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BUJİ ATEŞLEMELİ BİR MOTORDA PERFORMANS VE EMİSYON DEĞERLERİNİN YAPAY SİNİR AĞLARI İLE TAHMİN EDİLMESİ

***Kemal ATİK, ** Nafiz KAHRAMAN and ** Bilge ALBAYRAK ÇEPER**
* Erciyes University, Mustafa Çıkrıkçıoğlu Vocational School, 38039, Kayseri, Turkey
** Erciyes University, Faculty of Eng., Dept. of Mech. Eng., 38039 Kayseri, Turkey

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Özet: Bu çalışmada buji ateşlemeli bir motorun performansı ve egzoz emisyonları yapay sinir ağları (YSA) ile tahmin edilmiştir. YSA modeli Visual Basic dilinde yazılan bir programla çözülmüştür. Eğitim ve test için önerilen YSA, 4 silindirli 4 zamanlı bir test motorunda metan hidrojen karışımının farklı hidrojen yüzdeleri (0, 10, 20, ve 30), farklı hava fazlalık katsayıları (0.9, 1, 1.1, 1.2, 1.3 ve 1.4) ve farklı motor hızlarında (1500, 2000, 2500 ve 3000 dev/dak) çalıştırılmıştır. Standart geriye yayılım algoritması kullanılan YSA' da üç katman bulunmaktadır. Giriş katmanında üç hücre (motor hızı, H_2 ve hava fazlalık katsayısı) çıkış katmanında ise 8 hücre bulunmaktadır (HC, CO, CO_2, ve O_2 emisyonları, tork, özgül yakıt tüketimi, güç ve egzoz sıcaklığı). YSA'nın performansı deneysel verilerle tahmin edilen verilerin karşılaştırılmasıyla belirlenmektedir. Gizli katmanında 28, 29, 30, 31 ve 32 hücresi olan yapıdaki YSA'larda eğitimde başarılı olunmuştur. Sonuçlara göre elde edilen korelasyon katsayıları CO, CO2, O_2 ve HC emisyonları için sırasıyla 0.9880, 0.9728, 0.9930 ve 0.9623, tork, özgül yakıt tüketimi, güç ve egzoz sıcaklığı için sırasıyla 0.8650, 0.9840, 0.9252 ve 0.9605 olmuştur. Bütün sonuçlar YSA'nın buji ateşlemeli motorlar için performans ve emisyon tahmininde alternatif bir yöntem olabileceğini göstermiştir. YSA için en iyi sonuç 28 gizli hücresi olan yapıda elde edilmiştir.
Anahtar Kelimler: Yapay sinir ağları, Metan hidrojen karışımı, Emisyonlar, Buji ateşlemeli motor.

PREDICTION OF PERFORMANCE AND EMISSION PARAMETERS OF AN SI ENGINE BY USING ARTIFICIAL NEURAL NETWORKS

Abstract: This study deals with artificial neural network (ANN) modeling of a spark ignition engine to predict the engine performances and exhaust emissions of the engine. The proposed ANN model was solved by a developed computer program which was written in the Visual Basic programming language. For training and testing of the proposed ANN, a four-cylinder, four-stroke test engine were used to be fuelled by methane hydrogen blended with various percentages of hydrogen (0, 10, 20, and 30%), at different excess air ratios (0.9, 1, 1.1, 1.2, 1.3 and 1.4) and operated at different engine speeds (1500, 2000, 2500 and 3000 rpm). An ANN model based on standard back-propagation algorithm for the engine was developed using some of the experimental data for training. The used ANN has three layer, three cells in the input layer (Speed, H_2 and Excess air ratio) and 8 cells in the output layer (HC, CO, CO_2, and O_2 emissions, torque, specific fuel consumption, power and exhaust temperature). The performance of the ANN was validated by comparing the prediction dataset with the experimental results. In the hidden layer, 28, 29, 30, 31 and 32 cells were tested with artificial neural network structures. Results showed that the ANN provided the best accuracy in modeling of the emission indices with correlation coefficient equal to 0.9880, 0.9728, 0.9930 and 0.9623 for CO, CO2, O2 and HC and 0.8650, 0.9840, 0.9252 and 0.9605 for torque, brake power, specific fuel consumption and exhaust temperature, respectively. The overall results show that the networks can be used as an alternative way for predicting the performance and emission parameters of SI engine. The best result was obtained in the ANN with 28 hidden cells (R2 = 0.9860).
Keywords: Artificial Neural Network, Methane-Hydrogen blends, Emissions, SI Engine.

NOMENCLATURE

ANN	Artificial neural network
ATDC	After top dead center
BSFC	Break specific fuel consumption
BTDC	Before top dead center
CA	Crank shaft angle
CH4	Methane
CNG	Compressed natural gas
CO	Carbon monoxide
CO2	Carbon dioxide
d	Desired or actual value
e	Square error
F	Transfer function

HC	Hydrocarbon
MAPE	Mean absolute percentage error
MRE	Mean relative error
n	Number of output data
nB	Engine Speed
NET	Net calculation result of layer 1 and 2
NO	Nitrogen oxide
NOx	Oxides of nitrogen
O	Network output
O2	Oxygen
PB	Breake Power
R2	The statistical coefficient of multiple determination or correlation coefficients
RMSE	Root mean squared error
SI	Spark ignition engine
SSE	Sum squared errors
T	Temperature
TB	Torque

INTRODUCTION

The artificial neural network (ANN) technique can be used as an alternative method in modeling of highly complex and ill-defined problems, engineering analysis and prediction. ANNs do not require a precise formulation of the physical relationship of the concerned problem. In other words, they only need examples of solutions to the problem. ANNs have been used for energy systems, such as internal-combustion engine performance, thermodynamic analysis of an ejector–absorption cycle, mapping and estimation of solar potential in Turkey, prediction of axial- piston pump performance and energy consumption prediction of passive solar buildings (Arcaklioğlu and Celikten, 2004, Sözen et al., 2003, Sözen et al., 2004, Atik et al. 2010, Kalogirou and Bojic M, 2000).

Kiani Deh Kiani and et al. (2010), investigated ANN modeling of a spark ignition engine to predict the engine brake power, output torque and exhaust emissions (CO, CO_2, NOx and HC) of the engine. They used a four-cylinder, four-stroke test engine as a fuel ethanol-gasoline blended which included various percentages of ethanol (0, 5, 10, 15 and 20%), and operated at different engine speeds and loads. Their results showed that the ANN provided the best accuracy in modeling of the emission indices with correlation coefficient equal to 0.98, 0.96, 0.90 and 0.71 for CO, CO2, HC and NOx, and 0.99 and 0.96 for torque and brake power, respectively.

Akçayol and Çınar (2005), used an artificial neural network (ANN) for prediction of catalyst temperature, HC emissions and CO emissions. The training data for ANN was obtained from experimental measurements. In comparison of performance analysis of ANN, the deviation coefficients of standard and heated catalyst temperature, standard and heated catalyst HC emissions, and standard and heated catalyst CO emissions for the test conditions were less than 4.925%, 1.602%, 4.798%, 4.926%, 4.82% and 4.938%, respectively. The statistical coefficient of multiple determinations for the investigated cases was about 0.9984–0.9997. The degree of accuracy was acceptable in predicting the parameters of the system.

Gölcü and et al. (2005), researched intake valve-opening timing changed from 10o crankshaft angle (CA) to 30^{o} CA for both advance and retard with 10^{o}CA intervals to the original opening timing. They used artificial neural-networks (ANNs) to determine the effects of intake valve timing on the engine performance and fuel economy. Intake valve-timing and engine speed have been used as the input layer; engine torque and fuel consumption have been used as the output layer. For the torque testing data, root mean squared-error (RMSE), fraction of variance (R2) and mean absolute percentage error (MAPE) were found to be 0.9017%, 0.9920% and 7.2613%, respectively. Similarly, for the fuel consumption, RMSE, R2 and MAPE were 0.2860%, 0.9299% and 7.5448%, respectively. Their results show that the ANN can be used for the prediction of engine performance as an appropriate method for spark-ignition (SI) engines.

Yusaf and et al. (2010), studied brake power, torque, break specific fuel consumption (BSFC), and exhaust emissions of a diesel engine modified to operate with a combination of both compressed natural gas CNG and diesel fuels with artificial neural network (ANN) modeling. A single cylinder, four-stroke diesel engine was modified for their work and was operated at different engine loads and speeds. The experimental results reveal that the mixtures of CNG and diesel fuel provide better engine performance and improve the emission characteristics compared with the pure diesel fuel. For the ANN modeling, the standard back-propagation algorithm was found to be the optimum choice for training the model. A multi-layer perception network was used for non-linear mapping between the input and the output parameters. It was found that the ANN model was able to predict the engine performance and exhaust emissions with a correlation coefficient of 0.9884, 0.9838, 0.95707, and 0.9934 for the engine torque, BSFC, NOx and exhaust temperature, respectively.

Some Author (Sayin et al., 2007, Kara Togun and Baysec, 2010, Najafi et al., 2009, Ghobadian , 2009), deal with artificial neural network (ANN) modeling of an internal combustion engine to predict the brake specific fuel consumption, brake thermal efficiency, exhaust gas temperature and exhaust emissions of the engine. Their study shows that, as an alternative to classical modeling techniques, the ANN approach can be used to accurately predict the performance and emissions of internal combustion engines.

MEASUREMENT OF EXPERIMENTAL DATA

The experimental study was conducted on a Ford-1.8 gasoline engine in the Erciyes University Engine laboratory. This engine is four-cylinder, four stroke engine, water cooling, and compression ratio 10:1 with a swept volume of 1796 cc. The general specifications of the engine are shown in Table 1. Exhaust emission was measured by Sun MGA-1500 type emission gas analyzer device. A Cussons P8160 type engine test-bed was used.

The schematic view of the test equipments is shown in Figure 1. For all the measurements, the engine is primarily operated at its design temperature and the throttle valve positioned to be wide open: the engine is loaded with a dynamometer. Experiments were conducted at four different engine speeds(1500, 2000, 2500 and 3000 rpm) and four different mixtures (100% CH_4, 10% H_2-90% CH_4, 20% H_2-80% CH_4, and 30% H_2-70% CH_4). Properties of hydrogen, methane and gasoline are given in Table2.

Table 1. Technical specifications of the test engine.

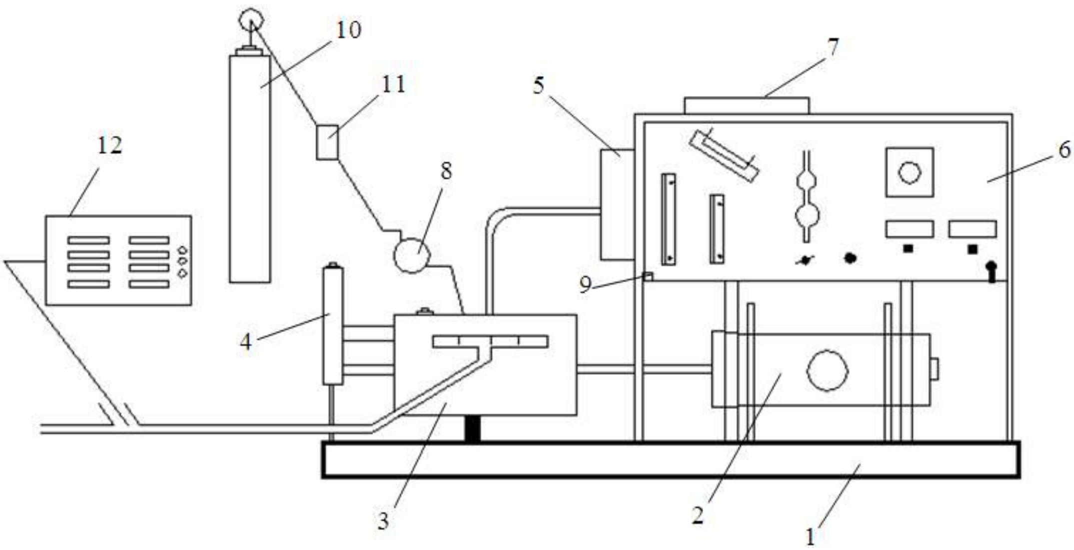
Bore	80.6	mm
Stroke	88	mm
Compression Ratio	10:1	-
Exhaust valve opening	55	BBDC
Exhaust valve closing	50	ATDC
Intake valve opening	13	BTDC
Intake valve closing	47	ABDC

APPLICATION OF ANN

ANNs are computational model, which is based on the information processing system of the human brain. In general, it is composed of three layers, which are an input layer, some hidden layers and an output layer. Each layer has a certain number of small individual and highly interconnected processing elements called neurons or nodes. The neurons are connected to each

Table 2. Properties of hydrogen, methane, and gasoline.

	Hydrogen (H_2)	Methane (CH_4)	Gasoline (C_8H_{18})
Equivalence ratio ignition lower limit in NTPa air	0.10	0.53	0.70
Mass lower heating value (kJ=kg)	119,930	50,020	44,500
Density of gas at NTP (kg=m^3)	0.083764	0.65119	4.4
Volumetric lower heating value at NTP (kJ=m^3	10,046	32,573	195,800
Stoichiometric air-to-fuel ratio (kg=kg)	34.20	17.19	15.08
Volumetric fraction of fuel in air,ϕ=1 at NTP	0.290	0.095	0.018
Volumetric lower heating value in air, ϕ=1 at NTP(kj/m^3)	2913	3088	3446
Burning speed in NTP air (cm=s)	265-325	37-45	37-43
% thermal energy radiated from flame to surroundings	17-25	23-33	30-42
Molar carbon to hydrogen ratio	0	0.25	0.44
Flame temperature in air (K)	2318	2148	2470



1-Engine Chassis, 2- Hydrokinetic Dynamometer, 3- Engine, 4- Engine Cooling Unit, 5-Air Tank, 6- Control Unit, 7-Main Fuel Tank, 8- Regulator, 9- Fuel Select Key, 10-Fuel Tank, 11-Mass Flow Meter, 12- Exhaust Gas Analyzer
Figure 1. Schematic diagram of experimental setup.

other by communication links that are associated with connection weights. Signals are passed through neurons over the connection weights. Each neuron receives multiple inputs from other neurons in proportion to their connection weights and generates a single output signals which may be propagated to other neurons (Kalogirou, 2001, Kurt et al., 2007).

To develop an ANN model, the network is processed through two stages: training/learning stage and testing/validation stage. In the training stage, the network is trained to predict an output based on input data. In the testing stage, the network is compared to experimental data with predict data. It is also used to calculate different measures of error. The process of network training is stopped when the testing error is within a desired tolerance (Kalogirou, 2001, Yang et al., 2003, Kurt et al., 2007). The back propagation algorithm is the most popular and extensively used algorithm. It consists of two phases: the feed forward pass and backward pass process. During the feed forward pass, the processing of information is propagated from the input layer to the output layer. In the backward pass, the difference between obtained network output value from feed forward process and desired output is compared with the prescribed difference tolerance and the error in the output layer is computed. This obtained error is propagated backwards to the input layer in order to update the connection (Kalogirou, 2001 , Nasr and Bedr, 2003).

The back propagation training algorithm is a gradient descent algorithm. It tries to improve the performance of the network by minimizing the total error by changing the weights along its gradient. Training was halted when the testing set of sum squared errors (SSE) value stopped decreasing and started to increase, which is an indication of over training. The prediction performances of the networks were evaluated using the SSE, the statistical coefficient of multiple determination or correlation coefficients (R^2) and mean relative error (MRE) values, which were calculated by the following expressions:

Activation function used in both layers:

fnet=1/(1+ enet) (1)

$$SSE = \sum_{i=1}^{n} (d_i - O_i)^2 \quad (2)$$

$$R^2 = 1 - \frac{SSE}{\sum_{i=1}^{n} O_i^2} \quad (3)$$

$$MRE = \frac{1}{n} \sum_{i=1}^{n} \left(100 \frac{|d_i - O_i|}{O_i}\right) \quad (4)$$

where di is the desired or actual value, Oi is the network output or predicted value, n is the number of output data (Kurt et al., 2007).

ANN modeling was used in the present work to predict the relationship of brake power, torque, specific fuel consumption, exhaust temperature and emission components with the engine speed, excess air ratio and percentage methane-hydrogen mixtures as inputs. For this work, totally 102 experimental data was used.

Approximately 70% (72 values) of the total experimental data was selected at random and was used for training purpose, while the 30% (30 values) was reserved for testing. A multi-layer perception network (MLP) was used for non-linear mapping between the input and the output variable. To improve the modeling, several architectures were evaluated and trained using the experimental data. The back-propagation algorithm was utilized in training of all ANN models. Data at input and output was normalized between 0.1 and 0.9. The input layer consisted of three neurons and the output layer had eight neurons. The number of hidden layers and neurons within each layer can be tuned to suit the complexity of the problem and data set. Square error condition of e < 0.02 was tried to be realized in training and it was achieved for the ANN. ANN reached to the desired error value after repeating 150,000 times.

The number of neurons was increased from 15 to 35 based on the trial and error method in the hidden layer. Some of neuron numbers was not give positive results however between 28-32 neuron numbers were achieved. Correlation coefficient graphics was presented in figure 2. This graphics was given conformity between experimental result and ANN estimation. It is found that, the best structure of the ANN model has 28 neurons in the hidden layer (R^2 = 0.9860). Therefore, developed ANN architecture has a configuration of 3–28-8 neurons. Table 3 shows R^2 values obtained in the training and figure 3 shows configuration of multilayer neural network for predicting engine parameters.

Table 3. R^2 values obtained in the training.

cell	Cell number in the hidden layer				
	28	29	30	31	32
O2	0.9966	0.99711	0.99717	0.99468	0.99611
CO2	0.97878	0.97715	0.98620	0.97480	0.98449
CO	0.99290	0.99307	0.99453	0.99109	0.99500
HC	0.97684	0.97328	0.96593	0.97593	0.97668
Torque	0.97783	0.97545	0.97467	0.97628	0.97564
SFC	0.92461	0.92692	0.94660	0.95087	0.95319
Power	**0.99582**	**0.99621**	**0.99636**	**0.99564**	**0.99596**
T_{exh}	**0.98271**	**0.97891**	**0.98069**	**0.98668**	**0.99014**
Average	**0.98604**	**0.98581**	**0.98430**	**0.98591**	**0.98517**

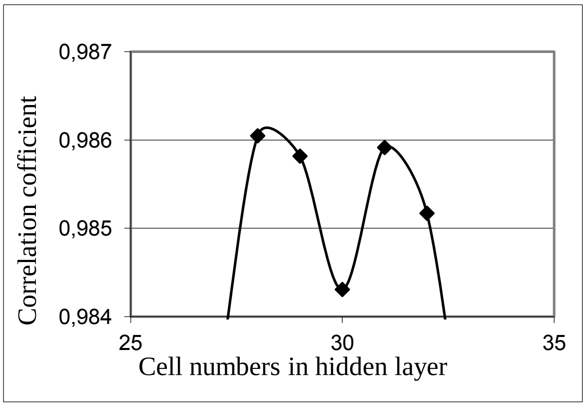


Figure 2. Correlation cofficient versus the cell numbers in hidden layer.

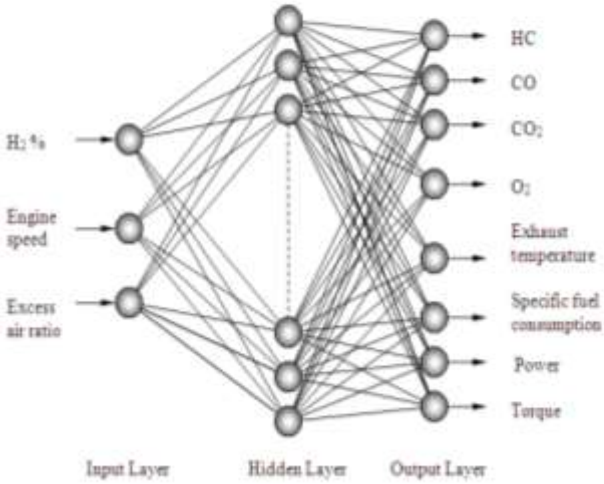


Figure 3. Configuration of multilayer neural network for predicting engine parameters

Mathematical models including the measured size, variables affecting measurement and uncertainty ratios of variables were developed in the literature for the uncertainty analysis purposes (Holman, 2001, Atik and Aktaş, 2011)]. Thus, the following well known equations may now be used for to calculate the uncertainty (∂P_B) of the power. The accuracies of the measurements and the uncertainties in the calculated results are shown in Table 4.

$$P_B = f(T, n) \quad (5)$$

$$U\left(\frac{dP_B}{P_B}\right) = \frac{dP_B}{P_B} \quad (6)$$

$$\partial P_B = \sqrt{\left(\frac{\partial P_B}{\partial T_B}\right)^2 \partial T_B{}^2 + \left(\frac{\partial P_B}{\partial n_B}\right)^2 \partial n_B{}^2} \quad (7)$$

Table 4. The accuracies of the measurements and the uncertainties in the calculated results.

Measurements	Accuracy
Temperatures	$\mp$1 °C
Speed	$\mp$2 rpm
Load	$\mp$2 N
Time	$\mp$1 %
NOx	$\mp$10 ppm
CO	0.05 %
CO2	0.05 %
HC	$\mp$1 ppm
Torque	$\mp$2%
Thermal efficiency	$\mp$2.5%
Calculated results	Uncertainty
Power	2.46 %

RESULTS AND DISCUSSIONS

In general, using methane and hydrogen in SI engines will lead a leaner and cleaner to combustion. It was experimentally demonstrated that using hydrogen led to an increase in the engine brake power, torque and brake thermal efficiency and decrease the brake specific fuel consumption (Akansu et al., 2007, Kahraman et al., 2009, Ceper et al., 2009, Akansu et al., 2004). The ANN is useful for these experiments. Engine performances and emission parameters can be estimated with ANN. In this study, the predicted and experimental results of engine performance parameters are indicated in Figure 4. The obtained correlation coefficients are as follow: for power 0.9840, for specific fuel consumption 0.9252, for engine torque 0.8650, and for exhaust temperature 0.9605. At mean relative error (MRE), for power 3.54%, for specific fuel consumption 3.20%, for engine torque 2.98%, and for exhaust temperature 1.58 %.

A plot of the predicted versus experimental CO emissions is presented in Figure 5a. In the prediction of CO emissions, the ANN results in a correlation coefficient (R^2) of 0.9880, a MRE of 7.25%. Figure 5b indicates the predicted versus experimental values for the O2 emission with correlation coefficient of 0.9930, MRE of 6.95%.

Figure 5c indicates the predicted versus experimental values for the CO2 emission with correlation coefficient of 0.9728, MRE of 1.87%. The CO2 emission is occurred complete combustion. The ANN predictions for the HC emission versus the experimental one are shown in Figure 5d. Since the combustion process involves a series of complex and fast chemical reactions, the exhaust emissions from the internal combustion engines usually contain some unburned hydrocarbons. Besides polluting the environment, excessive HC emissions increase operating costs of the engines. For the HC emission, the ANN yields a correlation coefficient of 0.9623, a MRE of 5,10% .

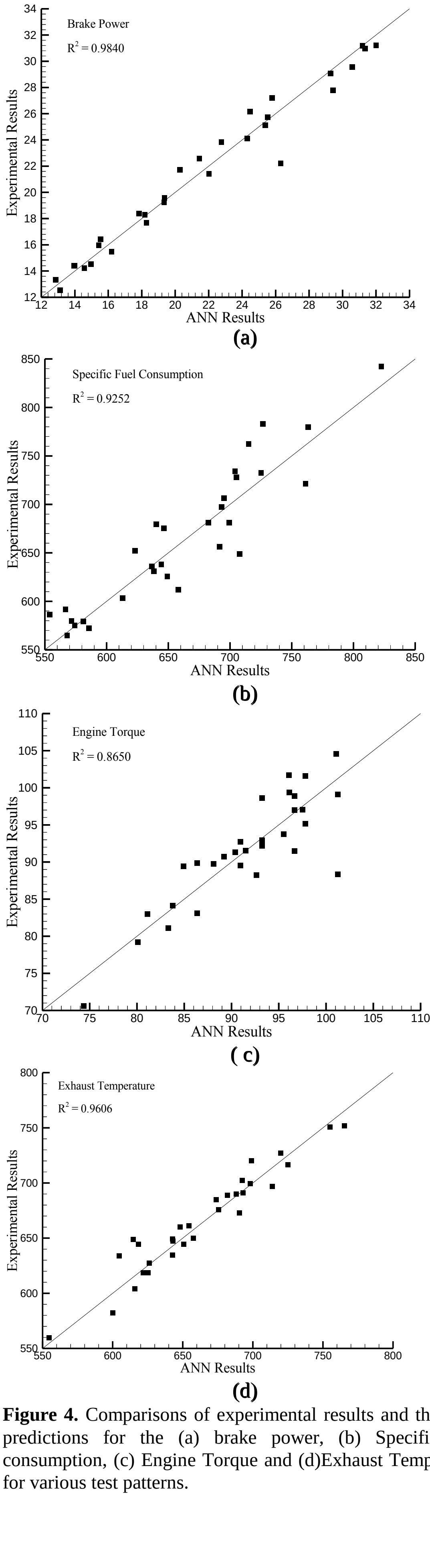


Figure 4. Comparisons of experimental results and the ANN predictions for the (a) brake power, (b) Specific Fuel consumption, (c) Engine Torque and (d)Exhaust Temperature for various test patterns.

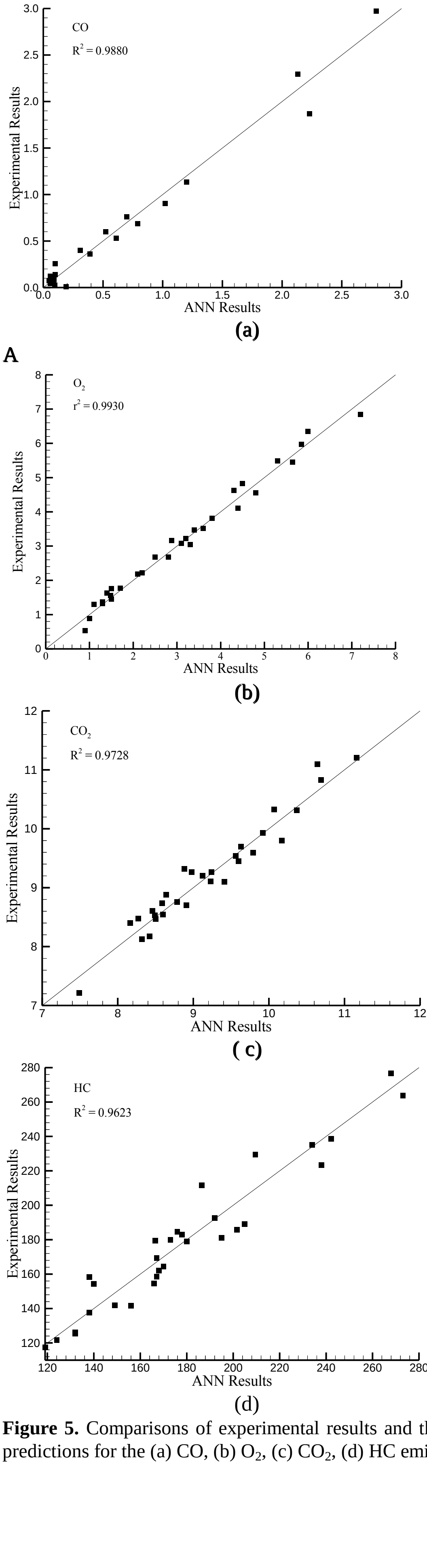


Figure 5. Comparisons of experimental results and the ANN predictions for the (a) CO, (b) O_2, (c) CO_2, (d) HC emissions.

CONCLUSIONS

The aim of this paper was to use neural networks for the estimation of the performance and emission of parameters of a spark-ignition engine using different hydrogen-methane mixtures, excess air ratios and engine speeds. The results of the system indicate a relatively good agreement between the predicted values and the experimental ones. The obtained correlation coefficients are as follow: for power 0.9840, for specific fuel consumption 0.9252, for engine torque 0.8650, and for exhaust temperature 0.9605. At mean relative error, for power 3.54%, for specific fuel consumption 3.20%, for engine torque 2.98%, and for exhaust temperature 1.58 %. The experimental study to determine power, torque, exhaust temperature and fuel consumption in a spark-ignition engine is complex, time consuming and costly. It also requires specific tools. To overcome these difficulties, an ANN can be used for the prediction of performance and emission of parameters in a SI engine. ANN analyses can be adjust all alternative fuels.

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