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2015 IOP Conf. Ser.: Mater. Sci. Eng. 100 012070

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Adaptive neuro-fuzzy inference system (ANFIS) to predict CI engine parameters fueled with nano-particles additive to diesel fuel

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Abstract. This paper studies the use of adaptive neuro-fuzzy inference system (ANFIS) to predict the performance parameters and exhaust emissions of a diesel engine operating on nanodiesel blended fuels. In order to predict the engine parameters, the whole experimental data were randomly divided into training and testing data. For ANFIS modelling, Gaussian curve membership function (gaussmf) and 200 training epochs (iteration) were found to be optimum choices for training process. The results demonstrate that ANFIS is capable of predicting the diesel engine performance and emissions. In the experimental step, Carbon nano tubes (CNT) (40, 80 and 120 ppm) and nano silver particles (40, 80 and 120 ppm) with nano-structure were prepared and added as additive to the diesel fuel. Six cylinders, four-stroke diesel engine was fuelled with these new blended fuels and operated at different engine speeds. Experimental test results indicated the fact that adding nano particles to diesel fuel, increased diesel engine power and torque output. For nano-diesel it was found that the brake specific fuel consumption (bsfc) was decreased compared to the net diesel fuel. The results proved that with increase of nano particles concentrations (from 40 ppm to 120 ppm) in diesel fuel, CO₂ emission increased. CO emission in diesel fuel with nano-particles was lower significantly compared to pure diesel fuel. UHC emission with silver nano-diesel blended fuel decreased while with fuels that contains CNT nano particles increased. The trend of NO_x emission was inverse compared to the UHC emission. With adding nano particles to the blended fuels, NO_x increased compared to the net diesel fuel. The tests revealed that silver & CNT nano particles can be used as additive in diesel fuel to improve combustion of the fuel and reduce the exhaust emissions significantly.

1. Introduction

Effects of cerium oxide nano-particles addition in diesel and diesel-biodiesel-ethanol blends on performance and emission characteristics of a CI engine has been studied and results showed that the cerium oxide acts as an oxygen donating catalyst and provides oxygen for the oxidation of CO or absorbs oxygen for the reduction of NO_x. The tests revealed that cerium oxide nano-particles can be used as additive in diesel and diesel-biodiesel-ethanol blend to improve complete combustion of the fuel and reduce the exhaust emissions significantly [1]. The investigation on the performance



comparison of learning methods in prediction of engine parameters is limited. Hosoz, Ertunc [2] investigated the applicability of adaptive neuro-fuzzy inference system (ANFIS) for predicting several parameters of a diesel engine fueled with diesel and biodiesel blends. Yücesu, Topgül [3] proposed a model based on sparse Bayesian extreme learning machine (SBELM) for engine performance prediction. A comparison was made between SBELM, extreme learning machine (ELM), Bayesian ELM and back-propagated neural network (BPNN) methods. The predicted engine parameters were fuel consumption, Lambda value, HC, CO and CO₂ emissions. In another research, Wong, Wong [4] presented a biodiesel engine modelling by kernel-based extreme learning machine (K-ELM). The used fuel was gasoline, and three parameters of specific fuel consumption, engine power and exhaust temperature were predicted. Because ANNs follow empirical risk minimization (ERM) principle, they have some drawbacks like poor generalization, greater computational burden and proneness to over fitting [5]. The disadvantages cause a performance reduction in modelling. In the literature, there are a few works that have used other machine learning methods which have some advantages over ANNs. In addition, the investigation on the performance comparison of learning methods in prediction of engine parameters is limited. The K-ELM model was compared with least-square support vector machine (LS-SVM) model [4, 6-15]. Previous researches using nano diesel have been mentioned that blending the nano particles with diesel fuel improves the combustion parameters of CI engine [16-33].

In this study, Adaptive Neuro-Fuzzy Inference System (ANFIS) has been employed to determine the engine power, torque, brake specific fuel consumption (bsfc), and emission components based on various diesel-biodiesel and nano particles blends and speeds. The main objective of this research is to investigate the ability of ANFIS for predicting engine performance parameters and exhaust emissions, and also compare their performances in modelling. In this research, the optimum values for the parameters of ANFIS are found, and then the performances of this method are thoroughly evaluated.

2. Experimental Setup

2.1. Methodology

In this study, the experiments were performed on a CI engine, 6 Cylinder. A 190 kW SCHENCK-WT190 eddy-current dynamometer was used in the experiments. Fuel consumption rate was measured in the range of 0.4- 45 kg/h by using laminar type flow meter, Pierburg model. The emission parameters (CO, CO₂, HC and NO_x) from an online and accurately calibrated exhaust gas analyser AVL DIGAS 4000 were recorded (figure 1). Considering the accomplished researches about nano fuels and diesel fuel nano additives, two silver nano-particles (Ag) and carbon nano tubes (CNT) were applied as nano additives to these fuels. Furthermore based on researches conducted about the effect of concentrations of used nano-particles in reduction of exhaust emissions, in this study three concentrations (40, 80 and 120 ppm) were applied. Stability of nano fuel was tested at standard conditions. In order to ensure the validity of nano-particles utilized in this research, SEM and TEM pictures were taken (Figure 2). Also the use of carbon nano tubes (CNT) and silver nano particles in neat diesel blend has the tendency to settle down at the fuel tank. An ultrasonic processor (UP400S, Hielscher, USA) was used to perform the reaction and even mixing nano-particles with diesel fuel before the engine tests. The processor operated at 400W and 24 kHz frequency (figure 2). Main characteristics of the test engine has been described in table 1. Engine speeds varied in the range of 700-1000 rpm.

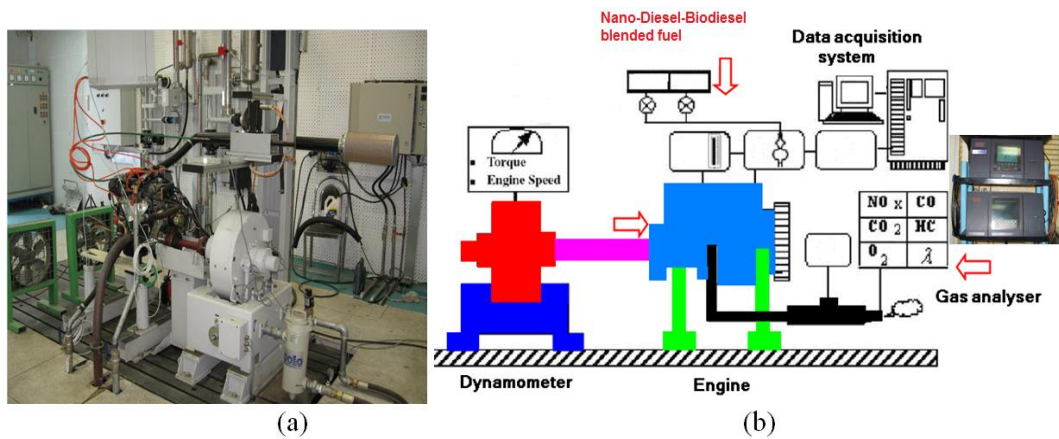


Figure 1. Engine test set-up and test instruments (a) real and (b) schematic.

Table 1. Main characteristics of the test engine.

Engine Type	CI engine, 6 Cylinder
Combustion Order	1-5-3-6-2-4
Bore ×Stroke(mm)	98.6 * 127
Displacement Volume (Lit)	5.8
Max. Torque (N.m/rpm)	376 / 1300
Max. Power(kW/rpm)	82 / 2300

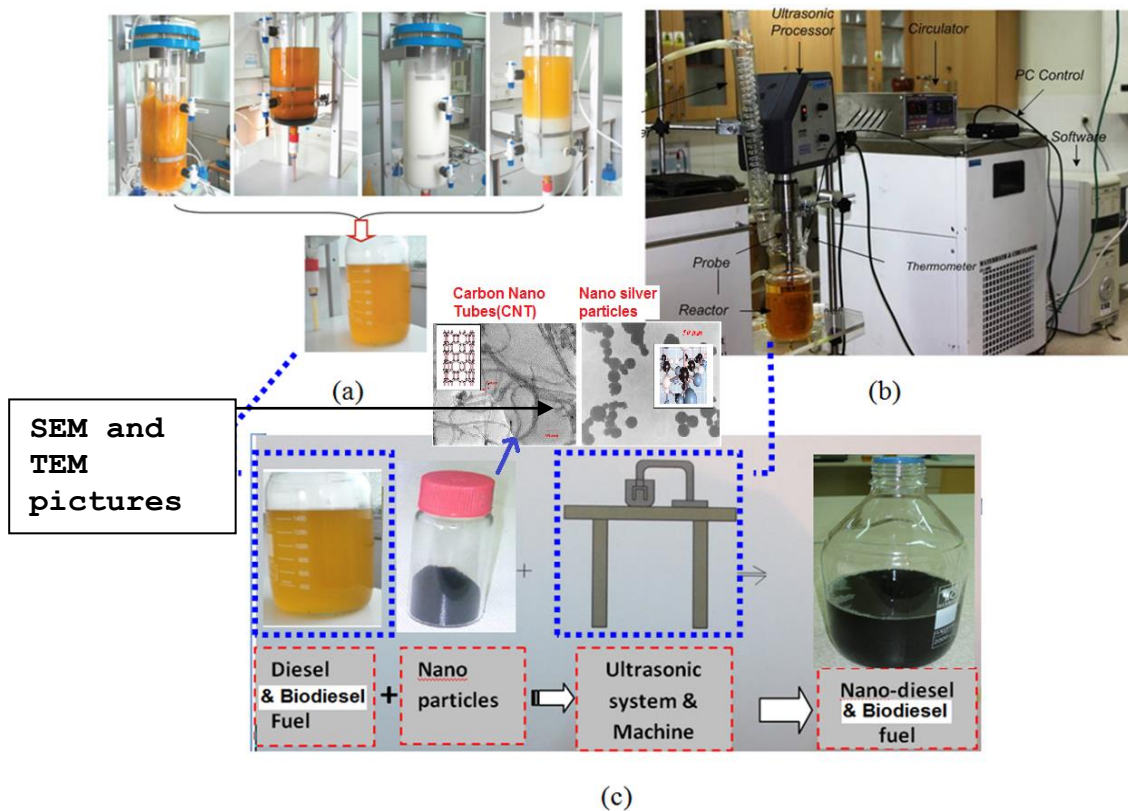


Figure 2. The Set up for ultrasonic-assisted nano-diesel production process (a)reaction, (b) ultrasonic set-up and (c) nano-diesel blend.

In this paper, the quantity B_x represents a blend consisting of $X\%$ biodiesel by volume, e.g., B20 indicates a blend consisting of 20% biodiesel in 80% diesel. Laboratory tests were then carried out using ASTM test standards to determine the fuel properties.

2.2. ANFIS.

ANFIS model introduced by Jang is a model consisting of fuzzy logic and ANNs. ANFIS which is based on the Sugeno fuzzy inference model (SFIM), constructs an input–output mapping according to both the fuzzy if–then rules and the stipulated input–output data pairs. The if–then rules of fuzzy system are usually employed to obtain the inference of imprecise model, which can process information in system as well as the human experience. Using stipulated input–output training data pairs by good membership functions, the if–then rules are built. ANFIS can adjust the membership function using back propagation gradient descent. ANFIS simulates Takagi–Sugeno–Kang (TSK) fuzzy rule of type-3 where the consequent part of the rule is a linear combination of the inputs and a constant. The final output of the system is weighted by average of each rule's output. The form of the type-3 rule simulated in the system is as follows:

$$\text{If } x_1 \text{ is } A_1 \text{ and } x_2 \text{ is } A_2 \text{ and } \dots \text{ and } x_p \text{ is } A_p \text{ then } y = c_0 + c_1x_1 + c_2x_2 + \dots + c_px_p$$

where $[x_1, x_2, \dots, x_p]$ are the input variables, $[A_1, A_2, \dots, A_p]$ are fuzzy sets which are determined during the training process, $[c_0, c_1, \dots, c_p]$ are the consequent parameters and y is the output variable. In order to evaluate the performance of a method in prediction, several criteria are calculated. The criteria used in this research are correlation coefficient (R), root mean square error (RMSE), mean relative error (MRE) and accuracy. The correlation coefficient (R) which evaluates the strength of the relationship between the experimental and predicted results is defined as:

$$R(a, p) = \frac{\text{cov}(a, p)}{\sqrt{\text{cov}(a, a) \text{cov}(p, p)}} \quad (1)$$

where $\text{cov}(a, p)$ is covariance between a and p sets. a and p denotes the actual output and predicted output sets. RMSE is determined by:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (a_i - p_i)^2} \quad (2)$$

where n is the number of the points in the data set. MRE which indicates the mean ratio between the error and the experimental values, is obtained by:

$$MRE(\%) = \frac{1}{n} \sum_{i=1}^n \left| 100 \times \frac{(a_i - p_i)}{a_i} \right| \quad (3)$$

Accuracy which is a simple representation of prediction performance is calculated as:

$$Accuracy = \left(1 - \frac{|a_i - p_i|}{a_i} \right) \times 100 \quad (4)$$

3. Flow dynamic of LLHC

The performance of ANFIS is highly depend on the type and number of membership function. In this research after testing several membership functions, it was found that ANFIS based on Gaussian curve membership function (gaussmf) had better performance. Figure 3 illustrates the performance of ANFIS in the brake power prediction under various numbers of the two parameters. It is seen that ANFIS performance with two numbers of membership function is higher. Moreover, the performance

of ANFIS improved by increasing the training epoch number up to 200, but the performance did not change with further increase. Hence, the number of 200 is selected as an optimum number for the training epoch. After determining the optimum numbers, the ability of ANFIS in prediction of the engine parameters was evaluated by calculating the criteria of correlation coefficient (R), RMSE, MRE and accuracy.

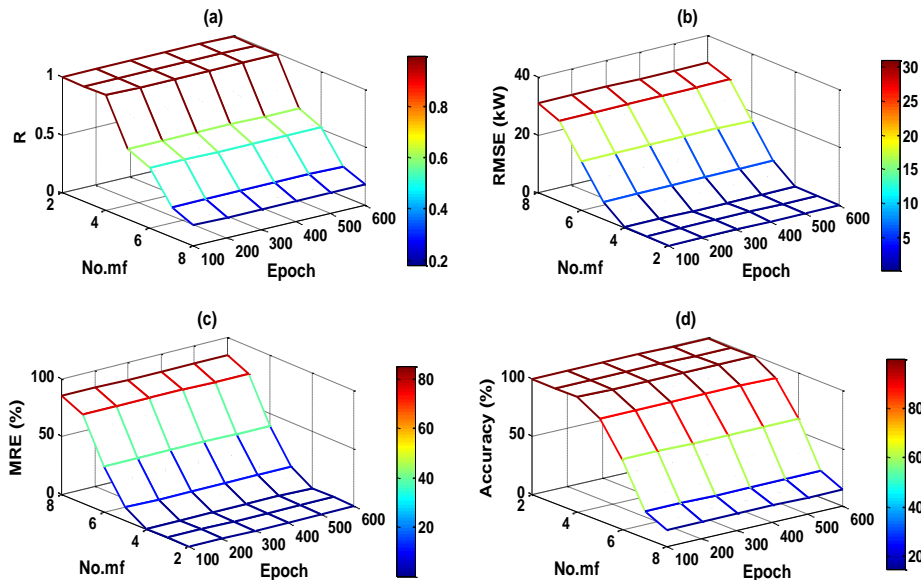


Figure 3. The values of the performance criteria of ANFIS for the brake power under different numbers of membership function and training epoch: (a) R, (b) RMSE, (c) MRE and (d) Accuracy.

Figure 4(b) shows the predicted versus experimental values for the brake power. ANFIS predictions for the brake power yielded a correlation coefficient (R) of 1, RMSE of 0.119 kW, MRE of 0.261% and accuracy of 99.739%. ANFIS predictions for the engine torque yielded a correlation coefficient (R) of 0.996, RMSE of 1.323 Nm, MRE of 0.274% and accuracy of 99.726% (Figure 4a). In predicting the bsfc, ANFIS resulted in a correlation coefficient of 0.949, RMSE of 1.973 g/kWh, MRE of 0.805% and accuracy of 99.195% (Figure 4(c)).

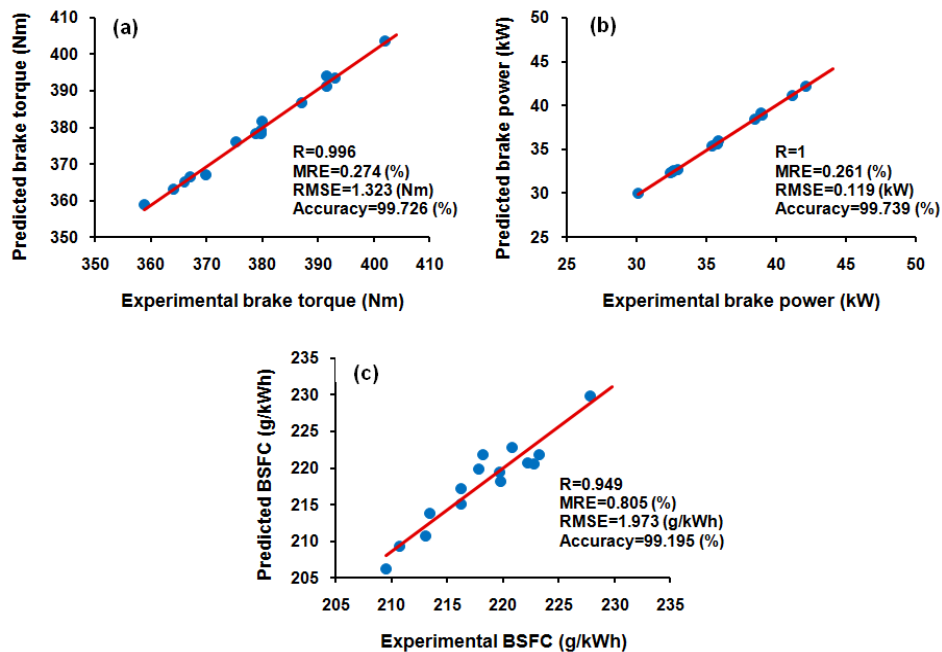


Figure 4. ANFIS predictions for the (a) brake torque, (b) brake power and (c) BSFC versus experimental values.

Figure 5 shows the predicted versus experimental values for the exhaust emission parameters. ANFIS predictions for the CO, CO₂, HC and NO_x yielded a correlation coefficient (R) of 0.945, 0.934, 0.966 and 0.967, respectively. It was found that the RMSE values were 0.072 %V, 0.354 %V, 0.916 ppm and 62.315 ppm for the CO, CO₂, HC and NO_x, respectively. ANFIS predictions for the CO yielded a MRE of 3.547% (Fig. 5(a)). MRE value for the CO₂ was 2.844% (Fig. 5(b)). Fig. 5c shows the predicted versus experimental values for the HC with MRE of 4.186%. According to Fig. 5(d), MRE of the NO_x was 3.229%. ANFIS accuracy for prediction of the CO, CO₂, HC and NO_x was 96.453%, 97.156%, 95.814% and 96.771%, respectively. The above results demonstrate that ANFIS can predict the exhaust emission parameters well.

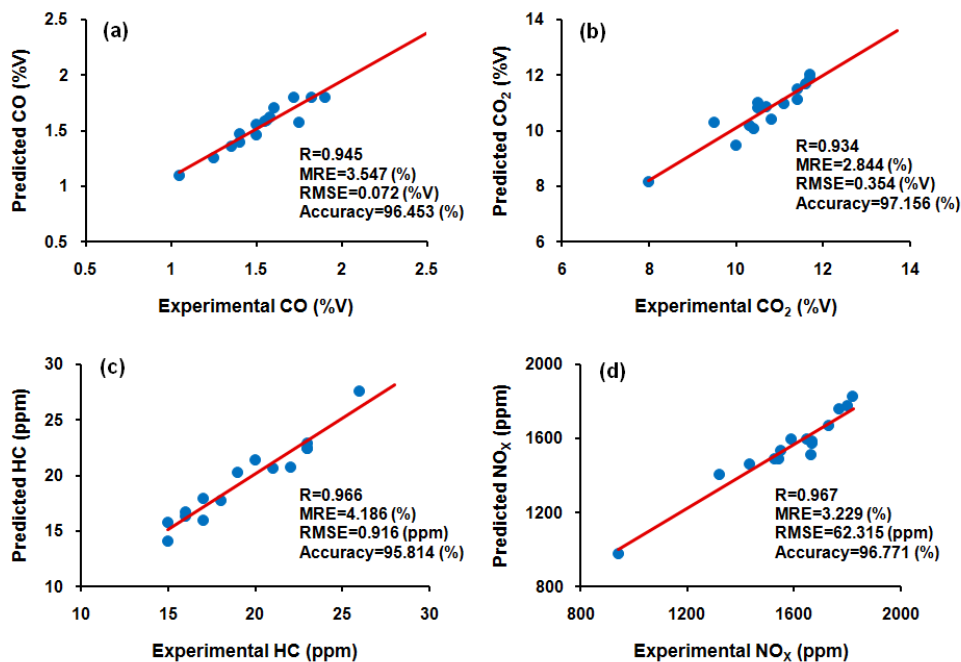


Figure 5. ANFIS predictions for the (a) CO, (b) CO₂, (c) HC, (d) NO_x versus experimental values.

4. Conclusions

According to experiments and results obtained by the proposed methods, findings can be summarized as follows: The results of this research study demonstrated that nanodiesel could be efficiently utilized as blended fuel in diesel engine. The produced nanodiesel was blended with biodiesel and diesel fuels in different concentrations and the CI engine emission parameters were evaluated with these new blended fuels. Adding nano particles in diesel fuel can improve engine performance and reduce CO and HC emissions. But it can cause an increase in CO₂ and NO_x emissions. SVM can be employed to predict the engine performance and exhaust emissions.

ANFIS can be employed to predict the engine performance and exhaust emissions. But there is a need for finding the optimum values of its parameters. The ANFIS results were very good, R values in this model are very close to one, while root mean square error (RMSE) was found to be very low. The results showed that ANFIS predicted the engine performance and exhaust emissions with correlation coefficient (R) and accuracy in the range of 0.6–1 and 60–99.9%. The results demonstrate that ANFIS is capable of predicting the CI engine performance and emissions. Analysis of the experimental data by the ANFIS method revealed that there is a good correlation between the ANFIS predicted results and the experimental data. Therefore ANFIS proved to be a useful tool for correlation and simulation of engine parameters.

Acknowledgments

The authors wish to thank the Iranian Fuel Conservation Organization (IFCO) of NIOC for the research grant provided (Grant no.:1393-2) and UMP (Grant No.:RDU130313) to complete this project and Mega Motor Company for providing of laboratory facilities..

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