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PREDICTION OF DENSITY AND VISCOSITY OF DISTILLED TIRE PYROLYSIS OIL BLENDS WITH DIESEL BY ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

Density and viscosity are key physical properties of fuels with regard to utilization in the compression ignition engine. In this study, Diesel and Distilled Tyre Pyrolysis oil (DTPO) were blended at various ratios by mass. Experimental data was then obtained for density and viscosity of the blends at temperature range of 20 – 80°C. The data was then used to train an Analytical Neural Network model with blend concentration and temperature being inputs while viscosity and density were outputs. ***.*** *Both the density and viscosity increased with increase in the concentration of DTPO in the blend, and both decreased with rise in temperature. Levenberg–Marquardt learning algorithm for was used with logsig and purelin transfer function for the hidden and output layers respectively. Different numbers of neuron were tried for the hidden layer. It was found that a network with seven neurons in the hidden layer was able to make accurate predictions. The correlation coefficients (R) for Training, testing and validation of the model were 0.99846, 0.99882 and 0.99915 respectively, while that for the whole network was 0.99858. The Mean Square error between the predicted and desired values was found to be 0.002 by this model.*

Key words: ANN, Density, Viscosity, Temperature, Distilled tyre pyrolysis oil, diesel**.**

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1. INTRODUCTION

There is a high demand for energy, and currently two thirds of the worlds energy requirement is met with fossil fuels (Pandey et al., 2012). With the current finite sources on fossil fuels and their rise in demand, there has been need to identify alternative sources of fuels. Biodiesel, alcohols and tire pyrolysis oils have been considered by researchers to possibly replace or supplement the diesel fuel. Biodiesel is considered an attractive option since it comes from renewable sources. In addition, its aromatic and Sulphur free, oxygenated thus lower emissions due to better combustion and has better lubricity properties (Pandey et al., 2012; Ramírez-Verduzco et al., 2011). A major difficulty in adopting biodiesel is that the cost of production is higher than that of diesel (Pandey et al., 2012) and the possible competition with food crops leading to concerns of food security. Tyre Pyrolysis (TPO) oil from scrap has also been considered; it is produced from pyrolysis of tire. Its attractive because it provides a means of disposing used tires as well as producing valuable energy. Nonetheless, TPO has some disadvantages that include high Sulphur content and a wider distillation range than that of diesel (Maube et al., 2017).

Two import key properties of a fuel that affect engine performance and combustion are density and viscosity. Density is defined as the mass per unit volume. If a fuel has high density, the fuel injection system will deliver a high mass of fuel as the injection system delivers fuel volumetrically. Kinematic viscosity is the property that characterizes the resistance of a fluid to flow. It is regarded as an important fuel property as it plays an important role in fuel spray atomization and mixing in the combustion chamber subsequently affecting the combustion process (Maube et al., 2016). Increase in density and viscosity of fuels have also been found to have significant effect on the fuel system of a compression ignition system such as pump, fuel filters and the air fuel mixing behavior (Tesfa et al., 2010). Injection timing, atomization and droplet size is also affected by density and viscosity of the fuel (Pandey et al., 2012). Both density and viscosity are vary with temperature.

There are ongoing studies on the combustion process models of diesel engines; in these models, the input parameters are the physical properties of the fuels (Özgür & Tosun, 2017). Thus, it is important to have readily available data of physical properties of the fuel to be used in these models. It is a challenge to experimentally measure the properties of each fuel blend and variation with temperature when the properties are required for modeling. This may require costly and time-consuming experiments. Subsequently, it may be vital to develop models for predicting fuel properties while studying combustion models. Different models can be used to predict fuel properties, though one that stands out is artificial intelligence methods such as Artificial Neural Network (ANN). ANN is a fast and powerful tool for modelling processes since most of these phenomena are nonlinear (Ghobadian et al., 2009).

ANN has been found to be suitable for predicting various fuel properties. Özgür & Tosun, (2017) compared the accuracy of ANN and Linear regression models in predicting the density and viscosity of blends of cotton oil biodiesel and diesel at various temperatures, they found ANN to be more accurate. Jahirul et al., (2021) investigated the use of ANN to predict eight biodiesel properties including density and viscosity, from various feed stocks based on their chemical composition, the authors found ANN to be a suitable tool. Meng et al., (2014) used ANN to Prediction kinematic viscosity of biodiesel at 313 K from mass fractions of nineteen fatty acid methyl esters and compared to two previously developed methods; Knothe–Steidley method and the RamírezVerduzco method. They found the ANN method was more accurate than the two methods. Rocabruno-Valdés et al., (2015) developed and tested models based on ANN which showed a satisfactory performance in prediction of density, dynamic viscosity and cetane number of biodiesels, based on composition of the methyl esters and temperature.

In the present work, ANN model was developed to predict the density and viscosity based on temperature and blend concentration of Distilled Tre Pyrolysis Oil (DTPO) and Diesel.

2. MATERIALS AND METHODS

2.1. Fuel Preparation

TPO was distilled and characterized as described in a previous publication (Maube et al., 2017). Distilled Tyre Pyrolysis oil (DTPO) was blended with diesel at 20, 40, 60, 80% by mass designated DTPO X. X being the mass percentage DTPO in the blend. Hence, the blends were, DTPO 0, DTPO 20, DTPO 60, DTPO 80 and DTPO 100. The viscosity and density were measured at temperatures varying from 20 to 100° C in increment of 10° C. The density and viscosity were measured simultaneously using standard methods at the chemistry laboratory of Vaal University of Technology using SVM 3000 Stabinger Viscometer.

2.2. Artificial Neural Network Design

The network model created had three layers; Input, hidden and output. The network had two input nodes corresponding to blend concentration and temperature, and two outputs nodes corresponding to density and viscosity. Figure 1. shows the three-layer network with two input nodes and two outputs nodes. A total of 54 data sets obtained experimentally were used in training the network. The data was randomly partitioned into three sets; 70% for training, 15% for testing and 15% validation of the model. The training set is used to train the network, the purpose of the test data is to evaluate the performance of the network while the validation data prevents the network from overfitting(Hosseini et al., 2019; Meng et al., 2014). The logsin and pureline transfer functions were used in the hidden and output layers respectively. The ANN model was developed on MATLAB R2014b platform and the Training parameters are showed in Table 1. The number of neurons in the hidden layer were increased from a value of two until there was no change performance. At each increment, several iterations were carried out and the optimum noted. The performance indicators were the MSE and correlation coefficient as per (1 and (2, high R values and low MSE are desired.

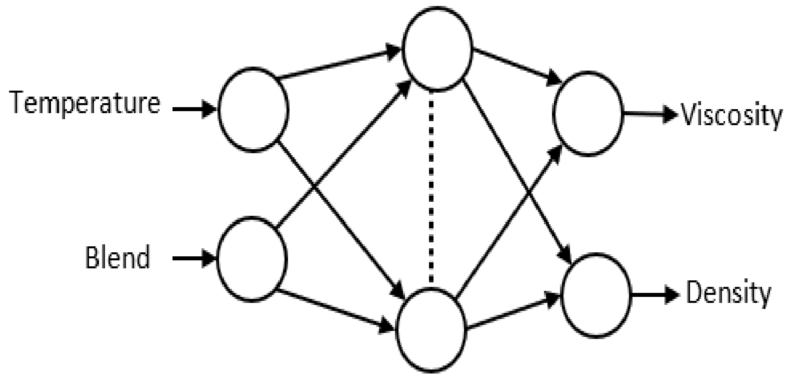

Figure 1 Neural network architecture for the two inputs and two outputs

Table 1 ANN training parameters

Soft ware	MATLAB 2014a
Training algorithm	Levenberg–Marquardt algorithm
Input layer nodes	2
out layer nodes	2
Hidden layer activation function	logsig
Output layer activation function	purelin
Data	Training 70%
	Testing 15%
	Validation 15%

$$MSE = \left(\left(\frac{1}{P}\right)\sum_j \left|t_j - o_j\right|^2\right) \quad (1)$$

$$R^2 = 1 - \left(\frac{\sum_j (t_j - o_j)^2}{\sum_j (o_j)^2}\right) \quad (2)$$

3. RESULTS AND ANALYSIS

3.1. Fuel Properties

Table 2 and Table 3 shows the actual experimental data for density and viscosity of the fuel blends that was used in training the ANN. It can be seen that values for the density of the fuels increased with increase in the proportion of DTPO in the blend. As temperature increased, the density reduced for all fuel samples. From

Table 3 it can be seen that an increase in DTPO content in the blend lead to an increase in viscosity and increase in temperature lead to a decrease in viscosity.

Table 2 data for density variation of the fuel samples with temperature

TEMPERATURE	DTPO0	DTPO20	DTPO40	DTPO60	DTPO80	DTPO100
20	0.8255	0.8395	0.854	0.87	0.8863	0.9042
30	0.8186	0.8339	0.8487	0.864	0.8816	0.899
40	0.8117	0.8252	0.84	0.8572	0.8737	0.8901
50	0.8044	0.818	0.8328	0.85	0.8652	0.884
60	0.7966	0.8122	0.8272	0.8427	0.86	0.8763
70	0.7894	0.8044	0.8192	0.8352	0.8522	0.868
80	0.7822	0.797	0.8108	0.8267	0.8441	0.8609
90	0.7743	0.7894	0.8034	0.8213	0.8362	0.8537
100	0.7673	0.7815	0.796	0.8125	0.8286	0.8452

Table 3 Data for viscosity variation of the fuel samples with temperature

temperature	DTPO0	DTPO20	DTPO40	DTPO60	DTPO80	DTPO100
20	3.1557	3.419	3.5539	3.82	4.05	4.39
30	2.6624	2.7434	2.8379	3.027	3.1709	3.411
40	2.208	2.2765	2.334	2.4689	2.573	2.7417
50	1.8679	1.9145	1.9638	2.0623	2.1419	2.261
60	1.6019	1.6381	1.6766	1.76	1.8142	1.9011
70	1.3911	1.4246	1.4564	1.5264	1.56	1.63
80	1.2171	1.253	1.2851	1.3376	1.369	1.424
90	1.05	1.11	1.137	1.1821	1.21	1.26
100	0.936	0.99605	1.0038	1.0675	1.04	1.0706

3.2. Artificial Neural Network Model

A network with one hidden layer and seven neurons was found to be suitable. From Figure 2, is noted that the MSE kept reducing with increase in number of neurons, but beyond 7 neurons, there was very insignificant change in MSE. Thus, seven was considered as the optimum number of neurons. The MSE between the desired outputs and actual values obtained by this network was 0.002. The correlation coefficients (R) for Training, testing and validation of the model were 0.99846, 0.99882 and 0.99915 respectively for the network with seven neurons as seen in Figure 3 while that for the whole network was 0.99858. These shows a strong correlation between the actual and predicted values. The low MSE and high correlation coefficient means that the model was able to generalize well.

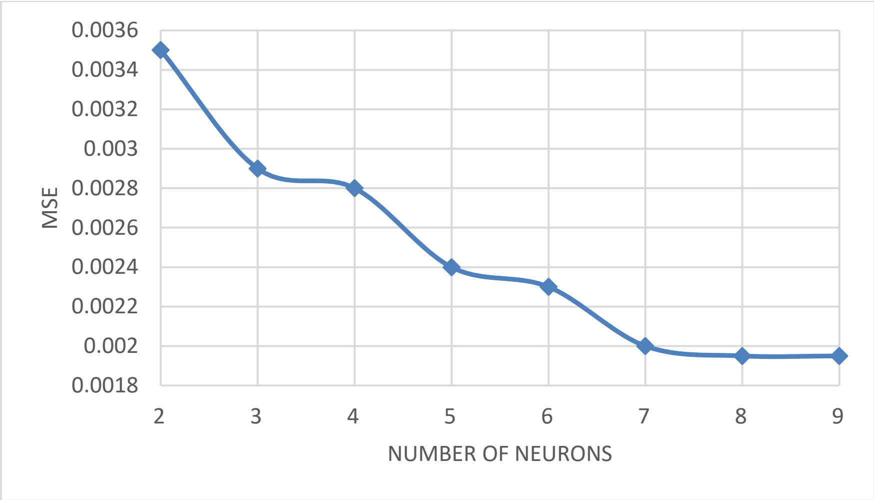

Figure 2 Optimum number of neurons

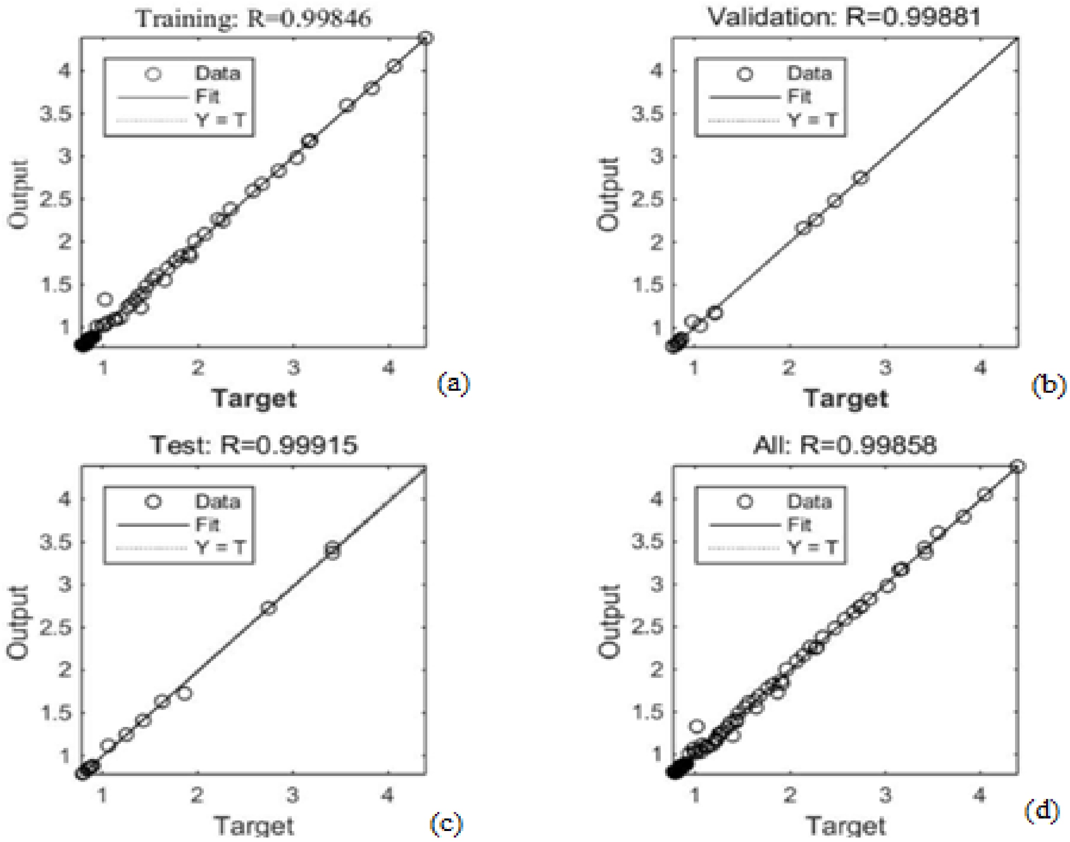

Figure 3 Comparison between the predicted and Target values by ANN for (a) training (b) validation (c)testing and (d) All combined

To further investigate the model, a regression analysis of the predicted and actual values for density and viscosity was performed. Comparison of the ANN prediction and actual measurements are shown in Figure 4 and Figure 5. It can be seen that from Figure 4, R^2 value was 0.995, meaning that the predicted viscosity was very close to the actual viscosity. From Figure 5, the R^2 value was 0.883. Normally R^2 values between 0.7 and 1 are deemed acceptable (Samuel & Okwu, 2019), thought the closer to 1 the better the correlation. Thus, the model the model produced satisfactory results.

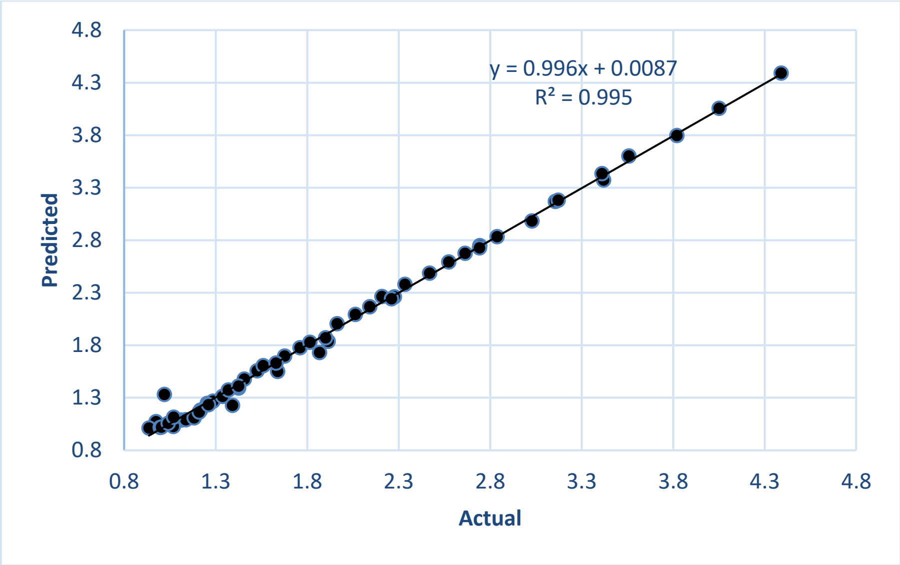

Figure 4 Predicted vs Actual viscosity mm^2/s

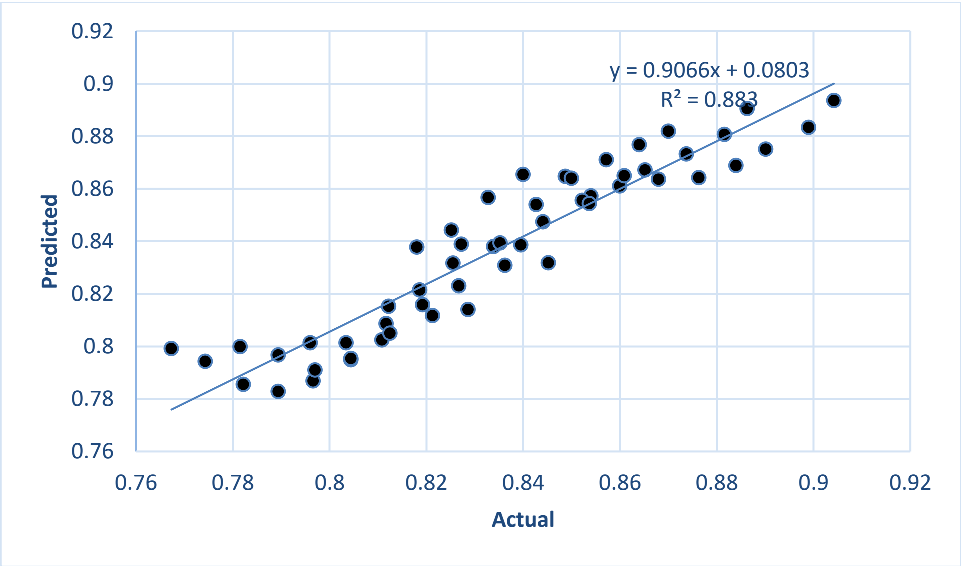

Figure 5 Predicted vs actual density (kg/m^3)

4. CONCLUSION

In this work, density and viscosity values of DTPO blends with diesel were measured at temperatures ranging from 20 – 100°C. The data obtained was used to develop models for predicting density and viscosity of DTPO blends with diesel based on ANN. It was observed that both the density and viscosity increased with DTPO concentration in the blends. It was also noticed that the density and viscosity of each sample reduced with increase temperature. The correlation coefficient for the model which was close to one and the low MSE showed that the network generalized well. Based on the regression analysis, the actual and predicted density and viscosity showed that there is a good correlation between actual and predicted data. Thus, the relationship between the fuel blend concentration and temperature can accurately be predicted by the ANN.

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