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Abstract. The dual fuel engine is getting more attention in recent years due to its capability to reduce various harmful emissions in a diesel engine. In this study, an artificial neural network (ANN) is used to predict and to model the relationship between dual fuel emissions and operating parameters of a dual fuel engine fuelled with natural gas and diesel. Data such as engine power for training and testing of the network are acquired experimentally at Engines and Energy Conversion Lab (EECL), Colorado State University Energy Institute. The engine is a tier II 6 cylinder, 6.8 liter, 4-stroke compression ignition engine with a compression ratio of 17:1 and a power rating of 168 kW at 2200 rpm. The engine was operated at 1800 rpm through five different load points in dual fuel operating modes. Emissions data analyzed during the day were carbon monoxides (CO), carbon dioxides (CO_2), nitrogen oxides (NO_x), nitrogen monoxides (NO), nitrogen dioxides (NO_2), oxygen (O_2) and total hydrocarbons (THC). A total number of 6005 data points from five different loads have been used for ANN development based on standard a back-propagation algorithm. The ANN model was developed using 70% of the experimental results for training, while the rest of the data was used for performance testing and validation. Results show that the ANN model is able to predict the exhaust emissions of a dual fuel engine with regression coefficients at 0.9381 (training), 0.93533 (validation) and 0.93607 (testing), meanwhile the mean squared errors are in the range of 0.09 to 0.1%. These results show that the ANN network is able to predict the engine emissions of a dual fuel engine with 93.47% model performance.

1. Introduction

Emissions from the combustion of fossil fuels, coal and natural gas have become the major source of air pollution and greenhouse gas emissions globally. The economic activities that lead to these statistics are electricity and heat generation, transportation and industry sector. According to US EPA, in 2016 the largest contributor to the greenhouse gas emissions are the transportation sector which accounts for 28% of the total US greenhouse gas emissions [1]. Other than the greenhouse gas emissions, transportation sector also emits other major harmful emissions such as nitrogen oxides (NO_x), carbon monoxide (CO), particulate matters (PM) and hydrocarbons (HC). CO emissions are formed as a result

of the incomplete combustion where the oxidation process does not occur completely. The concentration of CO is strongly dependent on the air-fuel mixture ratio [2]. HC emissions are composed of unburned fuels as a result of lower flame speed during the combustion while NO_x is formed due to high combustion temperature in the cylinder [3]. Meanwhile, PM emissions are the product from the combustion process. Exposure to these emissions leads to various health effects including asthma, bronchitis, respiratory infections, mortality and heart disease as shown by epidemiological studies [4-6].

World's vehicle population rose at 3.83% in 2015, an increase of 6 million tonnes of CO_2 globally, with much of the growth coming from the developing countries despite ever stringent vehicle emission standards were implemented [7, 8]. The demand for vehicle has increased due to the revolution in the global automotive market, government policy on emissions and fuel efficiency. To reduce emission from the exhaust, vehicle emissions control is the key. Therefore, it is of great interest to evaluate and predict the vehicle emission characteristics for more efficient vehicle emission control policies and emission reduction solutions.

The dual fuel engine is getting more attention due to stricter emission standards. It also offers a good option for diesel replacement while maintaining high thermal efficiency and lower PM emissions especially at high loads [9-12]. The dual fuel engine is one of the concepts used to overcome problems with diesel engines. A dual fuel engine is a diesel engine with an aftermarket or original equipment manufacturer (OEM) kit that allows for utilization of natural gas during combustion. No major modification to the diesel platform is required in order to convert the diesel engine to dual fuel operation.

Experimental investigations can be time and cost consuming. Alternative ways of performing the investigation are by predicting the emissions using an artificial neural network (ANN) with a fewer number of experimental study. Previous research has shown that the ANN is able to predict and forecast engine emissions with minimal error. Previous studies have revealed that the best training algorithm for engine emissions predictions are back-propagation neural networks with Levenberg–Marquardt [13-16]. For engine applications, most studies have shown that the number of neurons for the hidden layer to be between 6 and 28 for the network [17-21]. The number of sample for training, validating and testing purposes also plays an important role in the building of ANN architecture. Previous studies have shown various data ratio have been performed for training, validating and testing for engine emissions and performance prediction. The percentage of training data is between 70 and 90%, validation data is between 0 -15 % and testing data is between 10 -30% [17-26]

In this study, an ANN model is developed to predict the relationships of engine input and engine outputs of a dual fuel engine with natural gas. In the designed ANN model, HC, CO, NO_x and CO_2 were selected as the output layer while engine power was selected as the input layer.

2. Methodology

2.1 Test Rig Setup and Plan
The experimental work was carried out constant at 1800 rpm while loads were varied at five different scenarios i.e. 12, 25, 50, 75 and 100%. The maximum power production of this engine is rated at 136 kW with normal injection timing. Detailed experimental setup and schematic diagram can be found from a previous publication [27]. All tests were performed at steady-state condition where the temperature for intake manifold reached 43°C and block coolant was 88°C. For dual fuel engine testing, the substitution ratio between diesel and natural gas determined the power produced by the engine. The throttle was tuned to deliver the desired diesel fuel and natural gas into the system. Table 1 shows this substitution ratio and named as diesel replacement percent. The programmable logic controller controls the relative amounts of diesel and natural gas supplied to the engine based on the load, indicated by intake manifold pressure. Diesel fuel replacement is calculated on a mass-basis using Equation 1.The content of natural gas deviated throughout the day and load, hence only natural gas composition at high load were shown in Table 2. Emissions data such as total HC (THC), O_2, CO, NO, NO_2 and CO_2 were collected and measured by a Rosemount 5-gas analyzer. NO and NO_2 were grouped as NO_x.

Table 1. Substitution and equivalence ratio at different load

Properties					
Load (%)	12	25	50	75	100
Diesel replacement (%)	35.0	59.6	70.0	69.4	58.7
Equivalence ratio	0.15	0.23	0.22	0.27	0.24

Table 2. Natural gas content measure at high load

Composition	Quantity
Methane	94%
Nitrogen	1%
Carbon dioxide	1.3%
Ethane	3.14%
Propane	0.45%
Butane	0.11%
Carbon dioxide	1.3%

$$\text{Diesel replacement (\%)} = 100\ x\ \frac{\dot{m}_{diesel\ 1} - \dot{m}_{diesel\ 2}}{\dot{m}_{diesel\ 1}}$$

(1)

where $\dot{m}_{diesel\ 1}$ is mass flow rate of diesel fuel in diesel engine and $\dot{m}_{diesel\ 2}$ mass flow rate of diesel fuel in the dual fuel engine.

2.2 Correlation Analysis

The measured data were analysed using the Pearson's correlation coefficient to find the strength and direction between parameters. The correlation analysis provides useful information for the most suitable inputs in the ANN development [28]. Values that fall among 0 to 0.3 is rated as weak correlation, 0.3 to 0.7 is evaluated to have a moderate relationship while 0.7 to 1.0 is defined as strong relationship between variables. The direction of the relationship is implied by the negative (downwards) and positive (upwards) sign [29].

2.3 Data Normalization

The ANN for an automotive application requires the input and output to be between 0.1 and 0.9 [30]. This is an important measure in order to reduce data redundancy and to increase consistency of the variables in terms of scale and unit. The measured data was normalized using Equation 2 which was adopted from [31].

$$Xnormalized = \frac{X - Xmin}{Xmax - Xmin}\ x\ (0.9 - 0.1) + (0.1)$$

(2)

where;

$Xnormalized = normalized\ data$
$X = measured\ data$
$Xmin = minimum\ value\ of\ the\ measured\ data$
$Xmax = maximum\ value\ of\ the\ measured\ data$

2.4 Development of ANN
The architecture of the ANN is composed of 3 layers that are interconnected as shown in Figure 1. Measured power data is set as the input and 7 measured data for emissions is set at the output layer. This study utilized a Matlab app called Neural Net Fitting which solves a problem in data-fitting using a two-layer feed-forward network. For this study, 70% of the data was set into training, 15% for validation and 15% for testing. For fast learning, the back propagation network training function was chosen. Back propagation amends weight and bias values according to Levenberg–Marquardt method [32-33]. The network performance was evaluated using mean squared error (MSE) and regression correlations (R). The MSE calculates the average squared difference between the measured and predicted output using Equation 3. A value closer to 0 indicates the best line fit. The R coefficient defines the strength of the measured and predicted value relationship. A value closer to 1 shows a close relationship.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(m_i - p_i)$$

(3)

where m_i is the measured value, p_i is the predicted output.
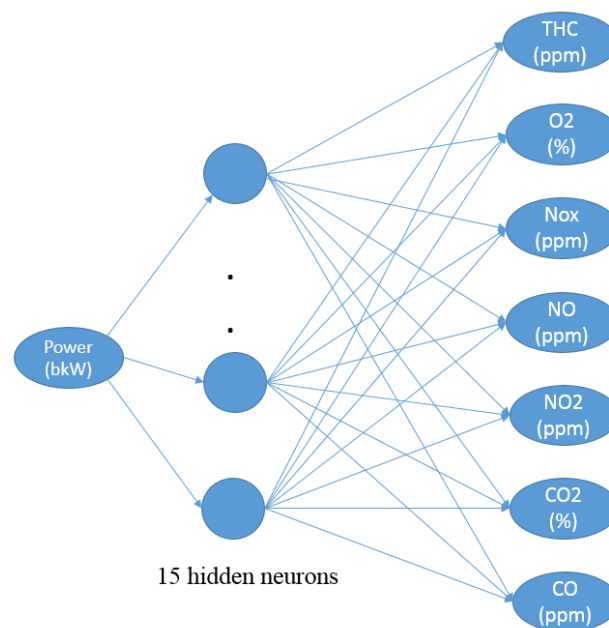

Figure 1. The structure of the artificial neural network for the dual fuel engine

3. Analysis of Results

The ANN was developed using the experimental results of a dual fuel engine with 6005 of data points. 70% of the data was set to training, 15% for validation and the rest for model testing. The architecture of the network was 1-15-7 (1 input, 15 hidden neurons and 7 output). Data for the output layer was determined after correlation analysis was done using Microsoft Excel. Table 3 shows the Pearson's correlation coefficient between variables. The trend of the coefficient indicates that all emissions are strongly correlated with brake power, except CO which is moderately correlated with brake power. Hence for the prediction of the emissions, all parameters were included in the output layer. Based on the data from laboratory work and a single input parameter, an ANN model was established to predict THC, O_2, NO_x, NO, NO_2, CO_2 and CO in a dual fuel engine. Prediction of output parameters using ANN achieved promising results with values of R at 0.9381 for training, 0.93533 for validation and 0.93607 for testing with MSE of 0.00103, 0.000924 and 0.000932, respectively. Overall performance of the network yielded 93.74%. This result indicates that the developed architecture was able to learn the training datasets. The comprehensive R of the selected network is shown in Figure 2.

Table 3. Pearson's correlation coefficient between power and exhaust emissions.

	Power (bkW)	*THC (ppm)*	*O_2 (%)*	*NO_X (ppm)*	*NO (ppm)*	*NO_2 (ppm)*	*CO_2 (%)*	*CO (ppm)*
Power (bkW)	1.000							
THC (ppm)	-0.865	1.000						
O_2 (%)	-0.944	0.874	1.000					
NO_X (ppm)	0.946	-0.926	-0.973	1.000				
NO (ppm)	0.941	-0.935	-0.961	0.999	1.000			
NO_2 (ppm)	-0.752	0.875	0.701	-0.834	-0.862	1.000		
CO_2 (%)	0.951	-0.892	-0.998	0.983	0.974	-0.739	1.000	
CO (ppm)	***-0.589**	0.835	***0.531**	***-0.695**	-0.728	0.929	***-0.571**	1.000

* Medium correlation

4. Conclusion

The engine has been tested experimentally on a diesel engine with gaseous fuel i.e. natural gas. An ANN was developed and trained using the data from the experiment. This study showed that the Levenberg-Marquardt training algorithm with back propagation method was able to predict engine emissions such as THC, O_2, NO_x, NO, NO_2, CO_2 and CO at various brake power. The MSE for 70% of data in training is 0.00103, for 15% validation is 0.000924 and for 15% testing is 0.000932. It is also shown that the R values are relatively close to 1 which shows the consistent and adequate accuracy of the predicted values with the measured data for the entire range of operation with 0.9381 for training, 0.93533 for validation and 0.93607 for testing. As a conclusion, the ANN approach is able to estimate the exhaust emissions in a dual fuel engine with precision and effortlessness in the analysis.
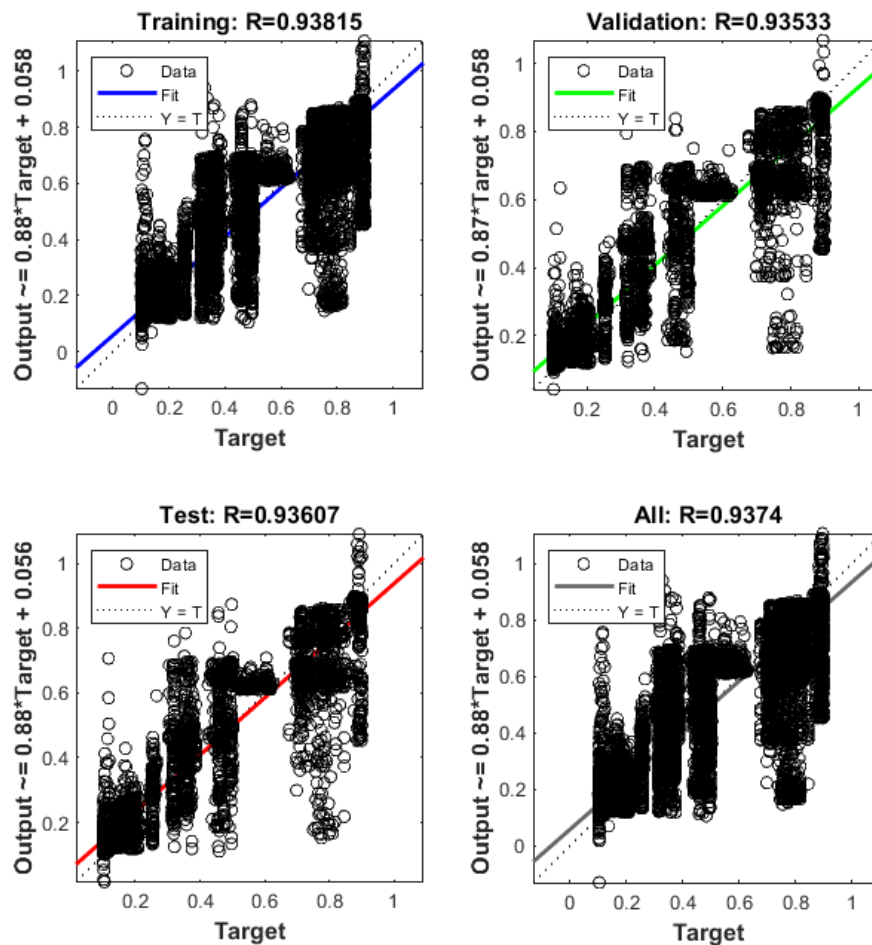
Figure 2. Overall correlation coefficients of the developed neural network.

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