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Support vector machine to predict diesel engine performance and emission parameters fueled with nano-particles additive to diesel fuel

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Abstract. This paper studies the use of adaptive Support Vector Machine (SVM) 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 SVM modelling, different values for radial basis function (RBF) kernel width and penalty parameters (C) were considered and the optimum values were then found. The results demonstrate that SVM 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, CO_2 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 NOx emission was inverse compared to the UHC emission. With adding nano particles to the blended fuels, NOx 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 complete combustion of the fuel and reduce the exhaust emissions significantly.

1. Introduction
A lot of studies have been conducted for predicting various engine parameters. Some of the works have concentrated on performance parameters, some of them on exhaust emissions and remaining on both of them. In these researches, spark ignition (SI) and compression ignition (CI) engines with traditional fuels and biofuels have been investigated. However, due to the development of biofuels and

our requirements to these fuel types for reducing pollutions and saving the fossil sources, studies about them can be more useful. Most studies are based on the use of traditional artificial neural network (ANN) for prediction. For example, Sharon et al. (2012) [1] employed ANN to predict performance and exhaust emissions of a diesel engine with 8 different blends of diesel and biodiesel fuels. Cay et al. (2013) [2] experimentally investigated the use of ANN for predicting performance and emission characteristics of an engine fuelled with methanol and gasoline. The inputs of ANN were fuel type, engine speed, torque and fuel flow. In another research, Cay (2013) [3] modeled engine performance by using ANN. 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 [4, 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. Hosoz et al. (2013) [6] investigated the applicability of adaptive neuro-fuzzy inference system (ANFIS) for predicting several parameters of a diesel engine fuelled with diesel and biodiesel blends. Wong et al. (2014) [4] 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 CO_2 emissions. In another research, Wong et al. (2015) presented a biodiesel engine modelling by kernel-based extreme learning machine (K-ELM). The K-ELM model was compared with least-square support vector machine (LS-SVM) model [7-16]. Previous researches using nanodiesel have been mentioned that blending the nano particles with diesel fuel improves the combustion parameters of CI engine [17-35].

In this study, support vector machine (SVM) 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 SVM for predicting engine performance parameters and exhaust emissions, and also compare their performances in modelling. In this research, the performances of SVM method were 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, specifications of diesel engine have been described in Table 1. Engine speeds varied in the range of 700-1000 rpm. 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, CO_2, HC and NOx) 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. In order to ensure the validity of nano-particles utilized in this research, SEM and TEM pictures were taken (figure 2). Stability of nano fuel was tested at standard conditions. 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 400 W and 24 kHz frequency (figure 2).
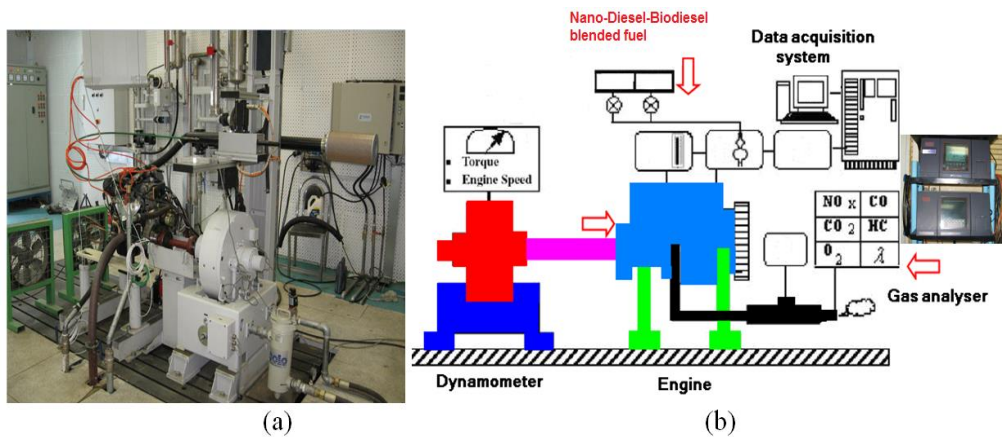
Figure 1. Engine test set-up and test instruments (a) real and (b) schematic.
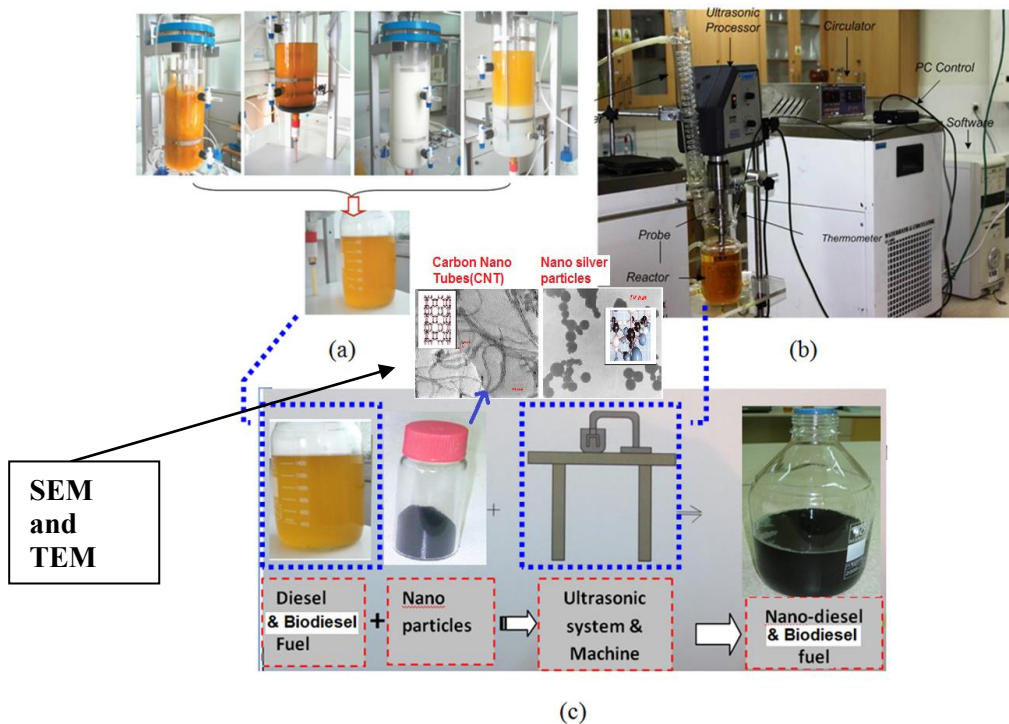

Figure 2. The Set up for ultrasonic-assisted nano-diesel production process (a)reaction, (b) ultrasonic set-up and (c) nano-diesel blend.

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

In this paper, the quantity BX 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.

SVM. This is an engine simulation tool. SVM is a supervised learning method developed by Vapnik based on statistical learning theory. Nowadays, SVM is successfully used for many applications like prediction, pattern detection and classification, due to its high ability and capability in solving learning problems. SVM has good generalization ability because it follows the structural risk minimization (SRM) principle which minimizes an upper bound on the generalization error. SVM can be considered as a regressive model. Suppose a set of training data $\{x_i, t_i\}$, $i = 1, 2, ..., n$, $x_i \in R^d$, $t_i \in R$, where xi is input data and ti is the corresponding target value. SVM tries to estimate target values by the linear equation as follows:

$$y_i = w^T x_i + b \tag{1}$$

where y_i is the output of SVM, w is d-dimensional vector and b is a scalar. By using a ε–insensitive loss function, the optimal linear regression function can be obtained by solving the following optimization problem.

$$\frac{1}{2} w^T w + C \sum_{i=1}^{n} (\xi_i^+ + \xi_i^-) \tag{2}$$

$$\begin{cases} -\varepsilon - \xi_i^- \le t_i - y_i \le \varepsilon + \xi_i^+ \\ \xi_i^+ \ge 0 \\ \xi_i^- \ge 0 \end{cases} \tag{3}$$

subject to $\forall i$

where C is penalty parameter, ε is a pre-specified value and ξ_i^+, ξ_i^- are slack variables representing upper and lower constraints on the output of the system. For nonlinear regression, SVM maps the input data into a high-dimensional feature space in which linear regression is performed. This is done by kernel function which is stated as $K(x_i, x_j) = \varphi(x_i).\varphi(x_j)$, where φ is a nonlinear function. Hence, the estimation of SVM is obtained by the following equation.

$$y_i = \sum_{i=1}^{n} (\alpha_i^+ - \alpha_i^-) K(x_i, x) + b \tag{4}$$

where α_i^+, α_i^- are Lagrange multipliers. The criterions 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:

$$R(a, p) = \frac{\text{cov}(a, p)}{\sqrt{\text{cov}(a, a) \text{cov}(p, p)}} \tag{5}$$

where 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:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(a_i - p_i)^2} \tag{6}$$

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:

$$MRE(\%) = \frac{1}{n}\sum_{i=1}^{n}\left|100\times\frac{(a_i - p_i)}{a_i}\right| \tag{7}$$

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

$$Accuracy = \left(1 - \frac{|a_i - p_i|}{a_i}\right)\times 100 \tag{8}$$

3. Results and discussion

Figure 3 illustrates the performance of SVM in the brake power prediction under various numbers of the two parameters. The performance of SVM improved by increasing the training epoch. After determining the optimum numbers, the ability of SVM in prediction of the engine parameters was evaluated by calculating the criterions of correlation coefficient (R), RMSE, MRE and accuracy.
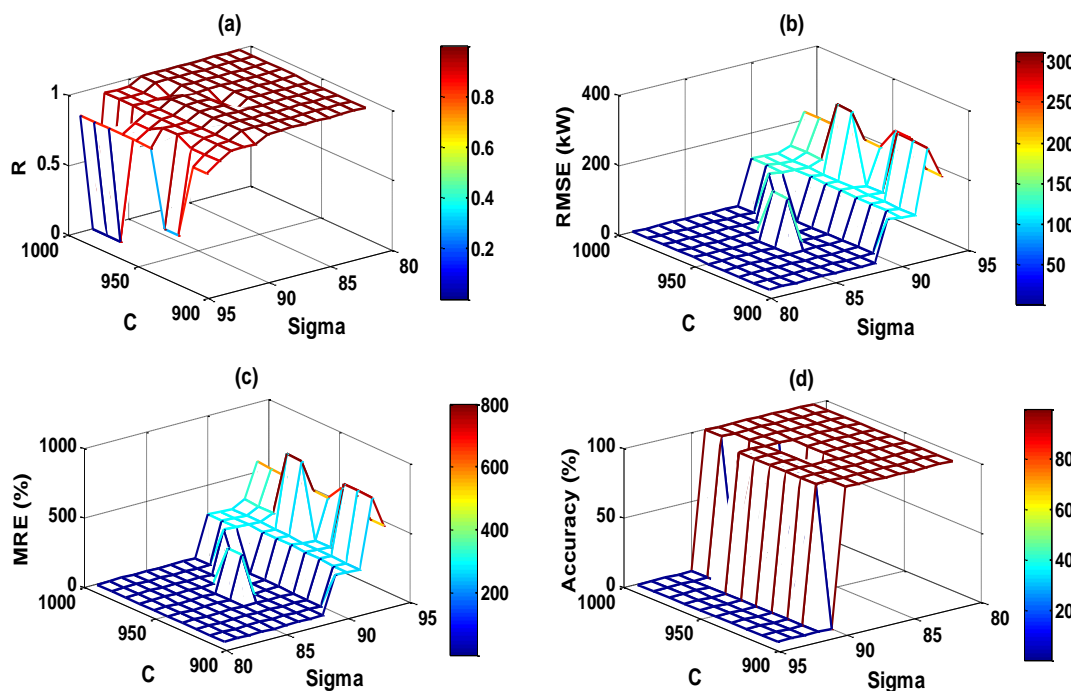

Figure 3. The values of the performance criterions of SVM for the brake power under changes of sigma and C: (a) R, (b) RMSE, (c) MRE and (d) Accuracy

Figure 4(b) shows the predicted versus experimental values for the brake power. SVM predictions for the brake power yielded a correlation coefficient (R) of 0.999, RMSE of 0.198 kW, MRE of 0.43% and accuracy of 99.57%. SVM predictions for the engine torque yielded a correlation coefficient (R) of 0.985, RMSE of 2.373 Nm, MRE of 0.511% and accuracy of 99.489% (figure 4(a)). In predicting

the bsfc, SVM resulted in a correlation coefficient of 0.824, RMSE of 3.079 g/kWh, MRE of 1.103% and accuracy of 98.897% (figure 4(c)). Figure 5 shows the predicted versus experimental values for the exhaust emission parameters. SVM predictions for the CO, CO_2, HC and NO_X yielded a correlation coefficient (R) of 0.965, 0.951, 0.803 and 0.631, respectively. It was found that the RMSE values were 0.063 %V, 0.309 %V, 2.107 ppm and 185.522 ppm for the CO, CO_2, HC and NO_X, respectively. SVM predictions for the CO yielded a MRE of 3.421% (figure 5(a)). MRE value for the CO_2 was 2.448% (figure 5(b)). Figure 5(c) shows the predicted versus experimental values for the HC with MRE of 2.107%. According to figure 5(d), MRE of the NO_X was 9.346%. SVM accuracy for prediction of the CO, CO_2, HC and NO_X was 96.579%, 97.552%, 90.211% and 90.654%, respectively. The above results demonstrate that SVM can predict the exhaust emission parameters well.
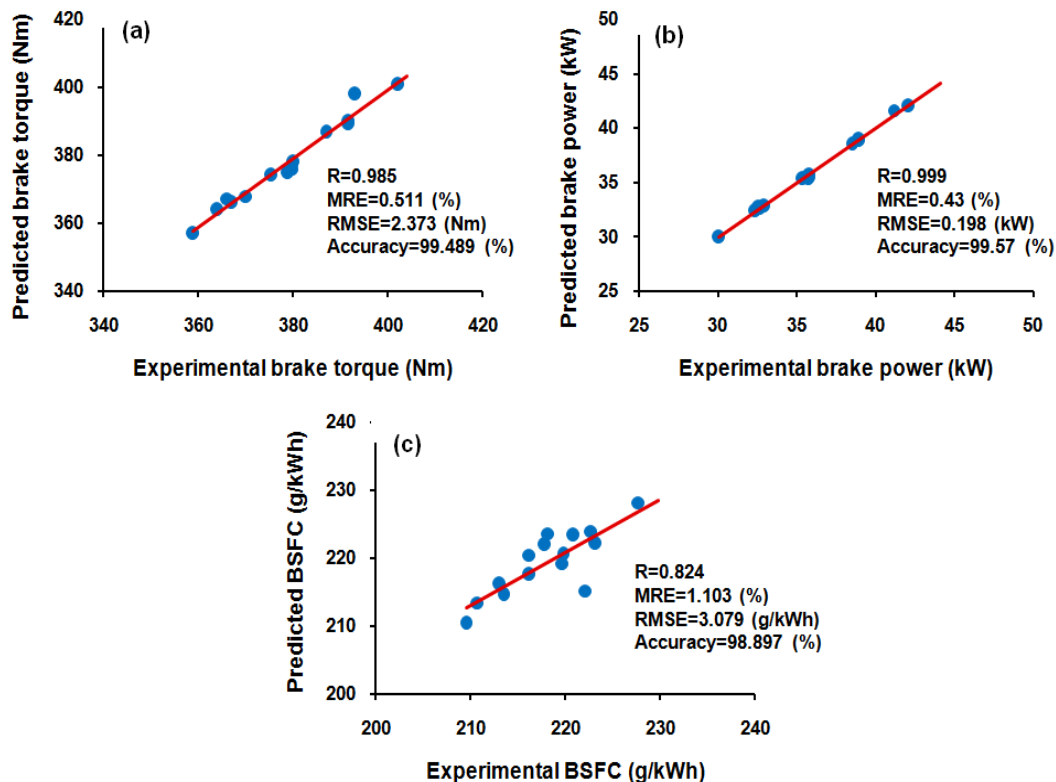

Figure 4. SVM predictions for the (a) brake torque, (b) brake power and (c) BSFC versus experimental values
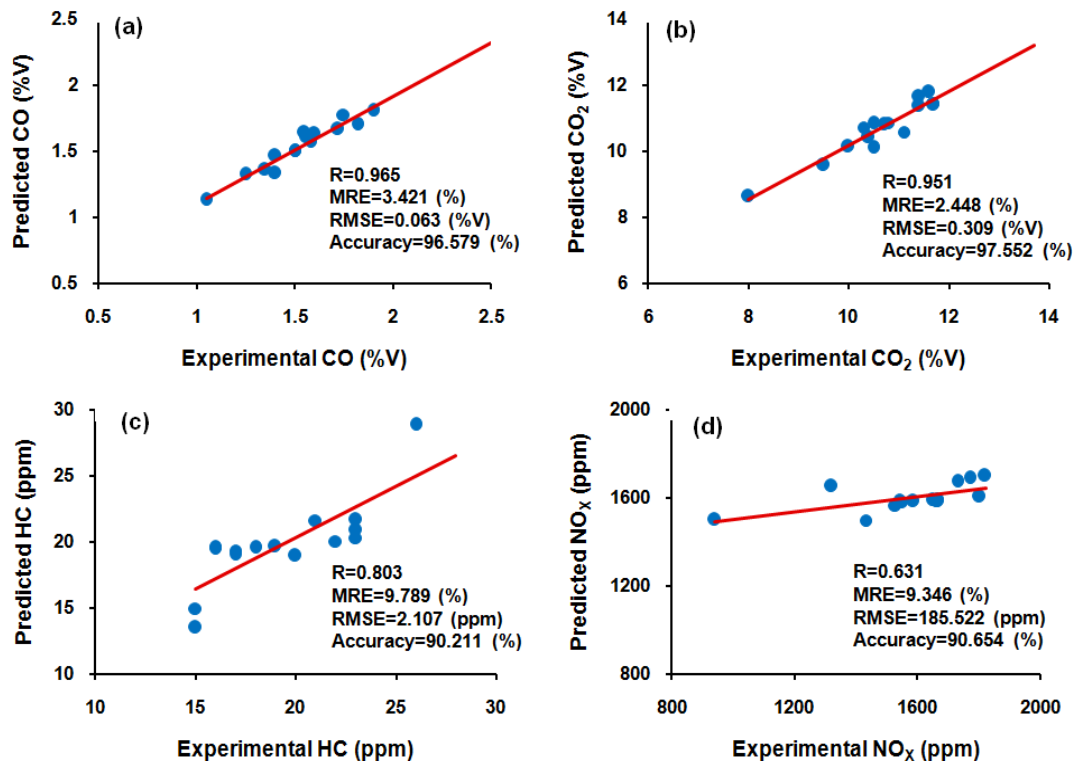
Figure 5. SVM predictions for the (a) CO, (b) CO2, (c) HC and (d) NO_X versus experimental values.

4. Conclusions

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 performance and 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 CO_2 and NO_X emissions. SVM can be employed to predict the engine performance and exhaust emissions.

SVM 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 SVM 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 SVM predicted the engine performance and exhaust emissions with correlation coefficient (R) and accuracy in the range of 0.66–1 and 65–99.5%. The results demonstrate that SVM is capable of predicting the CI engine performance and emissions. Analysis of the experimental data by the SVM method revealed that there is a good correlation between the SVM predicted results and the experimental data. Therefore SVM proved to be a useful tool for correlation and simulation of engine parameters.

Acknowledgements

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