



TECHNICAL UNIVERSITY OF CLUJ-NAPOCA

ACTA TECHNICA NAPOCENSIS

Series: Applied Mathematics, Mechanics, and Engineering  
Vol. 59, Issue III, September, 2016

## AN ARTIFICIAL NEURAL NETWORK APPROACH TO ESTIMATE THE VISCOSITY OF BIODIESEL-DIESEL-ETHANOL BLENDS

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**Abstract:** In order to estimate the viscosity of biodiesel-diesel fuel-bioethanol blends viscosity data of 15 ternary blends - measured between 273.15 K and 343.15 K - were used. Two artificial neural networks, with one and two neurons, were built using the temperatures and the compositions of the blends as input and the corresponding viscosities as output. The neural networks had been trained using 70% of the data and were tested and validated, using 15% of remained data for each of these actions. The precisions of the resulted models were compared with the precision of a simple additive and a semilogarithmic model developed in our earlier work. We found that the artificial neural network with two neurons had the strongest correlation ( $R^2 = 0.9982$ ) and the lowest standard deviation ( $RMSE = 0.0968$ ).

**Key words:** viscosity, model, artificial neural network, biodiesel, bioethanol, diesel fuel.

### 1. INTRODUCTION

Due to the fast growth of energy consumption and the rapid depletion of fossil fuel reserves [4], many research works have been focused to identifying alternative solutions for partial or total substitution of fossil fuels with alternative, renewable and sustainable ones [2]. In case of internal combustion engines, the most promising renewable fuels are the biodiesel and the bioethanol [5], both of them had already been standardized in the European Union as blending components for fossil fuels. The current quality standard of diesel fuel (EN 590) permits the introducing biodiesel obtained from rapeseed oil in the fossil diesel up to 7 % v/v.

The biodiesel quantity blended in fossil diesel is limited mainly because its higher density and viscosity, and lower energy content and oxidation stability of the biodiesel in comparison to fossil diesel [2].

Among other fuel properties, the viscosity is of great importance not only in the quality of air-fuel mixture – characterized by the atomization quality, the size of fuel droplet, and the jet penetration in combustion chamber, but also in its combustion and emission characteristics [1].

The viscosity of the fuel must be low enough to flow easily even at low environmental temperatures, but a too low viscosity may cause leakages in the fuel system of the engine. Too high viscosity may cause poor fuel atomization, incomplete combustion, increased specific fuel consumption and engine deposits. Moreover, a too high viscosity of the fuel can produce problems in cold weather because the viscosity increases as the temperature decreases. In addition, because of the dependence between viscosity and lubricity, the viscosity of the fuel also affects the lubrication of injectors and fuel pump. Consequently, the diesel-fuel standard limits the viscosity both lower and upper.

The increased viscosity of the fossil diesel–biodiesel blend can be reduced by adding in it a low viscosity fuel, e.g. bioethanol.

In order to determine the proper composition of resulting biodiesel–fossil diesel–bioethanol ternary blends the prediction of their viscosity as function of their composition and temperature becomes an important issue.

In our previous work [3] we have published two models to predict the viscosity of these types of ternary blends. Although these models predicted very accurately the viscosity of ternary blends, they are only able to predict the viscosity of the ternary blends at the tempera-

ture at which the viscosities of the constituents are known. In other words, this approach assumed a two-step modelling: 1 - modelling the temperature dependence of viscosity of their constituents, 2 - using a proper mixing rule to estimate the viscosity of blend at a certain temperature.

The aim of the present work is to establish new models capable to predict the viscosity of biodiesel–fossil diesel–ethanol blends taking account of both their composition and temperatures, using an artificial neural network approach. The artificial neural network method is a powerful modelling tool which is able to identify complex relationships among experimental inputs and outputs.

**2. EVALUATION OF THE MODELS**

In order to evaluate the accuracy and compare the viscosity models, the following statistical indicators were used:

- the average absolute deviation, *AAD*, or average absolute error:

$$AAD = \frac{1}{N} \sum_{i=1}^N |v_{exp\ i} - v_{est\ i}|, \text{ (mm}^2/\text{s)}, \quad (1)$$

where  $v_{exp\ i}$  and  $v_{est\ i}$  are the experimental and estimated kinematic viscosity, and  $N$  is the number of experimental values;

- the absolute average relative deviation, *AARD*:

$$AARD = \frac{1}{N} \sum_{i=1}^N \frac{|v_{exp\ i} - v_{est\ i}|}{v_{exp\ i}} \times 100, \text{ \%}; \quad (2)$$

- the root mean squared error, *RMSE*:

$$RMSE = \sqrt{\frac{\sum_{i=1}^N (v_{exp\ i} - v_{est\ i})^2}{N - m}}; \quad (3)$$

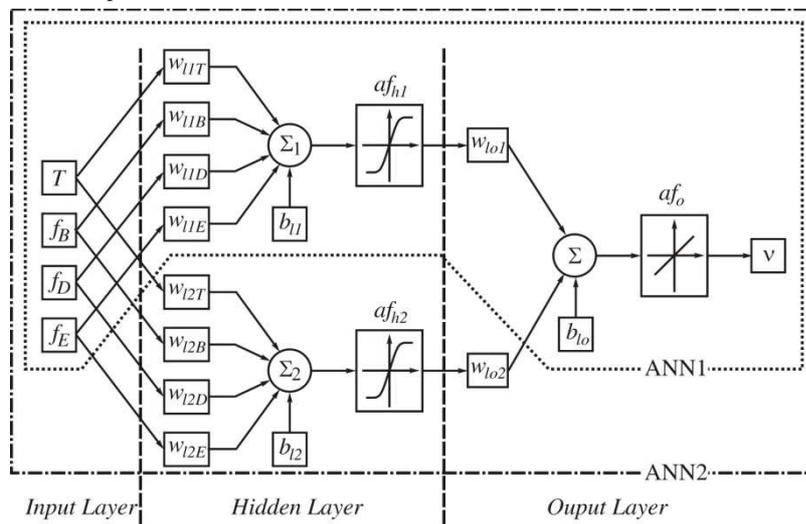
- the correlation coefficient:

$$R = \frac{\sum_{i=1}^N (v_{exp\ i} - \bar{v}_{exp})(v_{est\ i} - \bar{v}_{est})}{\sqrt{\sum_{i=1}^N (v_{exp\ i} - \bar{v}_{exp})^2 \sum_{i=1}^N (v_{est\ i} - \bar{v}_{est})^2}}, \quad (4)$$

where  $\bar{v}_{exp}$  and  $\bar{v}_{est}$  are the average values of the measured and estimated viscosities and  $m$  is the number of model parameters.

**3. PREDICTING VISCOSITY AND DENSITY USING ARTIFICIAL NEURAL NETWORKS**

The model proposes an evaluation of viscosity and density of biodiesel-diesel fuel-ethanol blends through a multi-input single-output (MISO) artificial neural network. Network inputs are the temperature  $T$  (K) and the composition of the blend, expressed in volume fractions  $f_B$  for biodiesel,  $f_D$  for diesel fuel and  $f_E$  for ethanol, and the output  $\nu$  is the kinematic viscosity ( $\text{mm}^2/\text{s}$ ). Two internal ANN architectures were evaluated: with a single neuron, ANN1 and with two neurons, ANN2 (Fig. 1).



**Fig. 1.** Structure of the ANN model for estimating the kinematic viscosity ( $w_1$  – weighting factors,  $b_1$  – biases,  $af$  – activation functions).

The activation function of hidden layers was of 'tansigmoid' type, and the activation function of output layer was of 'purelin' type.

Using the MathWorks-Simulink program, 132 sets of input data [3] were divided into three groups: training (comprising 70% of input data), testing and validation (each of the latter two consisting of 15% of input data). For network parameter evaluation 10 runs were carried out and those with maximum accuracy were considered.

At the ANN1 model with one neuron for predicting kinematic viscosity the following equation was obtained:

$$v = a_0 + \frac{b}{e^{A \cdot v_B + B \cdot v_D + C \cdot v_E + D \cdot T + a_1} + 1}, \quad (5)$$

where  $a_0=149.6076$ ;  $a_1=-2.7919$ ;  $b=148.5454$ ;  $A=11.0048$ ;  $B=9.9305$ ;  $C=8.9640$ ;  $D=-0.0382$ , while at the ANN2 model with two neurons the equation has the following form:

$$v = a_0 + \frac{b_1}{e^{A_{11} \cdot v_B + B_{11} \cdot v_D + C_{11} \cdot v_E + D_{11} \cdot T + a_{11}} + 1} + \frac{b_2}{e^{A_{21} \cdot v_B + B_{21} \cdot v_D + C_{21} \cdot v_E + D_{21} \cdot T + a_{21}} + 1}, \quad (6)$$

where  $a_0=6.0265$ ;  $a_1=0.1144$ ;  $a_2=24.8065$ ;  $b_1=499.6247$ ;  $b_2=-5.1418$ ;  $A_{11}=-5.3287$ ;  $B_{11}=-4.44769$ ;  $C_{11}=-2.0403$ ;  $D_{11}=0.0321$ ;  $A_{21}=2.4417$ ;  $B_{21}=6.5553$ ;  $C_{21}=21.0010$ ;  $D_{21}=-0.1276$ .

Expressing diesel fuel content depending on the biodiesel and ethanol content:

$$v_D = 1 - v_B - v_E, \quad (7)$$

and replacing the previous equations, the following are obtained:

$$v = a_0 + \frac{b}{e^{A \cdot v_B + C \cdot v_E + D \cdot T + a_1} + 1}, \quad (8)$$

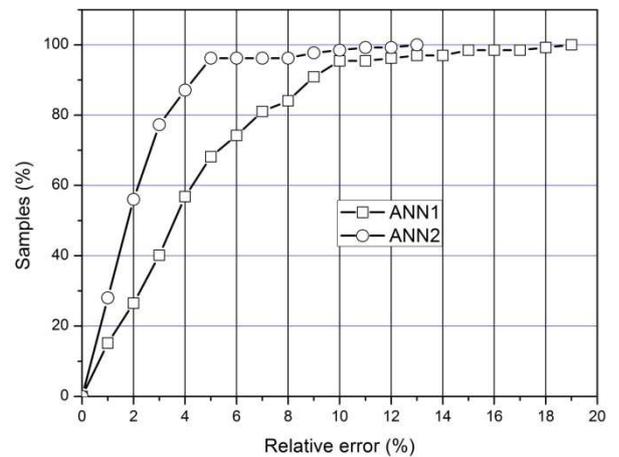
where  $a_0=149.6076$ ;  $a_1=7.1386$ ;  $b=148.5454$ ;  $A=1.0743$ ;  $C=-0.9665$ ;  $D=-0.0382$ , in the case of the architecture with a single neuron, and

$$v = a_0 + \frac{b_1}{e^{A_{11} \cdot v_B + B_{11} \cdot v_D + C_{11} \cdot v_E + D_{11} \cdot T + a_{11}} + 1} + \frac{b_2}{e^{A_{21} \cdot v_B + B_{21} \cdot v_D + C_{21} \cdot v_E + D_{21} \cdot T + a_{21}} + 1}, \quad (9)$$

where:  $a_0=6.0265$ ;  $a_1=-4.3332$ ;  $a_2=31.3618$ ;  $b_1=499.6247$ ;  $b_2=-5.1418$ ;  $A_{11}=-0.8811$ ;  $C_{11}=2.4073$ ;  $D_{11}=0.0321$ ;  $A_{21}=-4.1136$ ;  $C_{21}=14.4547$ ;  $D_{21}=-0.1276$ , in the case of the architecture with two neurons.

#### 4. DISCUSSION

The accuracy of the model with two neurons is significantly higher than that of the model with a single neuron, 90% of estimated values having a relative error below 4%, while in case of the model with a single neuron only 59% have a relative error below this value (Fig. 2).



**Fig. 2.** Distribution of relative errors for the ANN models.

In order to evaluate the developed models, they have been compared with other models, published in our previous work [3]. The first was a weighted semilogarithmic model (WSL):

$$\ln v_{blend} = k_B \cdot f_B \cdot \ln v_B + k_D \cdot f_D \cdot \ln v_D + k_E \cdot f_E \cdot \ln v_E, \quad (10)$$

where  $k_B$ ,  $k_D$  and  $k_E$  are the weighting factors of biodiesel, diesel fuel and ethanol,  $f_B$ ,  $f_D$  and  $f_E$  are the volumetric fractions of the fuels and  $v_B$ ,  $v_D$  and  $v_E$  are their kinematic viscosity. The

second model was a simple weighted additive model (SWA):

$$v_{blend} = k_B f_B v_B + k_D f_D v_D + k_E f_E v_E \quad (11)$$

The weighting factors in equations (10) and (11) were obtained using Solver in Excel and minimizing the AAD (Table 1).

The statistical accuracy-indicators of the models for evaluating the kinematic viscosity of biodiesel-diesel fuel-ethanol blends are presented in Table 2. It can be seen that the best fit is provided by the ANN2 model, having the lowest AARD, AAD and RMSE and the strongest correlation. This model is followed in accuracy by the SWA model. The worst correlation is yielded by the WSL model. This model provides the best accuracy if the composition is expressed in mass fractions. The accuracy of the SWA model is the highest when the composition of the blend is given in mole fractions [3].

Table 1

Values of the weighting factors in equations (10) and (11) and accuracy of the predictions

Model	$k_B$	$k_D$	$k_E$
WSL, eq. (10)	1.1443	0.8860	1.1842
SWA, eq. (11)	1.0119	0.8850	-0.0783

Table 2

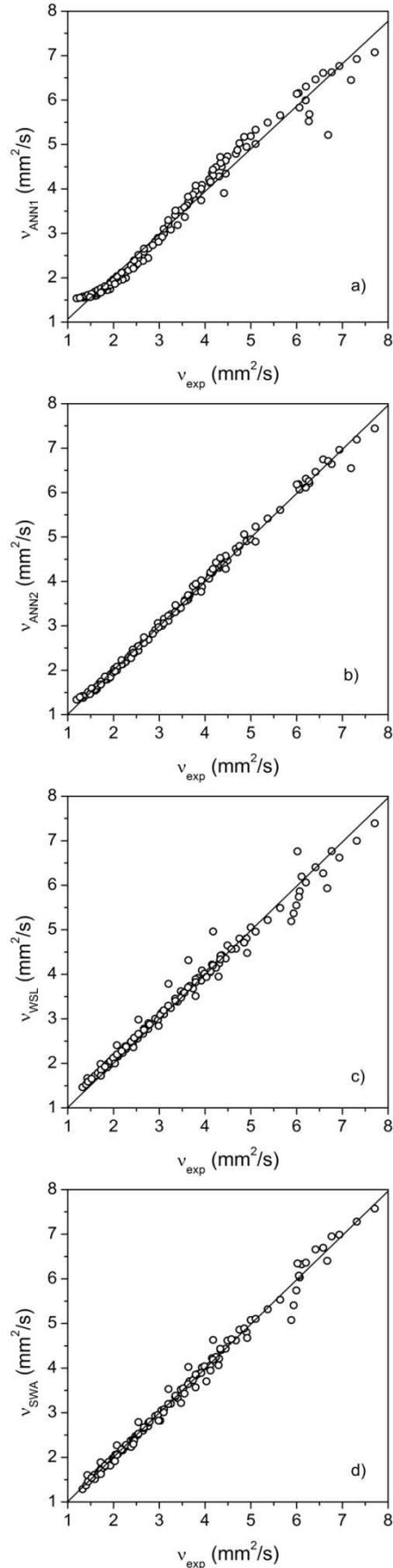
Statistical indicators for evaluation of ANN models

Model	AARD, %	AAD, %	RMSE	R <sup>2</sup>
ANN1, eq. (8)	4.3646	0.1327	0.2283	0.9896
ANN2, eq. (9)	<b>2.1946</b>	<b>0.0654</b>	<b>0.0968</b>	<b>0.9982</b>
WSL, eq. (10)	5.2975	0.1458	0.2122	0.9861
SWA, eq. (11)	2.6416	0.0847	0.1431	0.9960

The correlation between the measured and estimated values of kinematic viscosity is shown in Figure 3. In the case of the weighted semilogarithmic model and the weighted additive model the largest errors were found at low temperatures, especially in blends where the ethanol content was higher than the biodiesel content. This is because biodiesel cannot provide the solubility of the blend at these temperatures. For both models the estimated values are lower than those measured in approx. 70% of the cases.

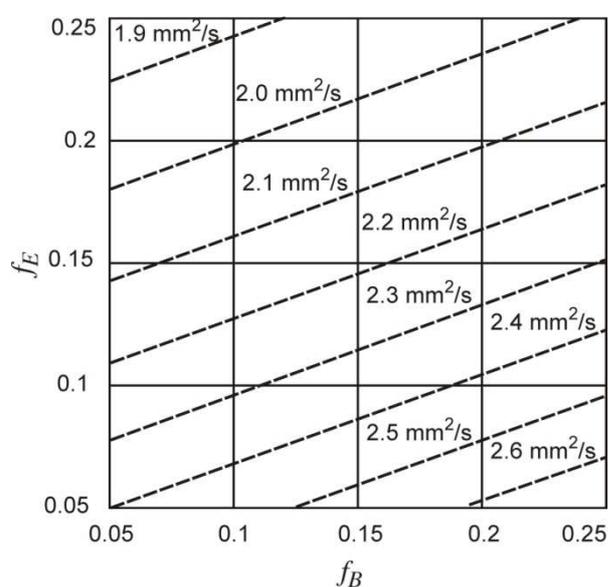
The model obtained by ANN with a single neuron provides values equally over- and under-evaluated, and in the case of the model with

two neurons approx. 60% of the estimated values are higher than those measured.



**Fig. 3.** Correlation between measured and estimated values of kinematic viscosity: a – equation (8), b – equation (9), c – equation (10), d – equation (11).

The models evaluated in this paper can be used for predicting viscosity of biodiesel-diesel fuel-bioethanol blends, providing useful information on the preparation of mixtures respecting the viscosity limitations given by quality standards for diesel fuels or for combustion process modelling of fuel-air mixtures. Figure 4 shows the kinematic viscosity variation of the blends studied based on their composition at 40 °C using the ANN2 model.



**Fig. 4.** Kinematic viscosity variation of biodiesel-diesel fuel-bioethanol blends based on their composition.

## 5. CONCLUSIONS

The models evaluated in this paper can be used for predicting viscosity of biodiesel-diesel fuel-bioethanol blends, providing useful information on the preparation of mixtures respecting the viscosity limitations of quality standards for diesel fuels or for combustion process modelling of fuel-air mixtures.

1. Most of the models evaluated for determining viscosity of biodiesel-diesel fuel-ethanol blends can be used to estimate their kinematic viscosity.
2. The complexity of the models evaluated for estimating viscosity of biodiesel-diesel fuel-ethanol blends is not always reflected in their accuracy. The results provided by the weighted additive model are comparable to ANN2.

3. The models can be used depending on the accuracy needed for the actual application they are used in.
4. The models obtained by ANN have the highest degree of generality, providing a viscosity-estimation of biodiesel-diesel fuel-ethanol blends depending on temperature and their composition through a single formula. The advantage of ANN models is that they are not based on the viscosity models of the components like the other methods, and the temperature range in which they can be used is 0-70 °C.
5. The parameters of the models evaluated and those proposed are determined for the fuels used in the experimental research of this paper. Given that biodiesel and diesel fuel composition depends on the nature and quality of the raw materials / components from which they are produced, the models developed in this paper can be used for other types of biodiesel and diesel fuels, taking the differences into account. Considering that the methods for determining the parameters of the models are described in detail, their adaptation to fuels with different characteristics is easy.
6. ANN2 can be considered the most accurate model, followed by the weighted additive model, the weighted semilogarithmic model and ANN1.

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#### ESTIMAREA VISCOZITĂȚII AMESTECURILOR DE BIODIESEL–MOTORINĂ–BIOETANOL UTILIZÂND REȚELE NEURONALE ARTIFICIALE

**Rezumat:** Pentru estimarea viscozității cinematice a amestecurilor de biodiesel–motorină–bioetanol au fost utilizate viscozitățile măsurate în intervalul de temperatură  $273,15\text{ K}$  și  $343,15\text{ K}$  a 15 amestecuri. În scopul estimării viscozității cinematice a amestecurilor au fost construite două rețele neuronale artificiale cu unul respectiv doi neuroni, utilizând ca și date de intrare temperatura și compoziția amestecurilor, iar ca mărime de ieșire viscozitatea cinematică a fiecărui amestec. Rețelele neuronale au fost instruite utilizând 70% din setul de date, iar câte 15% au fost utilizate pentru testarea și validarea modelelor. Pentru identificarea preciziei modelelor, astfel obținute, acestea au fost comparate cu alte două modele dezvoltate anterior, unul semilogaritm și altul aditiv ponderat. Modelul obținut prin rețeaua neuronală artificială cu doi neuroni a furnizat corelația cea mai puternică ( $0,9982$ ) și abaterea medie pătratică cea mai mică ( $0,0968$ ).

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