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Artificial Neural Network Model for Predicting Specific Draft Force and Fuel Consumption Requirement of a Mouldboard Plough

Kazım ÇARMAN[1,*], Ergün ÇITIL[1], Alper TANER[2]

[1]Selçuk University, Faculty of Agriculture, Department of Agricultural Machinery and Technologies Engineering, Konya, Turkey

[2]Ondokuz Mayıs University, Faculty of Agriculture, Department of Agricultural Machinery and Technologies Engineering, Samsun, Turkey

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ABSTRACT

A 2-(5-8)-2 artificial neural network (ANN) model, with a back propagation learning algorithm, was developed to predict specific draft force and fuel consumption requirements of mouldboard plough in a clay loam soil under varying operating conditions. The input parameters of the network were tillage depth and forward speed of operation. The output from the network were the specific draft force and fuel consumption requirement of the mouldboard plough. The developed model predicted the specific draft force and fuel consumption requirement of mouldboard plough with an error <1 % when compared to the measured draft force and fuel consumption values. Such encouraging results indicate that the developed ANN model for specific draft force and fuel consumption requirement prediction could be considered as an alternative and practical tool for predicting draft force and fuel consumption requirement of tillage implements under the selected experimental conditions in clay loam soils. Further work is required to demonstrate the generalised value of this ANN in other soil conditions.

1. Introduction

Tractors are recognized as main source of power supply for agricultural machinery. For conventional tillage, most of the farmers in Turkey utilise their available tillage implements with a range of tractor powers, consequently there is often improper matching of the tractor and its implement resulting in under loading of tractor and hence, poor efficiency.

To increase efficiency of agricultural production; it is necessary to increase machine working efficiency. Taylor (1980) estimated that in the U.S. for each 1 % improvement in traction efficiency, 284–303 million litres of fuel could be saved annually. Due to increasing world population and limited non-renewable resources, especially fossil fuels, it is necessary to reduce and manage fuel consumption in various agricultural activities (Karparvarfard and Rahmanian-Koushkaki, 2015).

Tillage plays a critical role in the technological development in the evolution of agriculture. The objectives of soil tillage are seedbed preparation, water and soil conservation, and weed control (Opara-Nadi 2008).

Determination of forces which are applied on tools during tillage operation is worthwhile and necessary for designing tillage equipments that are in direct contact with soil particles. The draft force of tillage equipments is one of the most important forces that has been used for measuring and evaluation of energy requirement for tillage equipments. This force is a function of following parameters (Godwin et al., 2007; Roul et al., 2009):

1. Soil conditions such as its moisture content and texture.

2. Tools' parameters such as depth of cutting, cutting angle, sharpness of the cutting edge.

3. Operational parameters including forward speed of tools.

Tillage is one of the major energy consumers in agricultural production; its efficiency is measured by the

* Corresponding author email: *kcarman@selcuk.edu.tr*

power consumption. Plowing as a part of tillage also accounts for more traction energy than any other field operation and often determines the size of the suitable tractor. It consumes from 29 % to 59 % of all diesel fuel required for the complete technology. One of the major factors that affect fuel consumption is tillage depth. Increasing tillage depth also means more work which needs more fuel, therefore the issue of reducing the fuel consumption of the tractor during tillage have been investigated and reported by many researchers (Bentaher et al., 2013; Mamkagh, 2019).

Many studies have been done in order to investigation and prediction of this force that the majority of these models are for symmetrical tools and have been developed based on the soil-implement related models. These models calculate the draft force and the forces which are applied vertically on soil particles, also, in some cases these models are predictable for some tillage implements such as disks and mould board ploughs with lateral force (Godwin and O'Dogherty, 2007).

A mathematical model which predicted the draft force applied on bottom of mould board plough has developed by Godwin et al. (2007). One of the important aspects of this model is the calculation of draft force using geometric parameters including the body of bottom, ploughing speed and physical properties of soil. A program had developed to perform complex calculations. In order to evaluating the total draft force, Empirical work had been conducted to give credit to this model by using two types of bottom materials in sandy soils. The comparison of measured and predicted forces showed that the values of predicted forces were 2.8 % lower than measured ones.

A number of empirical polynomial/multi-linear regression models have been developed in the past by several researchers for the prediction of draught of tillage implements (Upadhyaya et al., 1984; Kheiralla et al., 2004; Sahu and Raheman, 2006). However, most of these models are often subjected to multi-colinearity problems and their application is limited to those soils and implements conditions for which they were developed. Most recently, Godwin et al. (2007) reported the following relationship between the draft, speed and depth of operation for mouldboard plough:

$$H_t = (Ad^2 + Bd)v^2 + (Cd^2 + \mathrm{Dt})$$

where, H_t is the total draft force (kN), d is depth of operation (m), v is forward speed (ms^{-1}). The values of the constants A, B, C and D determined from this analysis were specific for the particular soil and plough body geometry.

Many studies have been conducted to measure draft force and fuel consumption of tillage implements (Al-Janobi et. al 2001, Sahu and Raheman, 2006). Predicting tractor fuel consumption can lead to more appropriate decisions on tractor management. Khalilian et al., (1984) presented the fuel equations corresponding to different diesel engine air intake types. Results showed that fuel efficiency equations more nearly reflect actual data than ASAE equations where predictions were at least 20% higher than experimental data.

A few researchers have attempted to develop artificial neural network (ANN) models to predict the draught of tillage implements. Zhang and Kushwaha (1999) developed a radial basis function (RBF) neural network to predict draught of narrow blades using operating speed, tools and soil types as input parameters. The data for the development of the model were obtained by conducting tests in three field sites using 5 different narrow blades. They reported that the developed neural network model for the draft force prediction had good generalisation ability within the range of input parameters. Roul et al., (2009) developed an ANN model for predicting the draught requirement of tillage implements, such as mouldboard ploughs, cultivators and disc harrows for different soil physical conditions, namely, moisture content and bulk density. A 5–9–1 neural network was capable of predicting draught requirement of tillage implements in sandy clay loam soil under varying operating and soil conditions as indicated by high coefficient of determination (0.99), low mean squared error (0.0264) and low percentage error (6.4 %).

Rahman et al. (2011) developed an ANN model to predict energy requirement of a tillage tool from the laboratory data. The ANN model was trained and tested with soil moisture content, plowing depths, and operating speeds as input parameters. The measured energy requirement for a tillage tool in silty clay loam soil was used as output parameter. Their results showed that the variation of measured and predicted energy requirement was small.

The literature studies have shown that empirical models can be useful alternative and practical tool for predicting both draft force and fuel energy requirement of tillage implement under different operating conditions. Therefore, the objective of this study was to develop, evaluate and validate a new ANN model to predict specific draft force and fuel consumption requirements of a mouldboard plough. The different forward speeds and working depths of tillage tool in a clay loam soil were used as inputs; the ANN. Using these inputs, the ANN was both trained and validated with data from field experiments.

2. Materials and Methods

Field experiments were conducted at experiment field of Agricultural Faculty, the Universitiy of Selcuk (38° 1′ N 32° 30′ E). The soil texture at the experimental site was clay loam (clay: 43%, sand:29%, silt:28%) with previous wheat crop residue. The plot size was 10 m wide and 100 m long (1000 m^2). Some physical properties of soil were given in Table 1.

Table 1
Some physical properties of soil

	Tillage depth (cm)			
	0-15	0-20	0-25	0-30
Soil moisture content (d.b %)	9.90±3.5	9.90±3.1	10.30±3.5	10.40 ± 3.8
Bulk density (g cm-3)	1.84±0.3	1.95±0.2	2.00±0.3	2.10 ± 0.2
Penetration resistance (kPa)	2400±320	2650±420	2690±430	2840 ± 710

A front wheel assist, New Holland tractor (TD 65D) with a maximum engine power of 65 BG was used in field evaluation (Table 2). A mounted-type mouldboard plough (Şakalak, Konya) with 3 badies used in this study. Treatments consisted of four levels of real forward speeds (3, 4, 5 and 6 km h^{-1}), four levels of tillage depths (0.15, 0.20, 0.25 and 0.30 m), three replications, giving 4 speeds × 4 tillage depths = 16 experimental cases × 3 replications per case = 48 tests.

Table 2
Specifications of New Holland TD 65D tractor and mouldboard plough used.

Tractor	
Maximum tork (Nm) at 1400 rpm	261
Total weight (kN)	32.0
Weight on front axle (kN)	9.60
Weight on rear axle (kN)	22.40
Wheelbase (mm)	2300
Mouldboard Plough	
Total weight (kN)	2.92
Share cutting widht (cm)	320
Share cutting angle (^{o})	16
Sharp edge angle (^{o})	37

Rate of fuel consumption was measured with two turbine flow transducers (Aquametro) having a range of 1-400 L h^{-1}. One transducer was accommodated between the fuel filter and the injector pump of the tractor; another was used to measure the excess fuel returning from both injectors and injection pump to the fuel tank. In order to determine the pulling force requirements of the machines, the draw pin of 30,000 N has been attached to three-point link arms of the tractor. The data logger that collects 20 data per seconds was used. The actual forward speed was measured using a Dickey-John (DJCMS200) (Figure 1).

The experimental data was analyzed by MINITAB statistical packet programme. Analysis of variance and least significance difference (LSD) test were performed to identify results that were statistically significant.

Artificial Neural Networks (ANN) model was developed by using the Matlab NN Toolbox (The Mathworks Inc., Natick, MA, USA). In the model, 16 data in total were used. In the ANN model, km h^{-1} and m were used as input parameters; and kN m^{-1} and L da^{-1} as output parameters.

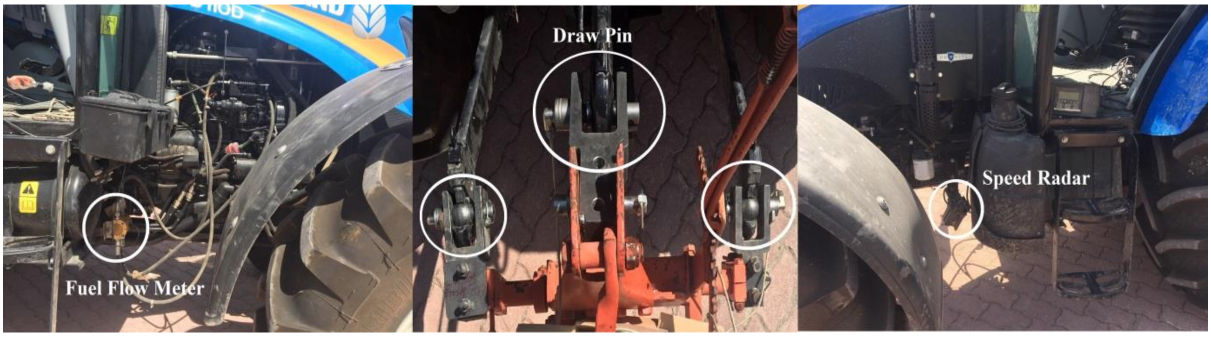

Figure 1
Connection points of the devices used in the study

While establishing the ANN model, all the data were normalized between 0 and 1 (Purushothaman and Srinivasa, 1994).

For normalization, the following equation was used:

$$y_{nor} = \frac{y - y_{min}}{y_{max} - y_{min}} \quad 1$$

To obtain real values from the normalized values, "y" value was calculated using the same formula.

To develop the ANN model, normalized data were divided into two data sets of training and test. In the training set, 12 data were used, whereas 4 data in the test set. The numbers of the most fit neurons in the hidden layers were found to be in the range of 5-8 by the trial and error method. In the ANN model, to obtain the most fit epoch number, epoch numbers from 1 to 10,000 were tried. As a result of trials, the most fit epoch number for the model was determined.

In the ANN model, Feed Forward Back Propagation, Multilayer Perceptron network structure was used. The back-propagation algorithm in this network is the most popular and commonly used algorithm. It minimizes the total error by varying the weights in order to enhance the network performance (Jacobs, 1988; Minai and Williams, 1990). The training algorithm used is the Levenberg-Marquart algorithm techniques (Levenberg, 1944, Marquardt, 1963).

Training of the network was continued until the test error reaches the determined tolerance value. After training of the network ended successfully, the network was tested by test data (Visen et al., 2002).

In order to determine the performances of the results, Root Mean Square Error (RMSE) and coefficient of determination (R^2) values that are considered to be principal accuracy measures and that are based on the concept of mean error and commonly used were calculated using the following formulas (Bechtler et al., 2001).

$$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(x_{1i} - x_i)} \quad 2$$

$$R^2 = 1 - \left(\sum_{i=1}^{m}(x_{1i} - x_i)^2\right) \Big/ \left(\sum_{i=1}^{m}(x_{1i})^2\right) \quad 3$$

Here, RMSE, Root Mean Square Error, R^2, coefficient of determination, m, number of data, x, measured value and, x_i, actual value.

The relative error between measured values and predicted ones was calculated by means of the following equation (Bağırkan, 1993).

$$\varepsilon = \frac{100}{m}\sum_{i=1}^{m}\left[\frac{(x_i - x_{1i})}{x_{1i}}\right] \quad 4$$

Here ε, relative error, m, data number, x, measured value and x_1, predicted value.

3. Results and Discussion

The specific draft force requirements of mouldboard plough in a clay loam soil under varying operating conditions were given in Figure 2.

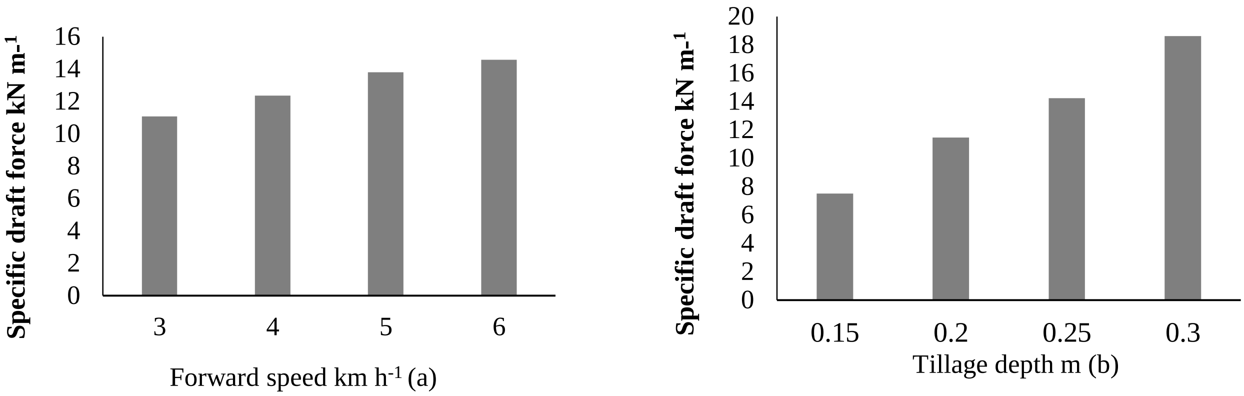

Figure 2
The specific draft force requirements of mouldboard plough based on forward speed (a) and on tillage depth (b)

The specific draft force was varied from 6.66 to 21.04 kN m^{-1} as depending on different forward speed and tillage depths. Averagely, the lowest value of draft force was obtained at speed of 3 km h^{-1} and tillage depth of 0.15 m, and the highest value was obtained at speed of 6 km h^{-1} and tillage depth of 0.3 m. Similar results were also obtained by Altinistik (2012). An increase of 100 % at forward speed resulted with increasing of 31.4 % in specific draft force, while the specific draft force was increased by 148% a increase of 100 % in tillage depth. The increase in tillage depth was more effective on the specific draft force compared to the increase in forward speed. Experimental data were analysed using the analysis of variance (ANOVA). The results showed a significant difference among the specific draft force values for the four different tillage depth and forward speed at 1% probability level.

The fuel consumption requirements of mouldboard plough in a clay loam soil under varying operating conditions were given in Figure 3.

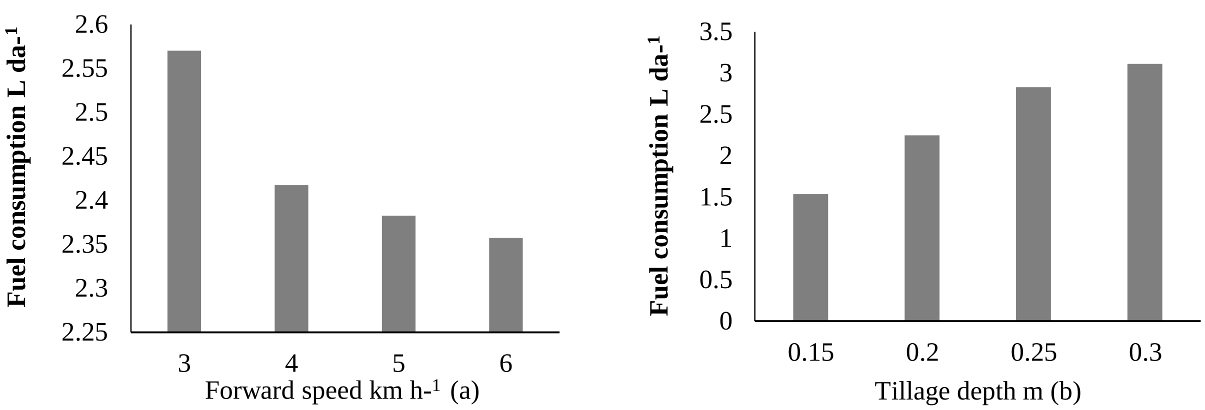

Figure 3
The fuel cosumption requirements of mouldboard plough based on forward speed (a) and on tillage depth (b)

The fuel consumption requirements were in the range 1.5-3.3 L da^{-1}. The greatest fuel consumption was found at tillage depth of 0.3 m and forward speed of 3 km h^{-1}. Approximately, to double the tillage depth resulted in a fuel consumption increase 101 %, whereas to double the forward speed caused a 8.26 % decrease of the fuel consumption. Altinişık (2012) found that specific fuel consumption decreased as a depending on increasing forward speed. Experimental data were analysed using the analysis of variance. The effects of tillage depth and forward speed on the fuel consumption were significant (P<0.01).

In the ANN model, the structure of the network was designed in the form of 2-(5-8)-2, consisting of 2 input, 2 hidden and 2 output layers (Figure 4). As training algorithm, the Levenberg-Marquart algorithm was used (Levenberg 1944, Marquardt 1963), as transfer function, linear function was used in the first hidden layer, tansig in the second hidden layer; and linear functions were used in the output layer. For the network, the lowest training error was obtained at the epoch number of 100.

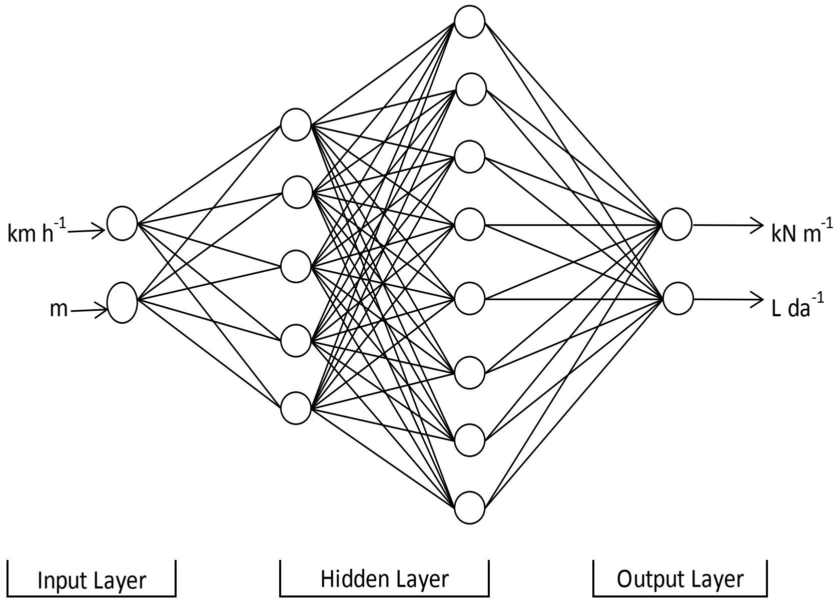

Figure 4
The network structure of the ANN model

Among the models obtained, the ANN model with the lowest RMSE and the highest R^2 value were determined to be the best fit. Whereas R^2 and RMSE values for kN m^{-1} in the training set were found to be 0.99 and 0.0921, respectively; in the test set, they were found to be 0.99 and 0.0629, respectively. While R^2 and RMSE values for L da^{-1} in the training set were found to be 0.99 and 0.0057, respectively; in the test set, they were found to be 0.99 and 0.0135 (Table 3).

Table 3
Performance of the ANN model

Output	Training Set		Test Set	
	RMSE	R^2	RMSE	R^2
kN m^{-1}	0.0921	0.99	0.0629	0.99
L da^{-1}	0.0057	0.99	0.0135	0.99

The coefficient of determination (R^2) between the experimental data and the predicted values obtained from the ANN model was found to be 99.96 % and 99.81% for kN m^{-1} and L da^{-1}, respectively (Figure 5). The proposed neural network model by Al-Janobi et al (2001), by testing, indicated that there was a small variation of measured and predicted data with linear correlation coefficient equals to 0.987 and mean squared error between experimental and predicted specific draft equals to 0.1445. Roul et al (2009) found that good agreement between measured and predicted draught requirement of tillage implements values was found with a coefficient of determination of 0.99, indicating that the ANN model had successfully learnt from the training data set to enable correct interpolation.

ANN model was developed for the prediction of the performance parameters (draft, unit draft and required energy) of the disk plow by Al-Hamed et al (2013). Based on the results, the ANN model appears capable of providing accurate predictions of the disk plow's performance. Altinisik (2012) developed three different artificial neural network (ANN) models depending on the tractor working speed, equipment ploughing depth. An average accuracy rate for all generated three models were greater than 89%.

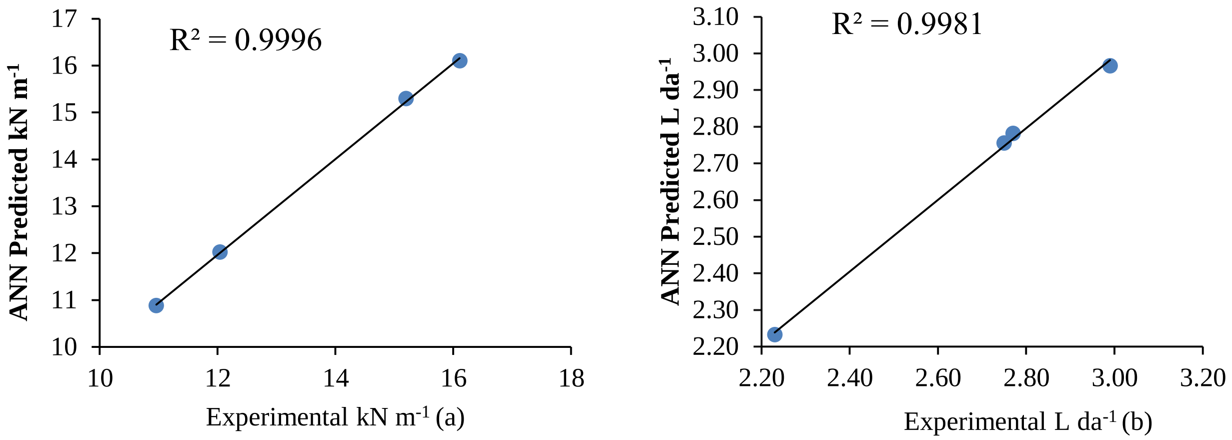

Figure 5
Regression graphics between ANN-predicted values and experimental data for kN m^{-1} (a) and for L da^{-1} (b)

Experimental data, predicted values calculated from the ANN model and the error values between them are given in Table 4. The mean error value for kNm^{-1} was found to be 0.38% and 0.45% for Lda^{-1}.

Table 4
Relative error values for the ANN model

Specific draft force (kN m^{-1})			Fuel consumption (L da^{-1})		
Experimental data	Predicted values	Error (%)	Experimental data	Predicted values	Error (%)
12.04	12.02	0.16	2.99	2.97	0.67
10.96	10.88	0.73	2.23	2.24	0.44
15.20	15.29	0.58	2.77	2.78	0.35
16.11	16.10	0.06	2.75	2.76	0.36
Mean error		0.38			0.45

4. Conclusions

The specific draft force and fuel consumption requirements increased due to increased tillage depth. At increasing forward speed, the specific draft force increased while fuel consumption requirement decreased. Tillage depth was the major contributory factor on the specific draft force and fuel consumption as compared to forward speed.

The specific draft force and fuel consumption requirements predicted by ANN were found to be quite close compared to the measured values. The validation for the specific draft force and fuel consumption models was acceptable. Consequently, the specific draft force and fuel consumption requirements magnitudes could be successfully predicted by the proposed model with good accuracy.

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