ESTIMATION OF OPERATIONAL PARAMETERS FOR A DIRECT INJECTION TURBOCHARGED SPARK IGNITION ENGINE BY USING REGRESSION ANALYSIS AND ARTIFICIAL NEURAL NETWORK

by

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Original scientific paper
DOI: 10.2298/TSCI160302151T

This study was aimed at estimating the variation of several engine control parameters within the rotational speed-load map, using regression analysis and artificial neural network techniques. Duration of injection, specific fuel consumption, exhaust gas at turbine inlet, and within the catalytic converter brick were chosen as the output parameters for the models, while engine speed and brake mean effective pressure were selected as independent variables for prediction. Measurements were performed on a turbocharged direct injection spark ignition engine fueled with gasoline. A three-layer feed-forward structure and back-propagation algorithm was used for training the artificial neural network. It was concluded that this technique is capable of predicting engine parameters with better accuracy than linear and non-linear regression techniques.

Key words: *turbocharged direct injection spark ignition engine, regression analysis, artificial neural network, estimation*

Introduction

Given their high power to weight ratio and good efficiency, internal combustion engines (ICE) are used on a wide scale for transportation and power production. The ICE are generally driven by conventional petroleum based fossil fuels. However, fossil fuel depletion has been identified as a future challenge by scientists [1]. Both alternative fuel investigations and studies aimed at efficiency enhancement require intensive laboratory work. Experimental studies are time consuming and costly processes. In parallel to the development of computer technology, use of various modeling techniques is being widespread. Artificial neural network (ANN) is one of the leading techniques among these. It is a computational modeling technique that consists of interconnected adaptive simple processing elements referred as neurons and nodes [2]. In recent years, several researchers have applied neural networks to ICE for prediction of performance, emissions, and combustion characteristics. Kapusuz *et al.* [3] investigated various alcohol-unleaded gasoline mixtures that can be used without modifications in a spark-ignition (SI) engine. Their paper demonstrated that ANN can successfully be used as an alter-

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native type of modeling technique for ICE. Rezaei *et al.* [4] used homogeneous charge compression ignition experimental data to characterize variations in seven engine performance parameters including indicated mean effective pressure, thermal efficiency, in-cylinder pressure, net total heat released, NO_x, CO, and total HC concentrations. Two types of ANN including radial basis function and feed-forward were developed to predict the seven engine performance parameters. Cay [5] studied ANN modeling of a gasoline engine to predict the brake specific fuel consumption (SFC), effective power, and exhaust temperature. His study showed that as an alternative to classical modeling techniques, the ANN approach can be used to accurately predict the performance, temperature, and other parameters of ICE. Yap *et al.* [6] presented an alternative tool for vehicle tuning applications by incorporating the use of ANN virtual sensors for a hydrogen-powered car. Their objective was to optimize simple engine process parameters to control the exhaust emissions. Oguz *et al.* [7] developed an ANN to apply in the automotive sector as well as many different areas of technology aimed at overcoming difficulties of the experiments, minimize the cost, time, and workforce effort. Ozgur *et al.* [8] prepared an ANN model in order to predict the exhaust emissions values of 100% soybean biodiesel using data recorded on a Diesel engine for different engine speeds at varying load conditions. Engine speed, torque and exhaust temperature values were used as input to predict CO, CO_2, NO_x emissions, and coefficient of correlation, R, and mean absolute percentage error (MAPE) values were calculated to define correlation between the target value and output value and identify the convergence between the target and the output values.

The introduction of direct injection (DI) on an ever wider scale in SI engines [9] has provided additional control on combustion, with significant benefits with regard to part load operation and reduction of knock intensity at full load [10]. Split injection can provide an improvement of stability due to more favorable mixture stratification and also result in lower exhaust gas emissions [11]. On the other hand, this also induces increased complexity; compared to the *classical* parameters of influence (in the form of engine speed, load, and spark timing); alternative control methods such as continuous variation of valves timing, injection phasing, and exhaust gas re-circulation are routinely used for achieving increased fuel economy. This needs to be considered in the context of ever lower limits imposed on pollutant emissions. Keeping the catalytic converter above the light-off temperature threshold is an essential requirement that basically entails operating the engine with stoichiometric air-fuel mixtures [12]. Therefore, there are a multitude of aspects that need to be considered when building so called *calibration maps* with the various values for control parameters that require extensive experimental trials. By applying numerical simulations, the costs and time effort associated with these measurements can be reduced. The computational effort associated with the application of different models is also an issue, especially when used for obtaining *real-time* results [13].

The ANN is an effective tool for estimation of the powertrain and it allows to reduce time consuming and costly experimental work. In literature, ANN architecture used for automotive applications is limited and needs more extensive investigation. Most of the studies are related to Diesel engines and there are fewer publications about SI engines modeling. On the other hand, this study serves new and efficient approach for the prediction of operational parameters for a DI turbocharged SI engine with its individual input-output data set. In this study, linear regression (LR), non-linear regression (NLR), and ANN methods were applied in order to predict several engine parameters such as duration of injection (DOI), SFC, exhaust gas at turbine inlet, T_{exh}, and exhaust gas temperature in the catalytic converter brick, T_{conv}.

Material and method

Experimental data

The experimental trials were performed on a turbocharged DISI engine fuelled with commercial 95 RON gasoline, and its main specifications are listed in tab. 1. The wall guided fuel system featured side mounted injector fitting, with a geometry that resulted in spray impingement mainly on the piston crown. Engine speed was varied from 1000 to 5500 rpm, with load levels up to 22 bar break mean effective pressure (BMEP). The DOI (*i. e.* the electronic signal for controlling the opening of the metering valve) was chosen as the main control parameter. Spark timing is shown in fig. 1 for the considered engine speed-load map, and it should be noted that the step for engine speed was 500 rpm and the load range was different for the low and high values of rotational speed (*i. e.* up to 12 bar for 1000 rpm and up to 18 bar at 5500 rpm).

Table 1. Engine specifications

Displacement	1368 cm^3
No. of cylinders	4
Bore × stroke	72 × 84 mm
Compression ratio	10:1
Valves per cylinder	4 (2 intake and 2 exhaust)
Valves timing	Variable through camshaft phasing on the intake and exhaust side
Intake system	Turbocharging with up to 1.49 bar gauge pressure
Fuel system	Wall guided DI at 100 bar, 6 holes nozzle

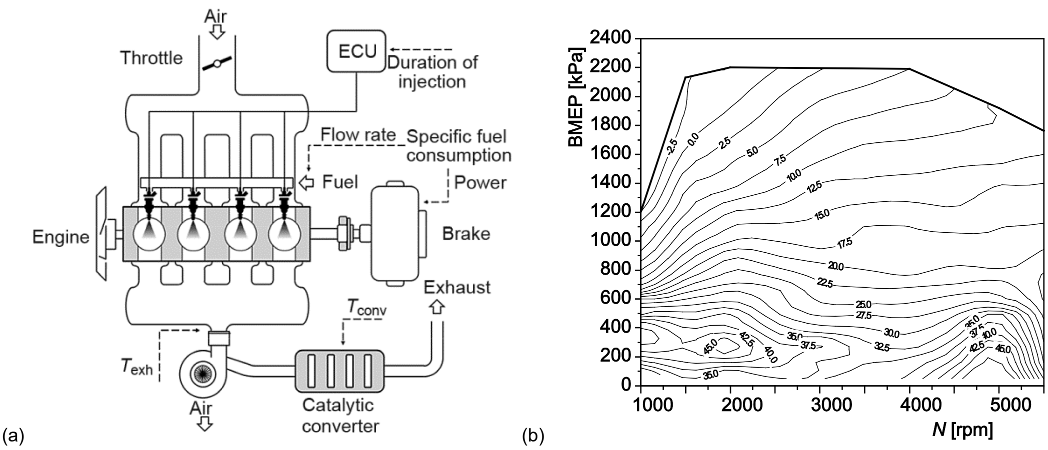

Figure 1. Schematic representation of the experimental set-up and points of measurement for the chosen parameters (a) and map of spark timing setting (b)

Figure 1 also shows a schematic representation of the experimental set-up, as well as the point of measurement for each of the chosen parameters. Fuel flow was measured with an accuracy of ±1% using a volumetric flow meter, engine speed was measured with a crank angle encoder that featured a resolution of 0.5 deg and break power was measured with an accuracy of ±2%. Stoichiometric fueling was maintained for most of the engine speed-load map; at rotational speeds over 4000 rpm and load higher than 18-20 bar, over-fueling was applied (up to 1.25 equivalence ratio) mainly for reducing the temperature at turbine inlet. Injection phasing ranged from 280 to 330 deg bTDC, thus ensuring homogenous charge operation.

For a clearer link between the experimental data, engine operation, and simulations, the choice of each measured parameter will be briefly explained. Engine speed and load are the two essential values that give the usable crank power that in the end propels the vehicle. Therefore, these parameters were chosen as input for the models and they can be easily correlated with the values given by the crank shaft and the throttle positioning sensors, therefore, making even real-world applications straight forward. The four measured values chosen as outputs (*i. e.* DOI, SFC, T_{exh}, and T_{conv}) have more complex interpretation. The DOI generally has a linear correlation with load. There are, however certain points in the engine speed-load map where over-fueling is required in order to maintain exhaust gas temperature at turbine inlet below a certain threshold. Therefore, it is useful to predict the trend of this parameter for feed-forward and diagnostic purposes. The SFC is an essential information for performing multi-objective optimization and was therefore chosen as the second predicted parameter. As previously mentioned, T_{exh} needs to be maintained below certain limits in order to protect the turbine from overheating; predicting its' variation throughout the engine speed-load map can be used as a safety measure against a failure common for turbocharged SI engines. Finally, T_{conv} needs to be kept within a certain range that ensures high enough temperatures for increased conversion efficiency and low enough to avoid over-heating of the converter brick. This is another essential parameter for exhaust gas after-treatment that can be used together with SFC, for optimizing engine operation with high fuel economy and reduced environmental impact.

Regression analysis

Regression analysis is a statistical technique for estimating the relationship among variables which have reason and result relation. It is performed to determine the correlations between two or more variables having cause-effect relations and to make predictions for the topic by using relation [14].

In LR, relationship between dependent and independent variables can be expressed in form of eq. (1), and for NLR as eq. (2) [15]:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n \tag{1}$$

$$Y = \alpha_0 X_1^{\alpha_1} X_2^{\alpha_2} \ldots X_n^{\alpha_n} \tag{2}$$

where Y is the dependent variable, β_0 to β_n – equation parameters for linear relationship, α_0 to α_n – equation parameters for non-linear relationships, and X_1 to X_n – independent variables.

Artificial neural networks

Biological neural networks consist of a cell body or soma where the cell nucleus is located. The fundamental unit of the network is called a neuron or a nerve cell [16]. Schematic of the structure of a neuron was shown in fig. 2.

The ANN are computational models inspired by nervous system of human. They are generally presented as systems of interconnected neurons which can compute values from the inputs [17].

Haykin [18] stated mathematically that, we can describe a neuron, k, by eqs. (3) and (4):

$$u_{\mathrm{k}} = \sum_{j=1}^{m} w_{\mathrm{k}j} x_j \tag{3}$$

$$y_{\mathrm{k}} = \varphi\,(u_{\mathrm{k}} + b_{\mathrm{k}}) \tag{4}$$

Bias, denoted by b_{k}, has the effect of increasing or lowering the net input of the activation function, $x_1, x_2, \ldots, x_m$ are the inputs, $w_{\mathrm{k}1}, w_{\mathrm{k}2}, \ldots, w_{\mathrm{k}m}$ are the weights of the neuron, k, u_{k} is the linear combiner output due to input signals, φ – the activation function, and y_{k} – the output signal of the neuron.

Back-propagation algorithm is commonly used as a learning algorithm of ANN in the multilayered feed-forward networks. In back-propagation networks, data is processed from the input layer to the hidden layer then to the output layer. Finding optimal weights is the purpose in order to obtain close values to targets as an output [15]. A typical ANN structure was shown in fig. 3.

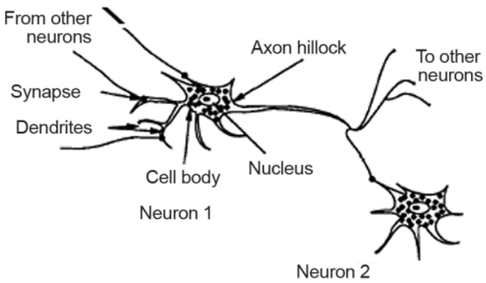

Figure 2. Schematic diagram of a typical neuron [16]

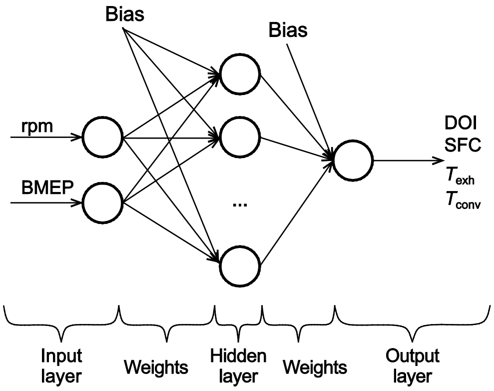

Figure 3. A typical multilayered feed-forward ANN structure

Results and discussion

Regression analysis results

The statistical analysis software SPSS, was used to relate dependent and independent variables with each other. In this study, engine parameters such as DOI, SFC, exhaust gas at turbine inlet, and exhaust gas temperature in brick were related with independent variables which are engine speed, X_1, and BMEP, X_2, by using regression analysis. The equation parameters and R^2 values of regression analysis were given in tab. 2.

Table 2. Results of regression analysis

Y	Linear regression					Non-linear regression				
	β_0	β_1	β_2	R^2	Adjusted R^2	α_0	α_1	α_2	R^2	Adjusted R^2
DOI [ms]	0.486	0.0000218	0.002	0.899	0.896	0.02851	–0.041	0.709	0.927	0.925
SFC [gkW^{-1}h^{-1}]	401.738	0.003	–0.101	0.35	0.334	990.8319	0.064	–0.26	0.755	0.749
T_{exh} [°C]	355.152	0.078	0.181	0.931	0.928	18.4502	0.289	0.212	0.957	0.955
T_{conv} [°C]	346.712	0.065	0.186	0.892	0.888	21.577	0.258	0.217	0.885	0.881

Results of both LR and NLR regression analysis can be seen from fig. 4. Table 3 shows the independent variables in testing period.

As an overall evaluation, both LR and NRL performed roughly the same, with NLR showing somewhat better results. This was to be expected, given the actual correlation between input and output. For example, the influence of engine speed on DOI is minimal, given

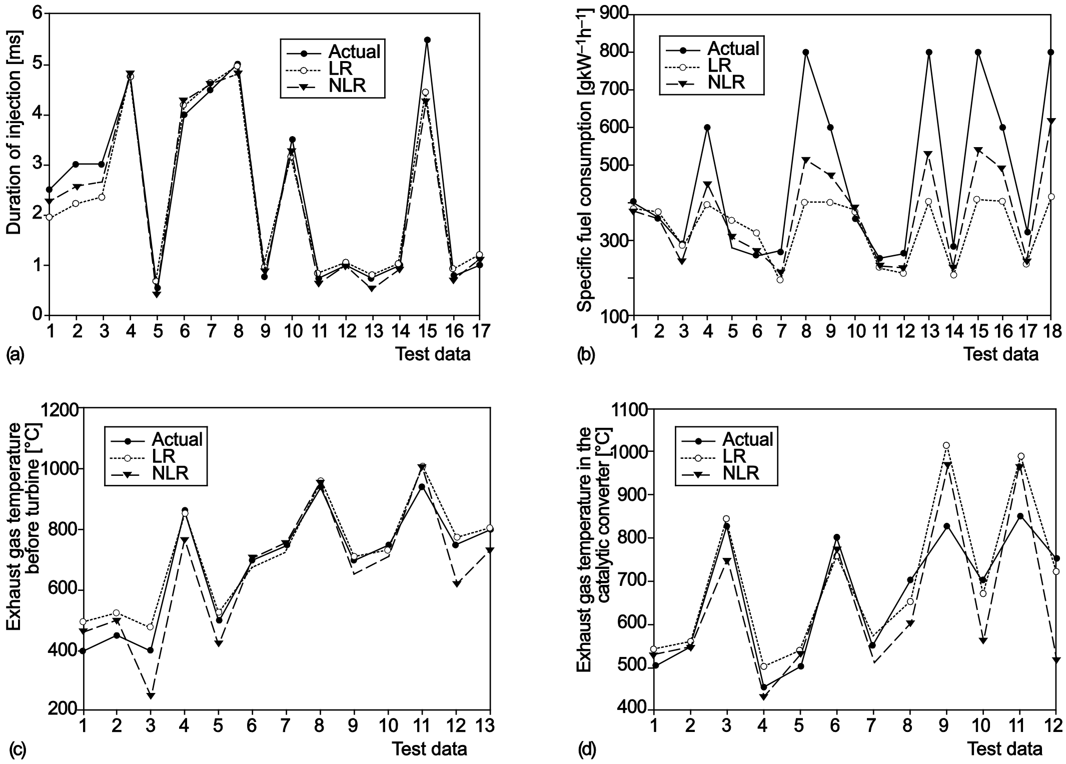

Figure 4. Comparison of actual and regression results of DOI, SFC, exhaust gas temperature before turbine, and in the catalytic converter brick

that increasing rotational velocity simply means a higher number of cycles within the same time period, cycles that require roughly the same amount of injected fuel at a fixed load point. As the latter parameter is higher at fixed rotational speed, more air is fed to the engine, thus requiring more fuel to be injected, with a correlation close to a linear one. This explains the fact that both models feature roughly the same prediction capabilities for DOI. The SFC, on the other hand, is the result of numerous complex interactions such as pumping, friction, and combustion losses for which variations are far from linear when changing both engine speed and load. Therefore, assuming an arbitrary correlation such as LR or NRL seems to have little chance of succeeding when trying to predict complex phenomena, such as combustion in SI engines that tend to feature more and more control parameters. Even for relatively simple variations such as DOI with load, care needs to be taken when applying the aforementioned correlations, given certain operating points for which over-fueling is required.

The ANN results

Neural network toolbox of MATLAB software was used for ANN modeling. The ANN architecture consisted of input, hidden, and output layers. To validate and to test the network, 70-15-15% of the data set was used to train, respectively. Since there is no certain rule of defining these ratios, it can clearly be seen from the literature that this data division configuration is very common and can be used [19-21].

Table 3.Independent variables in testing period

DOI [ms]			SFC [$gkW^{-1}h^{-1}$]		
Test data	Engine speed [revolutions per minute]	BMEP [kPa]	Test data	Engine speed [revolutions per minute]	BMEP [kPa]
1	1000	720	1	1000	230
2	1000	860	2	1000	280
3	1500	920	3	1000	1200
4	1500	2130	4	1500	120
5	2000	70	5	1500	540
6	2000	1830	6	1500	880
7	2500	2060	7	1500	2130
8	2500	2200	8	2000	80
9	3000	200	9	2000	110
10	3500	1300	10	2000	240
11	4000	130	11	2500	1800
12	4000	240	12	2500	1960
13	5000	100	13	3000	80
14	5000	220	14	3500	2040
15	5000	1930	15	4000	80
16	5500	150	16	4000	110
17	5500	290	17	5000	1800
-	-	-	18	5500	50
T_{exh} [°C]			T_{conv} [°C]		
Test data	Engine speed [revolutions per minute]	BMEP [kPa]	Test data	Engine speed [revolutions per minute]	BMEP [kPa]
1	1000	330	1	1000	690
2	1000	490	2	1000	790
3	1500	10	3	1500	2130
4	1500	2130	4	2000	120
5	2000	80	5	2000	310
6	2500	700	6	2500	1340
7	2500	970	7	3000	160
8	3500	1860	8	4000	240
9	4000	250	9	4000	2190
10	4000	370	10	4500	150
11	4500	1670	11	5000	1700
12	5000	150	12	5500	80
13	5000	330	-	-	-

Table 4. Epoch numbers from MATLAB platform (part of written program for ANN network)

DOI

net = newff(minmax(p), [5 1],{'logsig' 'purelin'}, 'trainlm');
net.trainParam.epochs = 500;
net.trainParam.goal = 0.00005;

SFC

net = newff(minmax(p), [3 1],{'logsig' 'purelin'}, 'trainlm');
net.trainParam.epochs = 500;
net.trainParam.goal = 0.00005;

T_{exh}

net = newff(minmax(p), [7 1],{'logsig' 'purelin'}, 'trainlm');
net.trainParam.epochs = 500;
net.trainParam.goal = 0.00005;

T_{conv}

net = newff(minmax(p), [4 1],{'logsig' 'purelin'}, 'trainlm');
net.trainParam.epochs = 500;
net.trainParam.goal = 0.00005;

Table 5. Weight and bias values between input and hidden layer for DOI prediction

i	w_{1i}	w_{2i}	i	b_i
1	–1.1603	1.878318	1	–17.3055
2	–6.82E-06	0.00509	2	–2.177
3	–0.01872	0.093073	3	–50.6196
4	–0.00179	–0.00611	4	18.02975
5	0.006188	–0.01287	5	10.75479

In the present study, Levenberg-Marquardt algorithm was selected as learning algorithm. Logistic sigmoid transfer function (logsig) and linear transfer function (purelin) were used in the hidden layers and output layer of the network as an activation function, respectively. There was an input layer, hidden layer, and output layer. Input layer consist of two neurons for both predicted parameter and output layer consist of one neuron (all output parameters analyzed separately). Using engine speed alone will be deficient for proper estimation of output parameters since it has same values at some lines. Therefore, in order to obtain good relationship between input and output parameters, we have also added representative of load, BMEP, as input parameter beside engine speed. Remaining parameters were chosen as output, predicted parameters.

Since there was not a certain number of hidden layer neuron, number of hidden layer was determined by trial and error method. Numbers of hidden layers for DOI, SFC, exhaust gas at turbine inlet, and exhaust gas temperature in the catalytic converter brick are 5, 3, 7, and 4, respectively. Engine speed, X_1, and brake mean effective pressure, X_2, were used as input neuron to predict various engine parameters in the network. Epoch numbers was shown in tab. 4, while weight and bias values between input and hidden layer only are given for DOI in tab. 5 to show calculations briefly.

For brevity, ANN details were not given for all four predicted values (*i. e.* DOI, SFC, T_{exh}, and T_{conv}). As an example of ANN application to the DOI parameter, the prediction equation can be stated in the form of eq. (5) and related sigmoid functions:

$$\mathrm{DOI} = 0.353968\, F_1 + 2.172024\, F_2 + 0.68372\, F_3 - 2.0028\, F_4 - 1.06189 \mathrm{F}_5 + 3.419145 \quad (5)$$

Sigmoid function was used to calculate each F values.

$$F_i = \frac{1}{1+\mathrm{e}^{-E_i}} \quad (6)$$

$$E_i = w_{1i} X_1 + w_{2i} X_2 + b_{1i} \quad (7)$$

The comparison of testing and validation results of ANN and actual values can be seen from figs. 5 and 6. When evaluating the test results, it is immediately evident that the results are much better with respect to the two previous predictive approaches (*i. e.* LR and NLR). For the simple correlation specific for DOI, the results are quite close for all models. It is for the other three parameters that the improved predictive capabilities of ANN are more

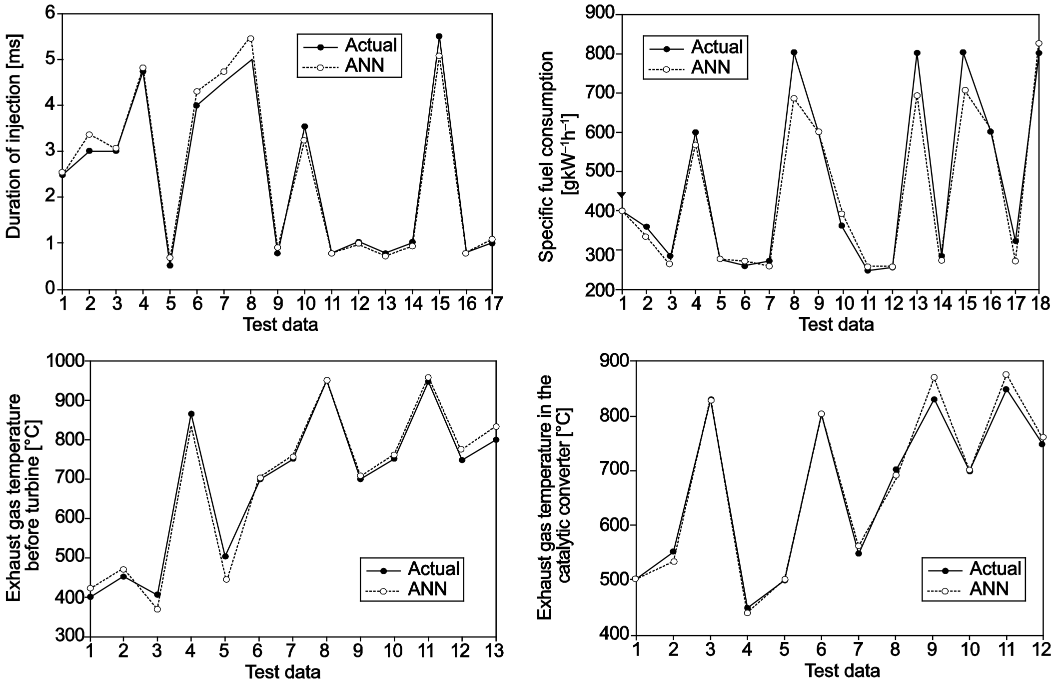

Figure 5. Testing results of actual and ANN results of DOI, SFC, exhaust gas temperature before turbine, and in the catalytic converter brick

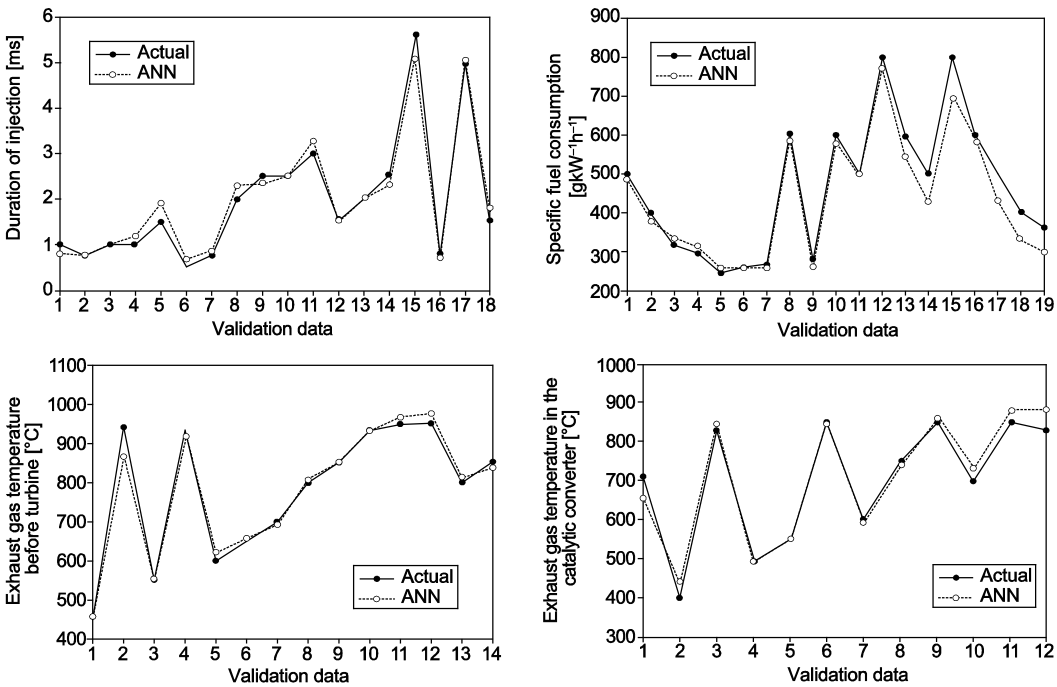

Figure 6. Validation results of DOI, SFC, exhaust gas temperature before turbine, and in the catalytic converter brick

prominent. This is directly related to the complex influences mentioned in the previous paragraph. The results for exhaust gas at turbine inlet and within the converter brick clearly show that with adequate training and validation, ANN can accurately predict the variation of these parameters. The major influence of engine speed and load is related to the actual gas mass flow and indirectly through heat transfer (mainly via the convective mechanism). The T_{conv} features even more complex heat and mass transfer problem, given the chemical reactions taking place within the catalytic converter; these phenomena are difficult to model even with high resolution computational tools, thus further emphasizing the ability of ANN to correctly predict the evolution of engine parameters within the operating speed-load map.

Performance comparison of models

Different performance parameters can be used to evaluate the convergence of experimental values to predicted values. Mean absolute error, MAPE, root mean-square error (RMSE), and correlation coefficient were used to study the convergence between the target values and the output values [15].

In this study, MAPE and normalized root mean square error (NRMSE) were used as performance parameter to compare models:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|o_i - t_i|}{t_i \cdot 100} \tag{8}$$

$$RMSE = \sqrt{\sum_{i=1}^{n}\frac{1}{n}(o_i - t_i)^2} \tag{9}$$

$$NRMSE = \frac{RMSE}{t_{i,\max} - t_{i,\min}} \tag{10}$$

where t is target value, o – the output value, and n – the total number of data.

The MAPE and RMSE values of LR, NLR, and ANN for each output parameters were given and compared in tab. 6. As shown in tab. 6, in testing period, MAPE values of LR, NLR, and ANN estimations varied between 6.52-26.24%, 10.66-17.3%, and 3.59-7.82%, re-

Table 6. Performance values of training and testing periods

	Training			Testing		
	LR	NLR	ANN	LR	NLR	ANN
MAPE						
DOI	9.5	10.46	6.88	13.83	10.7	7.82
SFC	16.72	9.58	5.41	26.24	17.3	5.87
T_{exh}	4.19	3.62	1.26	6.52	10.66	3.59
T_{conv}	5.72	5.73	2.95	7.66	11.14	1.77
NRMSE						
DOI	0.09	0.092	0.061	0.08	0.07	0.042
SFC	0.145	0.09	0.037	0.378	0.242	0.085
T_{exh}	0.066	0.062	0.02	0.081	0.134	0.046
T_{conv}	0.083	0.086	0.043	0.184	0.261	0.041

spectively. Especially, LR approach for SFC showed worst estimation performance. Emang *et al.* [22] gave typical MAPE values for model evaluation. According to these values, MAPE ≤ 10% can be evaluated as high accuracy forecasting model. Although performance of ANN is acceptable, it can be enhanced by supplying more training data. Training performance of the ANN structure is highly dependent on the number of data used in training. It means that supplying more experimental data in training section will improve the generalization capacity of model. Dependently, in testing period ANN model will give more accurate results. The difference between the actual and predicted data of all parameters can be improved by using more experimental data during training.

Eventually, ANN estimation was in acceptable ranges for all parameters and it can be stated as high accuracy forecasting model.

Conclusion

The purpose of this study is the estimation of several engine parameters with usage of three different methods in the form of LR, NLR, and ANN. Engine speed and BMEP were used as independent parameters to predict dependent variables. The first two techniques provided acceptable results only for simple correlations such as that between engine load and DOI. Furthermore, ANN method for prediction of all parameters provided better performance than the both regression methods, proving a good estimation method, thus providing a useful tool for optimizing engine operation within a multi-objective framework that ensures high fuel conversion efficiency and reduced environmental impact.

Nomenclature

b – bias
N – number of revolution, [rpm]
o – output
R – correlation coefficient
T – temperature, [°C]
t – target
u – linear combiner output
w – weight
x – input signal
y – output signal

Greek symbols

α, β – equation parameter
φ – activation function

Subscripts

conv – catalytic converter
exh – exhaust
k – neuron

Acronyms

ANN – artificial neural network
BMEP – brake mean effective pressure
bTDC – before top dead center
DI – direct injection
DOI – duration of injection
ICE – internal combustion engine
LR – linear regression
MAPE – mean absolute percentage error
NLR – non-linear regression
NRMSE – normalized root mean square error
RMSE – root mean square error
RON – research octane number
rpm – revolution per minute
SI – spark ignition
SFC – specific fuel consumption

References

[1] Hook, M., Tang, X., Depletion of Fossil Fuels and Anthropogenic Climate Change – A Review, *Energy Policy, 52* (2013), Jan., pp. 797-809
[2] Ismail, H. M., *et al.,* Artificial Neural Networks Modelling of Engine-Out Responses for a Light-Duty Diesel Engine Fuelled with Biodiesel Blends, *Applied Energy, 92* (2012), Apr., pp. 769-777
[3] Kapusuz, M., *et al.,* Research of Performance on a Spark Ignition Engine Fueled by Alcohol-Gasoline Blends Using Artificial Neural Networks, *Applied Thermal Engineering, 91* (2015), Dec., pp. 525-534
[4] Rezaei, J., *et al.,* Performance Prediction of HCCI Engines with Oxygenated Fuels Using Artificial Neural Networks, *Applied Energy, 138* (2015), Jan., pp. 460-473

[5] Cay, Y., Prediction of a Gasoline Engine Performance with Artificial Neural Network, *Fuel, 111* (2013), Sept., pp. 324-331
[6] Yap, *et al.,* Exhaust Emissions Control and Engine Parameters Optimization Using Artificial Neural Network Virtual Sensors for a Hydrogen-Powered Vehicle, *International Journal of Hydrogen Energy, 37* (2012), 10, pp. 8704-8715
[7] 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
[8] Ozgur, T., *et al.,* Prediction of Emissions of a Diesel Engine Fueled with Soybean Biodiesel Using Artificial Neural Networks, *Energy Education Science and Technology, Part a – Energy Science and Research, 27* (2011), 2, pp. 301-312
[9] Alagumalai, A., Internal Combustion Engines: Progress and Prospects, *Renewable and Sustainable Energy Reviews*, *38* (2014), Oct., pp. 561-571
[10] Turner, J., *et al*., Ultra Boost for Economy: Extending the Limits of Extreme Engine Downsizing, *SAE International Journal of Engines*, *7* (2014), 1, pp. 387-417
[11] Merola, S. S., *et al*., UV-Visible Digital Imaging of Split Injection in a Gasoline Direct Injection Engine, *Thermal Science*, *19* (2015), 6, pp. 1873-1886
[12] Wallner, T., *et al*., Fuel Economy and Emissions Evaluation of BMW Hydrogen 7 Mono-Fuel Demonstration Vehicles, *International Journal of Hydrogen Energy*, *33* (2008), 24, pp. 7607-7618
[13] Malbec, L., *et al*., Modelling Turbocharged Spark-Ignition Engines: Towards Predictive Real Time Simulators, SAE technical paper 2009-01-0675, 2009
[14] Uyanik, G. K., Guler, N., A Study on Multiple Linear Regression Analysis, *Procedia-Social and Behavioral Sciences*, *106* (2013), Dec., pp. 234-240
[15] Bilgili, M., Sahin, M., Comparative Analysis of Regression and Artificial Neural Network Models for Wind Speed Prediction, *Meteorol. Atmos. Phys, 109* (2010), 1-2, pp. 61-72
[16] Yegnanarayana, B., *Artificial Neural Networks,* Prentice-Hall of India Private Limited, New Delhi, India, 1999
[17] Ganesan, P., *et al.,* Artificial Neural Network Model to Predict the Diesel Electric Genarator Performance and Exhaust Emissions, *Energy, 83* (2015), Apr., pp. 115-124
[18] Haykin, S., *Neural Networks a Comprehensive Foundation,* Prentice-Hall International, Inc., Upper Saddle River, N. J., USA, 1999
[19] Javed, S., *et al*., Development of ANN Model for Prediction of Performance and Emission Characteristics of Hydrogen Dual Fueled Diesel Engine with Jatropha Methyl Ester Biodiesel Blends, *Journal of Natural Gas Science and Engineering, 26* (2015), Sept., pp. 549-557
[20] Ata, M. M., *et al*., Estimation Vehicular Waiting Time at Traffic Build-Up Queues, *International Journal of Distributed Sensor Networks, 2013* (2013), Aug., pp. 1-14
[21] Chiarazzo, V., *et al*., A Neural Network Based Model for Real Estate Price Estimation Considering Environmental Quality of Property Location, *Transportation Research Procedia, 3* (2014), July, pp. 810-817
[22] Emangi, D., *et al.,* Forecasting with Univariate Time Series Models: A Case of Export Demand for Peninsular Malaysia's Moulding and Chipboard, *Journal of Sustainable Development, 3* (2010), 3, pp. 157-161

Paper submitted: March 2, 2016
Paper revised: May 7, 2016
Paper accepted: June 8, 2016