusions

The operating parameters involving speed, intake air temperature, and mass fuel rate of a DI diesel engine have been used to train the ANN to predict NO_x emissions from the engine. The results of this research reveal that a three-layer neural network along with LM training algorithm leads to

FIGURE 7: A comparison of the predicted and measured NO_x emissions for different operating conditions.

a desirable mapping between the inputs and outputs of the network case. The proposed ANN model for prediction of the NO_x emissions gives the correlation factors of 0.92, 0.98, and 0.89 for training, validating, and testing the network, respectively. It is concluded that, ANN model is a potentially feasible tool for prediction of NO_x emissions from a diesel engine with respect to the engine operating parameters, especially in medium engine speeds.

Nomenclature

f : ANN output value
 M_f : Mass fuel injection (g/sec)
 N : Engine speed (rpm)
 Q : Number of pairs
 R : Correlation factor
 T_i : Intake air temperature ($^{\circ}\text{C}$)
 x : Input value
 y : Target value.

Greek Symbols

β : Estimated parameter
 δ : Updated delta value.

Abbreviations

AFR: Air-fuel ratio
 AI: Artificial intelligence
 ANN: Artificial neural network
 DI: Direct injection
 ECU: Electronic control unit
 EMS: Engineering management system
 GD: Gradient descent
 HD: Heavy duty
 LM: Levenberg-Marquardt
 MF: Mass fuel injection.

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