ARTIFICIAL NEURAL NETWORK APPROACH TO PREDICTING ENGINE-OUT EMISSIONS AND PERFORMANCE PARAMETERS OF A TURBO CHARGED DIESEL ENGINE

by

Orkun OZENER*, Levent YUKSEK, and Muammer OZKAN

Mechanical Engineering Department, Yildiz Technical University, Istanbul, Turkey

Original scientific paper
DOI: 10.2298/TSCI120321220O

This study details the artificial neural network modelling of a diesel engine to predict the torque, power, brake-specific fuel consumption, and pollutant emissions, including carbon dioxide, carbon monoxide, nitrogen oxides, total hydrocarbons, and filter smoke number. To collect data for training and testing the neural network, experiments were performed on a four cylinder, four stroke compression ignition engine. A total of 108 test points were run on a dynamometer. For the first part of this work, a parameter packet was used as the inputs for the neural network, and satisfactory regression was found with the outputs (over ~95%), excluding total hydrocarbons. The second stage of this work addressed developing new networks with additional inputs for predicting the total hydrocarbons, and the regression was raised from 75% to 90%. This study shows that the artificial neural network approach can be used for accurately predicting characteristic values of an internal combustion engine and that the neural network performance can be increased using additional related input data.

Key words: *artificial neural network, diesel engine, engine performance, emissions*

Introduction

The use of diesel engines, invented by Rudolf Diesel in 1892, on the world market is increasing annually because of its efficiency and inherent fuel economy characteristics [1, 2]. However, the combustion of diesel fuel in the engine results in production of pollutant emissions. The main pollutants emitted are nitrogen oxides (NO_x), carbon monoxide (CO), and particulate matter (PM), which is composed of soot. The stringent pollutant emission law limits of the European Union for manufacturers are getting narrower at each new euro emission stage. The European Automobile Manufacturers Association (ACEA) agreement with the European Union foresees the carbon dioxide (CO_2) limit of 120 g/km by the year 2012, which was proposed to be 140 g/km in 2008 (EC, 2008). The new Euro 6 regulation proposes a 55% reduction in NO_x emission (0.180 g/km to 0.080 g/km) without any change in the PM emissions and a 26% reduction in NO_x + hydrocarbon (HC) emissions (0.230 g/km to –0.170 g/km) for compression ignition (CI) diesel engine (EC, 2008). These stringent emission regulations compel the manufacturers to use research and development methodologies such as combustion modelling [3-5], artificial neural networks (ANN) [6, 7] to predict the cylinder pollutant emissions, which is an advantage during the research and development process.

The ANN approach is an evolutionary and fast calculation methodology that does not require complex mathematical equations to explain a non-linear and multidimensional system.

* Corresponding author; e-mail: oozener@yildiz.edu.tr

ANN are capable of acceptable prediction of the output values for the researched system. Over the last decade, more attention has been paid to ANN techniques, particularly in the automotive industry, which has widely accepted ANN as technology offering an alternative solution for engineering problems [7, 8]. "Artificial neuron" is used in the ANN terminology to show the similarities between the developed mathematical system and the human brain including the transfer of signals through synapses in the human body [9, 10].

The predictability of an ANN is a result of training with experimental data and validation with an independent set of data. The ANN has the ability to learn and improve its performance if new data are available [11]. If there are enough experimental data, a well-trained ANN can be used as a predictive model for specific applications, such as internal combustion engines, in research and development. In several research papers, the researchers have used the ANN modelling technique on the internal combustion engine for related issues such as predicting engine exhaust emission, cylinder pressure reconstruction and engine fault diagnosis.

He and Rutland [7] studied multilayer preceptors (MLP)-structured ANN to predict cylinder pressure (P_{cyl}), cylinder temperature (T_{cyl}), cylinder wall heat transfer (HT), NO_x emission, and soot emission (soot). They used seven diesel engine control parameters as the standard input package (SIP) for the MLP: engine speed (rpm), engine load (M_f), start of injection (SOI), injection pressure (P_{inj}), mass of the first injection pulse of a split injection (M1), boost pressure (P_{bst}) and exhaust gas re-circulation (EGR). The data they used for training and testing the ANN was obtained from the computational fluid dynamics (CFD) calculations of a known diesel engine using a KIVA code. They used the mean squared errors (MSE) algorithm and absolute errors for evaluating the MLP performances, which they found to be acceptable. For all five outputs, the ANN achieved good predictive capability. They also studied the effect of prior knowledge on ANN methodology. They added cylinder pressure and cylinder temperature traces as inputs that were predicted with another simulation technique, which had lower fidelity than the KIVA code [12, 13], to the SIP of the ANN. For predictive capability, they restructured and optimised the MLP regarding the neuron numbers and the number of hidden layers. Then, they trained and tested the newly designed networks with prior knowledge. They discovered that with prior knowledge, the general performance of the ANN was improved compared to the networks that were designed without prior knowledge.

Uzun [14] used the ANN method to perform parametric studies to investigate the effect of engine speed, injection advance (IA), and engine load variation on brake specific fuel consumption (BSFC) in an engine equipped with or without a turbocharger. They choose MLP-type ANN with a sigmoid activation function for their analyses. They first experimented on the engine test bench and collected the data. Then, they divided the data into two sets for training and testing the developed ANN. They identified the ANN geometry using a trial and error method, and they used sum of squares error (SSE) to control the convergence of the network to the real outputs. The correlations obtained with the real output and the simulated output of the ANN were found to be reliable. After they completed the development of the reliable ANN model, they used this model for completing their comprehensive parametric analysis. Yuanwang *et. al*. [15] presented a neural network model that predicts the exhaust emissions from an engine using the total cetane number, base cetane number and cetane improver, total cetane number and total nitrogen content in the diesel fuel as neural network inputs. The ANN prediction accuracy obtained was in an acceptable range. Additionally, Ganapathy [6], Oguz *et. al*. [11], Lucas *et al*. [16], Canakci *et al*. [17], Parlak *et. al*. [18], and Yuanwang *et. al*. [15] have used MLP architecture with ANN for predicting engine performance parameters.

In this study, the use of MLP structured ANN was proposed to determine the engine brake power, brake torque, BSFC, and the emissions of CO, CO_2, NO_x, soot, and total hydrocarbons (THC) using a group of characteristic engine operating parameters as the ANN inputs.

Experimental works

Experimental set-up and measurement system

In this study, experiments were performed on a Ford 1.8 L, CI diesel engine using conventional diesel fuel. The test engine specifications are given in tab. 1.

Table 1. Test engine specifications

Manufacturer	Ford
Model	1.8 L Lynx diesel engine
Combustion	Direct injection
Number of cylinders	4
Aspiration	VGT turbo charged
Type	Common rail injection
Bore	82.5 mm
Stroke	82 mm
Displacement	1753 cm³
Compression ratio	17/1
Rated speed	3750 rpm
Max. power	81 kW at 3750 rpm
Max. torque	250 Nm at 1750-2500 rpm

The instrumentation specifications used on the test bench are shown in tab. 2. The schematic picture of the test set-up is shown in fig. 1.

The experiments were run at maximum engine torque speeds (2000 rpm, 2500 rpm) and maximum engine power speed (3750 rpm). The intake manifold pressure was kept constant during the tests using variable geometry turbo control. Before starting the main experiments, the pre-experiments were performed to identify the engine's behaviour. The injected fuel mass was controlled by the engine control unit (ECU). The mass of fuel injected for each cycle is defined by considering the mechanical limits of the engine, such as the maximum cylinder pressure and the turbo compressor outlet temperature. For each test point, three different injection pressures were tested.

Table 2. Test bench instrumentation

Instrumentation	Type	Sensitivity
Dynamometer	AVL APA 204/8	±0.3%
Fuel flow	AVL 735C	±0.12%
Fuel temperature control	AVL 735S	±1 °C
Air flow	ABB sensy flow-P	±0.9%
Emissions		
CO, HC, CO_2, NO_x	Horiba mexa 7100 DEGR	±1.0%
Soot	AVL 415S	±0.1%
Test automation system	AVL Puma open 1.4 ISAC400	–
ECU	Siemens l200	–
ECU control, [19]	ATI vision 3.5 software [3]	–

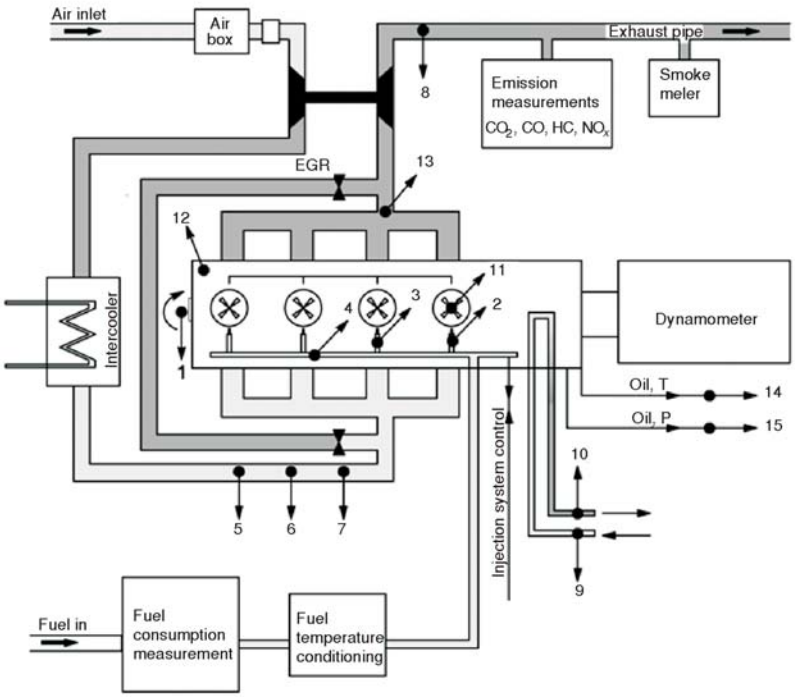

Figure 1. Experimental set-up

Table 3. Test points

Test point [rpm]	Mass of injection per cycle [mg per stroke]	Intake manifold pressure [hPa]	Rail pressure variation [MPa]	SOI variation [°CA] (aTDC*)
2000	25	2000	120, 130, 140	–15, –10, –5,0
	38	2200	130, 140, 150	
	43	2300	130, 140, 150	
2500	28	2000	130, 140, 150	
	37	2200	130, 140, 150	
	45	2300	130, 140, 150	
3750	25	2000	120, 130, 140	
	38	2200	130, 140, 150	
	40	2300	130, 140, 150	

* aTDC – after top dead centre

Test procedure and test points

In this study, engine speeds of 2000, 2500, and 3750 rpm were investigated. For each engine speed, three different fuel masses were injected. Only one injection strategy was pursued. No pilot or post injection was utilised. During the tests, the SOI and rail pressure were varied and the intake manifold pressure was kept constant within the predefined range, which was identified with two pre-tests.

EGR was not employed. In total, 108 experiments were performed on the test bench. The tested points are

listed in tab. 3. To make a steady-state analysis, the engine was warmed up to 90 °C before the experiments. Then, the engine speed and load were set to the desired values. Each measurement point had a stabilising time of 2 minutes and a recording time of 140 seconds.

Artificial neural network design

Haykin [10] stated, "ANN is a massively parallel-distributed processor, made up of inter-connected simple processing units, which has a natural propensity to store experiential information and to make it available for use. It resembles the brain in two respects: (1) Knowledge is acquired by the network from its environment through a learning process; (2) Interneuron strengths, known as synaptic weights, are used to store the knowledge."

The ANN methodology has different network types that researchers use for solving various problems. The MLP network is a feed-forward ANN that can map a set of input data to a set of appropriate outputs. MLP are particularly developed for the solution of non-linear behavioural problems. The MLP structure is mainly formed from three layers as shown in fig. 2. These layers are: (a) input layer – consisting of the input parameters, and these parameters are considered as they affect the outputs of the network, (b) hidden layer – the inputs are processed within the weights and biases with the predefined non-linear activation functions, and (c) output layer – consisting of the output parameters. The MLP working process includes three consecutive steps: (1) creating and configuring the network – the inputs, number of hidden layers, number of neurons at the hidden layer, activation function and the topology of the network is identified at this step, (2) training the network – initialise the weights and biases, and error minimisation with respect to targeting the data, and (3) usage of the network. At the beginning of the MLP process, each input is multiplied with an appropriate weight w; generally this w is identified arbitrarily at the initialisation step. We can call this result of multiplication the weighted inputs (wi), and the weights at this input layer are called input weights (iw):

$$wi_{\mathrm{n}} = \sum_{n=1}^{n} (iw_{\mathrm{min.}}\, ip_{\mathrm{n}}) \tag{1}$$

where m is the number of inputs and n – the number of neurons at the hidden layer. Then, these weighted inputs are summed with biases b, where b is the threshold value. The result is called the "net input – nip".

$$nip_{\mathrm{n}} = wi_{\mathrm{n}} + b_{\mathrm{n}} \tag{2}$$

Then, the net input is passed through a transfer function, which has to be differentiable (generally sigmoid) and produces the output (o):

$$o_{\mathrm{n}} = \frac{1}{1 + \mathrm{e}^{-nip_n}} \tag{3}$$

After the output is calculated, the outputs are multiplied with the layer weights (LW) and summed with biases. The result is called net output ($n$out):

$$n\mathrm{out}_j = \sum_{n=1}^{n} (LW_{nj}\, o_n + b_{\mathrm{l}}) \tag{4}$$

This step is called the feed forward calculation. After the output of the network is obtained, the desired j^{th} output is compared with the desired j^{th} target value (t) and the error (e) is calculated:

$$e_j = t_j - n\mathrm{out}_j \tag{5}$$

In the following step, to minimise the error, the error value is distributed to the weights with a predefined algorithm where the performance of the ANN is evaluated with the MSE algorithm:

$$MSE = \frac{1}{j}\left(\sum_j \left| e_j \right|^2 \right) \tag{6}$$

These two steps have to be repeated until the desired predefined error level is reached. These two consecutive steps can be generalised as the "training step" of an MLP-type ANN [9, 20, 21]. For training, any standard numerical optimisation algorithm can be used to optimise the performance function. Beale *et al*. stated [21], "there are a few key ones that have shown excellent performance for neural network training in which these optimisation methods use either the gradient of the network performance with respect to the network weights or the Jacobian of the network errors with respect to the weights. The gradient and the Jacobian are calculated using a technique called the back propagation algorithm, which involves performing computations backward through the network." When the error reaches a previously determined tolerance value, the training process is stopped [11]. According to Oztemel [20] "the information that is produced during this process is measured and stored within these adjusted weights and it is hard to reveal and interpret this information. "During these processes, the ANN learns the underlying function/physics of the system, while the results of the ANN learning are adjusted weights that could be used to accurately approximate the underlying function/physics of the system [7]. After the learning step, the network is tested with a different data set than that which was actualised before, and the performance of the network is analysed [20]. The structure of ANN is shown in fig. 2.

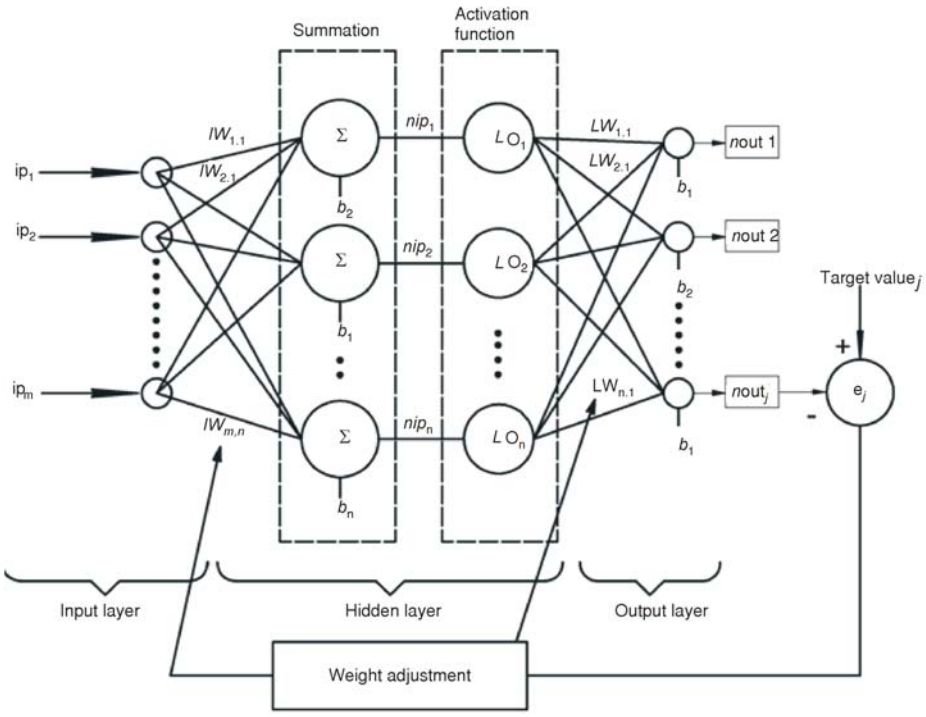

Figure 2. The structure of MLP ANN

Application of neural networks

The goal of using ANN for this work is estimating the desired engine output parameter by using some engine operating parameters as inputs for the designed neural network. The network groups studied in this work were divided into two main groups. The first network group (NG1) used 10 engine operating parameters as inputs at the input layer of the network. These inputs are listed in tab. 4. All NG1 inputs are indicated in fig. 1 with respect to their numbers (Nr). Each network is trained for estimating only one individual engine output parameter. This input group will be called the standard input package (SIP) after this point. The outputs are brake power [kW], BSFC , [$gkW^{-1}h^{-1}$]brake torque [Nm] and brake-specific engine out emissions, which are CO_2 [$gkW^{-1}h^{-1}$], CO [$gkW^{-1}h^{-1}$], THC [$gkW^{-1}h^{-1}$], NO_x [$gkW^{-1}h^{-1}$], and filter smoke number (FSN). This first group of networks has only one hidden layer, and during the training sessions, the neuron number of the hidden layer was increased from 1 to 20 to investigate the reaction of the network output to the hidden layer neuron number.

Table 4. Standard input package inputs

Nr.	NG1 input type	Unit	Physical explanation of the variable
1	Engine speed	rpm	The number of engine crankshaft rotations per minute
2	Start of main injection	°CA	The main injection timing with respect to engines TDC
3	Mass of injection	mg/stroke	The injected fuel mass into the cylinder per cycle
4	Rail pressure	MPa	The fuel injection pressure during the injection process
5	Manifold pressure	hPa	The engine intake air pressure
6	Manifold temperature	°C	The temperature of intake air
7	Inlet air mass flow	kg/h	The mass flow of intake air
8	Exhaust temperature	°C	The temperature at the exit of the turbocharger turbine
9	Cooling water inlet temperature	°C	The temperature of the water that enters the engine block for cooling
10	Cooling water outlet temperature	°C	The temperature of the water that exits the engine after re-circulating in the engine water jackets

After the design, training and analyses of the NG1 network, the THC estimation results were found to be unsatisfactory, and a new group (NG2) of networks were created to predict the THC. While designing the new individual networks for THC formation, the characteristics of this pollutant were considered. HC are the consequence of incomplete combustion, and HC emissions are sensitive to the oil and coolant temperature and increase from fuel absorbed in deposits and oil layers [22, 23. Therefore, in the newly designed networks, the parameters that were related to enhancing the phenomenon of HC oxidation and HC absorption at the oil layers were considered. All of the new parameters are listed in tab. 5.

Table 5. Additional NG2 inputs and physical explanations

Nr.	NG1 input type	Unit	Physical explanation of the variable
11	Maximum in-cylinder pressure	bar	The maximum pressure reached in the cylinder during the combustion process
12	Engine temperature	°CA	The temperature measured directly at the engine head
13	Turbine inlet temperature	mg/stroke	Temperature measured before the turbocharger turbine inlet
14	Oil temperature	MPa	Temperature measured at the oil sump
15	Oil pressure	hPa	Pressure measured at the pressurised oil transfer line

The first group of new parameters that can be correlated with HC oxidation consisted of the maximum in-cylinder pressure, engine temperature, and turbine inlet temperature. The turbine inlet temperature is measured directly from the plenum of the exhaust manifold (before the turbocharger turbine section inlet). These data reflect more precise information about the combustion process and the combustion temperature than the exhaust temperature that was taken from the exhaust line (after the exit of turbocharger turbine) and more directly affect the HC oxidation. The second group of new parameters consisted of the oil temperature and oil pressure, which can be correlated with oil absorption at the deposits and oil layers. Each NG2 input is indicated in fig. 1 relative to their numbers. The NG2, which has three subgroups, uses the aforementioned operating parameters in addition to the SIP to estimate the THC. The first subgroup of NG2 (NG21) has three parameters, and the second subgroup of NG2 (NG22) has two extra input parameters in addition to the SIP. The third subgroup of NG2 (NG23) uses these extra five parameters, which were used in NG21 and NG21, in addition to the SIP. The NG2 input parameters groups are listed in tab. 6. The main aim of creating new networks is develop a satisfactory THC estimation. During this process, the reaction of the network to the increased number of input parameters and to the input type was also investigated.

Table 6. NG2 networks inputs

Network name	Input parameters	Output
NG21	SIP + P_{max}* + Engine temperature + Turbine inlet temperature	THC
NG22	SIP + Oil temperature + Oil pressure	
NG23	SIP + P_{max} + Engine temperature + Turbine inlet temperature + Oil temperature + + Oil pressure	

* P_{max} – maximum in-cylinder pressure

The data group obtained in the experiments was composed of 108 data sets, and these data sets were divided into three subsets. The first subset was the training set, which was used to compute the gradient and update the network weights and biases. This first subset included 50% of the experimental data. The second subset was the validation set, which included 20% of the

experimental data. The error in the validation set was monitored during the training process. The validation error was expected to decrease during the initial phase of training, as did the training set error. However, when the network began to over-fit the data, the error on the validation set began to rise. Training continued until the validation error failed to decrease for six iterations. Then, the weights and biases at the minimum validation error were recorded and used. The third subset was the test set through which the network performance can be checked separately. The test set consisted of 30% of the experimental data set. The Matlab Programme ANN toolbox was used for developing and analysing the networks. A two-layer feed forward network with a tangent sigmoid (tansig) transfer function at the hidden layer and a linear transfer function at the output layer was formed for output estimation. In this study, the Levenberg-Marquardt algorithm was used for training, validation and testing that used the Jacobian of the network errors. The algorithm used is shown below:

$$H = J^T J \tag{7}$$

$$g = J^T e \tag{8}$$

$$x_{k+1} = x_k - [J^T J + \mu I]^{-1} J^T e \tag{9}$$

where, H is the Hessian matrix approximation, J – the Jacobian matrix that contains first derivatives of the network errors, μ – the Levenberg damping factor, k – the iteration number or the time step, x – the value of the weights, and e – the vector of network errors. This algorithm is the fastest method for training moderate-sized feed forward neural networks up to several hundred weights [21]. Extensive information about the Levenberg-Marquardt algorithm can be found in the literature [24]. The correlation coefficients (R) for the learning, validation, and testing stages were calculated to evaluate the ANN prediction capabilities. Additionally, the MSE obtained were provided for these stages [8, 21, 25]:

$$R = \frac{\sum_{j=1}^{j}(t_j - \bar{t})\overline{nout_j - (nout)}}{\sqrt{\sum_{j=1}^{j}(t_j - \bar{t})^2}\sqrt{\sum_{j=1}^{j}(nout_j - \overline{nout})^2}} \tag{10}$$

where t_j is the target (real) value of j^{th} test point output, the $nout_j$ – the output of the network estimated value (Est.), and $\bar{t}$ and $\overline{nout}$ are the mean values of the target and output values group, respectively.

Results and discussion

NG1 networks

The NG1 network overall regression (R) with an increasing neuron number at the hidden layer is given in fig. 3 for the CO, CO_2, NO_x, and FSN brake emissions, brake torque, brake power, and BSFC. The regression values presented in the figures are the values of the entire process (the combined training, validation, and testing phases). As seen from the figures and trend lines, the regression/performance of the networks increased with increasing neuron

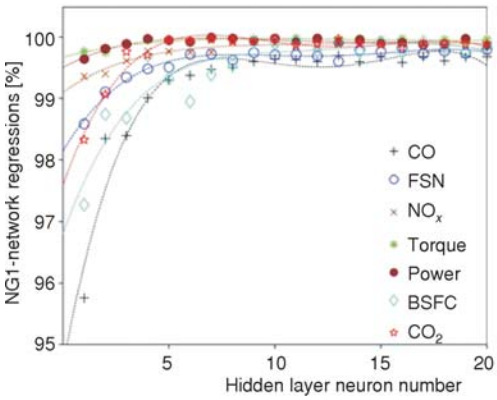

Figure 3. NG1 network regressions

number, and the average regression is over ~95%, which is a satisfactory result for this research. The neuron number of NG1 networks that show estimation performance superior to the others are: 13 neurons for CO_2 estimation, 5 neurons for CO estimation, 14 neurons for NO_x estimation, a 16 neurons for FSN estimation, 14 neurons for torque, 7 neurons for power estimation, and 11 neurons for BSFC estimation. The *R* and *MSE* values are shown in tab. 7. The performance graphs for the networks with the best regression are shown in fig. 4 (a-g). The THC estimation results for the NG1 networks and the best estimator network for the THC from NG1 group (13 neuron network, R-0.84945 and 0.24 MSE) and its performance graph are shown in fig. 5. As shown in the figure, the average estimation performance for THC is ~75, which is not satisfactory. Then, the new network group, which will be called the NG2 networks, were designed for THC estimation.

Table 7. Best NG1 networks *R* and *MSE* values

Output	Training		Validation		Testing		ALL		NN*
	R	*MSE*	*R*	*MSE*	*R*	*MSE*	*R*	*MSE*	
CO_2	0.9999	1.6E–17	0.9959	2.3E–1	0.99836	9.6E–1	0.9979	6.0E–1	13
CO_2	0.9992	3.8E–3	0.9938	3.3E–2	0.99442	1.2E–2	0.9969	1.2E–2	5
NO_x	0.9999	1.0E–2	0.9898	5.6E–2	0.99896	5.9E–2	0.9994	8.5E–2	14
FSN	0.9999	4.4E–6	0.9668	4.7E–3	0.96424	4.9E–3	0.9982	2.0E–3	16
THC	0.9463	1.6E–1	0.7307	3.4E–1	0.73600	3.2E–1	0.8494	2.4E–1	13
Torque	0.9999	4.1E–2	0.9996	1.2E–2	0.99957	1.9E–2	0.9998	8.4E–1	14
Power	0.9999	4.5E–3	0.9999	2.4E–2	0.99984	6.7E–2	0.9993	2.7E–2	7
BSFC	0.9999	1.9E–5	0.9990	1.3E–2	0.99757	3.6E–2	0.9992	1.3E–1	11

* NN – number of neutrons at hidden layer

NG2 networks

The NG2 networks were solely designed for THC estimation. The main aim is a better estimation of THC with an increased number of inputs and also increased prior knowledge. The three new network group performances and the reference NG1 network performances with the increasing neuron numbers are given in fig. 6. As shown in the indicated trend lines for the data sets, the estimation performance increased with an increasing number of inputs for the THC emissions. Whereas the NG1 reference performance, with the SIP input packet, remained at approximately 75%, the NG21 performance with its input packet of engine temperature, turbo turbine inlet temperature and the current SIP packet was approximately 80%. The NG22 performance with its input packet of oil temperature, oil pressure and the standard SIP packet was ~85%, and the NG23 performance with its input packet of engine temperature, turbine inlet temperature, oil temperature, oil pressure, and the standard SIP packet was ~90%. It is obvious that the NG22 network estimation performance (~85%) is higher than NG21 (~80%). Therefore, the

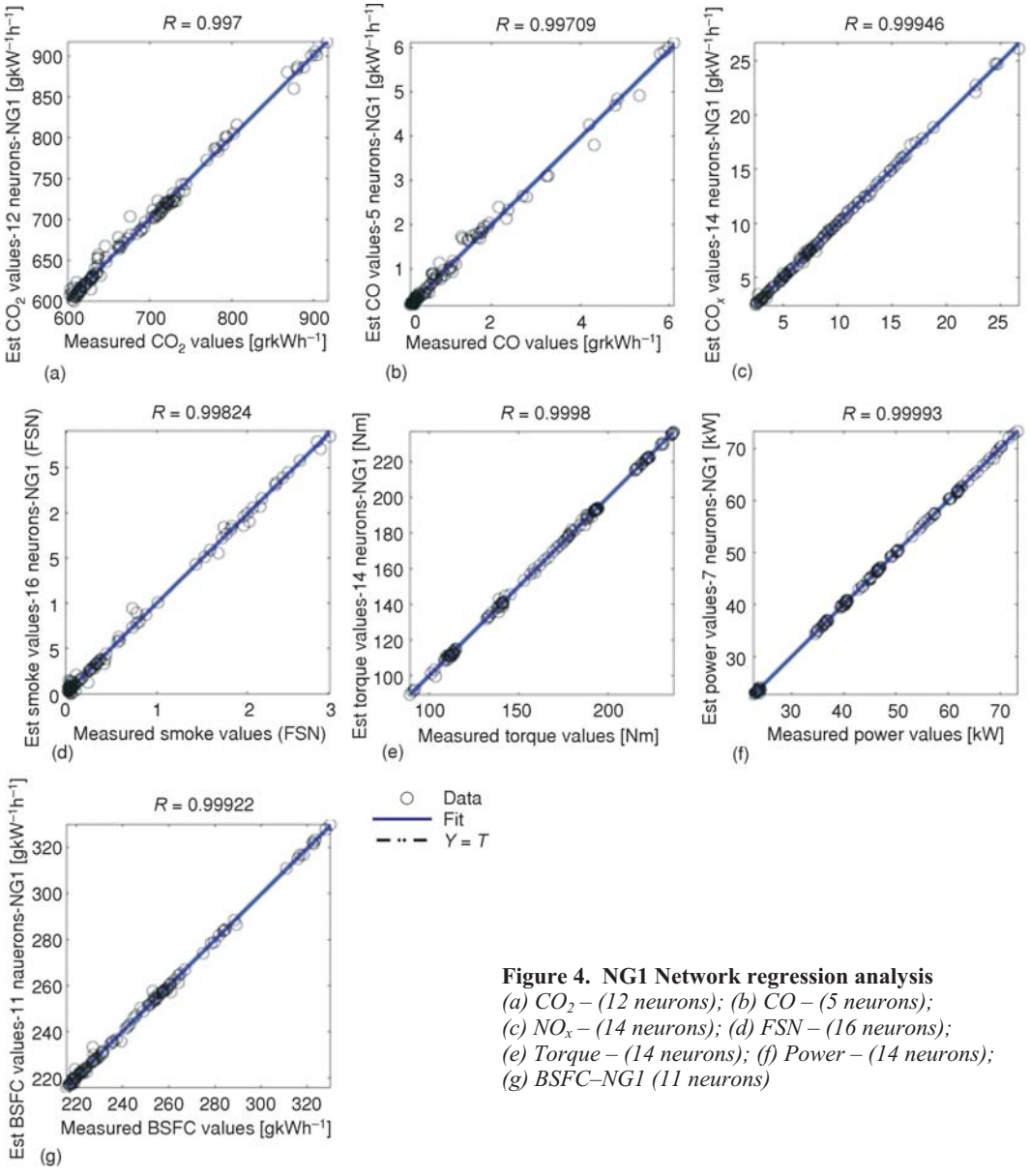

Figure 4. NG1 Network regression analysis
(a) CO_2 – (12 neurons); (b) CO – (5 neurons); (c) NO_x – (14 neurons); (d) FSN – (16 neurons); (e) Torque – (14 neurons); (f) Power – (14 neurons); (g) BSFC–NG1 (11 neurons)

networks for this experiment are more sensitive to the oil temperature and oil pressure data characteristics for THC estimation. The neuron numbers for the NG2 networks with superior estimation performance are: 11 neurons for the NG21 network, 10 neurons for the NG22 network, and 11 neurons for NG23. The *R* and *MSE* values are given in tab. 8. The performance graphs for these networks are given in fig. 7(a-c).

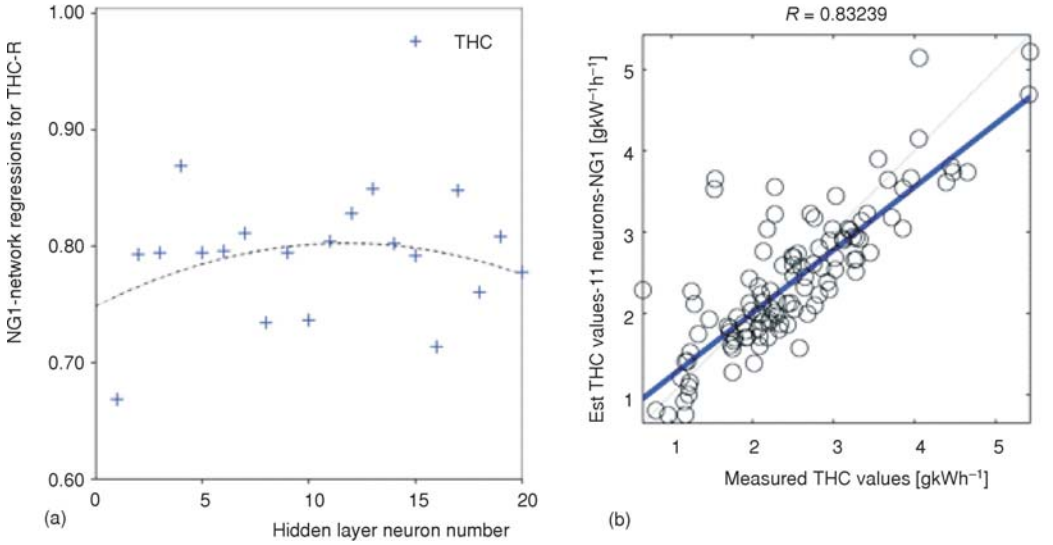

Figure 5. (a) NG1 network regressions for THC; (b) Regression analysis of THC– NG1(11 neurons)

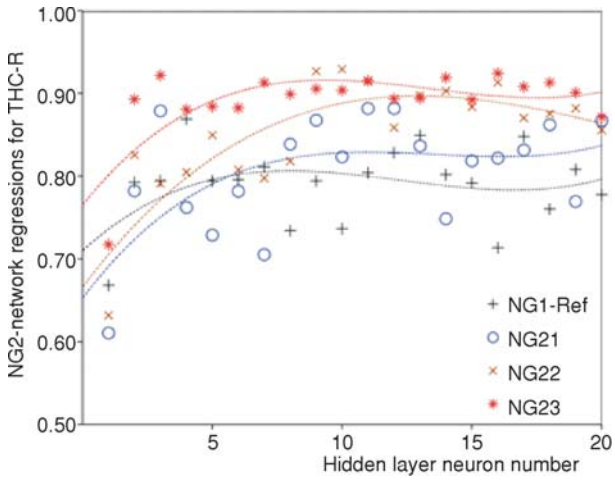

Figure 6. NG2 network regressions for THC

Table 8. Best NG2 networks *R* and *MSE* values

NG2 Network	Training		Validation		Testing		All		NN
	R	*MSE*	*R*	*MSE*	*R*	*MSE*	*R*	*MSE*	
NG21	0.9867	2.0E–2	0.7011	4.2E–1	0.8383	2.7E–1	0.8819	1.7E–1	11
NG22	0.9956	7.8E–2	0.8301	2.9E–1	0.9265	2.3E–1	0.9292	1.3E–1	10
NG23	0.9975	4.4E–3	0.775	3.2E–1	0.8839	2.4E–2	0.9155	1.3E–1	11

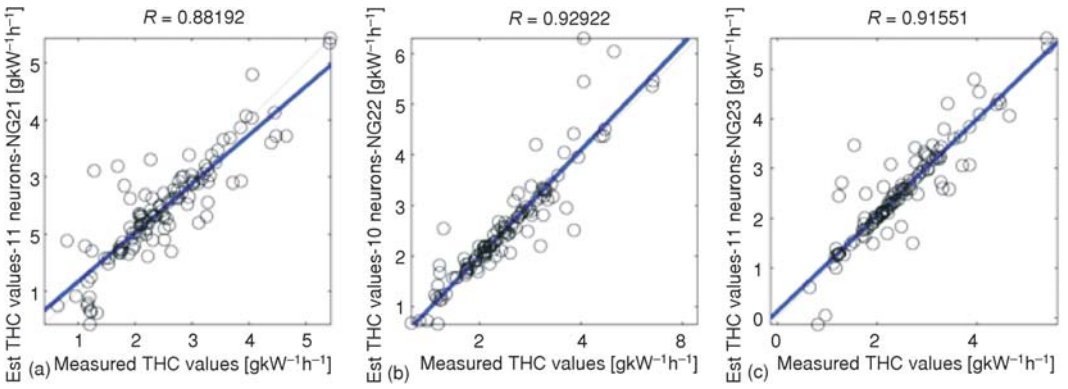

Figure 7. (a) Regression analysis of THC–NG21 network (14 neurons); (b) Regression analysis of THC–NG22 network (10 neurons); and (c) Regression analysis of THC–NG23 network (11 neurons)

Conclusions

In this study, the performance of the neural network calculation method was investigated to estimate two engine-out parameters. A regression analysis between the network response and the corresponding targets was performed. The results indicate the following.

- The estimation performance of neural networks increased with an increasing neuron number at the hidden layer in all cases.
- The NO_x, CO, CO_2, power, torque, and specific fuel consumption estimations are satisfactory (over 95%) using the SIP as the input layer of the neural network.
- An increased number of inputs at the input layer results in increased estimation performance (75% to 90%) for the THC estimations.
- For the same number of inputs, NG22 networks are more sensitive than the NG21 networks for THC estimation, which use only oil pressure and oil temperature at the input layer instead of engine temperature and turbo turbine inlet temperature.
- The overall performance of neural networks is satisfactory, and it is obvious that with the proper input layer and hidden layer characterisation, this method can be utilised to estimate the engine out parameters with high levels of confidence.

References

[1] ***, ACEA, EU Economic Report, in, European Automobile Manufacturers' Association, Brussels, 2010
[2] ***, ACEA, Europan Vehicle Fleet, in, European Automobile Manufacturers' Association, Brussels, 2010
[3] Bargezar, R., *et al.*, CFD Simulatýon of the Combustion Process, Emission Formation and the Flow Field in an In-Direct Injection Diesel Engine, *Thermal Science 17* (2013), 1, pp. 11-23 (in this issue)
[4] Sudeshkumar, M. P., Devaradjane, G., Development of a Simulation Model for Compression Ignition Engine Running with Ignition Improved Blend, *Thermal Science, 15* (2011), 4, pp. 1131-1144
[5] Moldovanu, D., Burnete, D., CFD Simulation of a Single Cylinder Research Engine Working with biodiesel, *Thermal Science, 17* (2013), 1, pp. 195-203
[6] Ganapathy T., *et al*., Artificial Neural Network Modeling of Jatropha Oil Fueled Diesel Engine for Emission Predictions, *Thermal Science, 13* (2009), 1, pp. 91-102
[7] He, Y., Rutland, C. J., Application of Artificial Neural Networks in Engine Modeling, *International Journal of Engine Research, 5* (2004), 4, pp. 281-296
[8] Zhou, H., *et al.*, Modeling and Optimization of the NO_x Emission Characteristics of a Tangentially Fired Boiler with Artificial Neural Networks, *Energy, 29* (2004), 1, pp. 167-183

[9] Karonis, D., *et al*., A Neural Network Approach for the Correlation of Exhaust Emissions from a Diesel Engine with Diesel Fuel Properties, *Energy & Fuels, 17* (2003), 5, pp. 1259-1265
[10] Haykin, S., Neural Networks: A Comprehensive Foundation, Prentice Hall, New York, USA, 1998
[11] Oguz, H., *et al*., Prediction of Diesel Engine Performance Using Biofuels with Artificial Neural Network, *Expert Systems with Applications, 37* (2010), 9, pp. 6579-6586
[12] Moskwa, J. J., Chen, S. X., Dynamic Engine Modeling for Diagnostics and Simulation., Inc. PPT Group, 1995
[13] Munns, S. A., Computer Simulation of Power Train Components with Methodologies for Generalized System Modeling., Department of Mechanical Engineering, University of Wisconsin-Madison, Wis., USA, 1996
[14] Uzun, A., A Parametric Study for Specific Fuel Consumption of an Intercooled Diesel Engine Using a Neural Network, *Fuel, 93* (2012), March, pp. 189-199
[15] Yuanwang, D., *et al.*, An Analysis for Effect of Cetane Number on Exhaust Emissions from Engine with the Neural Network, *Fuel, 81* (2002), 15, pp. 1963-1970
[16] de Lucas, A., *et al*., Modeling Diesel Particulate Emissions with Neural Networks, *Fuel, 80* (2001), 4, pp. 539-548
[17] Canakci, M., *et al*., Prediction of Performance and Exhaust Emissions of a Diesel Engine Fueled with Biodiesel Produced from Waste Frying Palm Oil, *Expert Systems with Applications, 36* (2009), 5, pp. 9268-9280
[18] Parlak, A., *et al*., Application of Artificial Neural Network to Predict Specific Fuel Consumption and Exhaust Temperature for a Diesel Engine, *Applied Thermal Engineering, 26* (2006), 8-9, pp. 824-828
[19] ***, ATI Vision, www.accuratetechnologies.com/content/view/240/237/lang.en/, 2012
[20] Oztemel, E., Artificial Neural Networks, Papatya Publishing, Istanbul, Turkey, 2003
[21] Beale, H. M., *et al*., Matlab Neural Network Toolbox User Guide, The Mathworks Inc., Natick, Mass., USA, 2010
[22] Heywood, J., Internal Combustion Engine Fundamentals, McGraw-Hill, New York, USA, 1988
[23] Borman, L. G., Ragland, K. W., Combustion Engineering, McGraw-Hill Book Co., New York, USA, 1998
[24] Hagan, M. T., *et al*., Neural Network Design PWS Pub. Co., Boston, Mass., USA, 1995
[25] Manjunatha, R., *et al*., Application of Artificial Neural Networks for Emission Modelling of Biodiesels for a CI Engine under Varying Operating Conditions, *Modern Applied Science, 4* (2010), 3, pp. 77-89

Paper submitted: March 21, 2012
Paper revised: September 14, 2012
Paper accepted: September 22, 2012