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Prediction of Specific Fuel Consumption of 60 HP 2WD Tractor Using Artificial Neural Networks

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Abstract

In this study, we aimed to determine the reliability of estimating the specific fuel consumption by using ANN instead of long and costly testing approaches. For this purpose, specific fuel consumption was determined at different axle loads, tire pressures and drawbar forces for a 60 HP tractor. In addition, the results were also estimated with the help of Artificial Neural Networks, which is one of the machine learning methods. The tests were carried out on the Tractor Draft Test Track. In the study, three different drive tire inner pressures (160 kPa, 120 kPa and 80 kPa), four different dynamic axle loads (1796 daN, 2076 daN, 2276 daN, 2476 daN) with adding extra loads and four different traction forces (500 daN,1000 daN, 1500 daN, 2000 daN) were tested for their effects on specific fuel consumption. Specific fuel consumption values varied between 290.7-542.1 g/kWh depending on the draft force in the tests. Despite the 38% increase in the axle load, a 3.5% decrease occurred in the specific fuel consumption values. Specific fuel consumption values increased when tire inner pressure increased. Specific fuel consumption increased by 1.03% when a 100% increase in tire pressure was realized. In ANN, the most successful model was determined by trying different training algorithms, transfer functions and the number of neurons in the hidden layer. In the most successful network model, MAE, RMSE values for the prediction of specific fuel consumption were found to be 0.005331, 0.007551 respectively.

Keywords: Axle load, Drawbar force, Tire pressure, Specific fuel consumption, Artificial neural networks.

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1. Introduction

Tractors are the main power source of tools, equipment and machinery used in agriculture. Tractor performance is needed to be determined because the farmers need to know the ability of tractors performance, which is the source of power, and to make clear decision on the tractor trade [1].

It is an important matter to obtain the sufficient power in the engine with the least fuel consumption. Technically, specific fuel consumption is more important than hourly fuel consumption. When comparing engines with each other, they should be compared not with the hourly fuel consumption, but with the specific fuel consumption, which expresses the amount of fuel consumed in the production of unit power. At the same time, the specific fuel consumption represents the ratio of the amount of energy consumed to the amount of energy taken from the engine [2].

Taylor [3] estimated that 284-303 million liters of fuel per year could be saved for every 1% improvement in traction efficiency in the United States of America (USA). Due to the increasing world population and limited non-renewable resources, especially fossil fuels, fuel consumption in various agricultural activities needs to be reduced and managed [4]. The most important factor affecting the draft forces in different soils is the weights carried out. Moreover, over 15% of the slippage increases the traction force a little, but it causes excessive wear on the tires. For this reason, tractor drawbar ability is not directly proportional to the total weight, it changes depending on the ground conditions. For example, the effect of axle weight is much higher on concrete than on meadow surfaces [5].

In power testing, the efficiency and fuel consumption of the tractor are determined and measured. Accurate and error-free results, that is, correct PTO (Power Take-Off) and drawbar power values, help the manufacturer to determine the appropriate tire type and size, appropriate weight selection and appropriate transmission ratios in order to improve the tractor's field success and PTO work. These test results also help the farmers in the selection of the power unit. In particular, the determination of soil tillage and its fuel consumption values is important in terms of practical studies [6].

Burt and Bailey [7] investigated the effects of dynamic load and tire pressure on tractor efficiency and determined that dynamic load and tire pressure increase traction efficiency. Damanauskas et al. [8] stated that lowering the tire inflation pressure when the tractor tire slip (skid) varies between 7 and 15%. They also suggested while reducing the slip of the drive wheel and fuel consumption, it increases the work efficiency. Increasing the tractor's additional mass (adding ballast weights) increases work productivity while reducing drive wheel slip. However, it also increases fuel consumption and soil compaction.

Battiato and Diserens [9], reported that a reduction in tire pressure and an increase in axle load result in higher drawbar force while providing improvements in drawbar efficiency, power delivery efficiency and specific fuel consumption. However they also reported that only at a tire pressure of 160 kPa and a slip of less than 15% is a reduction in specific fuel consumption achieved. An increase in tire pressure from 60 kPa to 160 kPa resulted in an increase in specific fuel consumption of up to 16% [10]. Ekinci et al. [11] experimentally investigated the effects of three different tread profile heights, axle load and inflation pressures of a radial tire on the traction performance. They reported that the traction efficiency increased depending on the increase in the dynamic axle load and decreased with the increase of the tire inner pressure. They further showed that the dynamic axle load is the most important factor contributing to the drawbar performance. In the study, they also designed seven different ANNs and two types of Support Vector Regression (SVR) models to predict draft efficiency. They also used various statistical measures to evaluate the success of the algorithms. Their results showed that the ANN model trained using the Levenberg Marquardt algorithm produced more accurate results. Parlak et al. [12] investigated the ability to predict fuel consumption and exhaust temperature in a diesel engine for various injection timings in an ANN model using back propagation learning algorithm and compared with experimental results. They revealed that the consistency between the experimental and network results was achieved with an average absolute relative error of less than 2%. In another study, Çay et al. [13] used ANN to estimate the performance of an alternative fuel engine. Using some experimental data for training, the performance of ANN predictions was measured by comparing the predictions of an ANN model they developed with the experimental results. They reported that the developed ANN model is powerful in predicting the performance of internal combustion engines. Kara Togun and Baysec [14] developed an ANN model based on back propagation learning algorithm to predict the torque and brake specific fuel consumption of a gasoline engine. As a result of the study, they stated that ANN is very efficient in estimating engine torque and brake specific fuel consumption. In another study, Rahimi-Ajdadi and Abbaspour-Gilandeh [15] used back propagation ANN models with six training algorithms for the prediction of tractor fuel consumption and obtained high prediction accuracy. Taghavifar and Mardani [16] applied feedforward ANN with back propagation algorithm to estimate the energy efficiency indices of the drive wheel. As a result of the study, they stated that the ANN model they used is a powerful technique for estimating energy efficiency indices. In a more recent study, Almaliki et al. [17] evaluated the predictive ability of various ANN configurations for performance evaluation in parameters such as tractor drawbar power, fuel consumption, rolling resistance and drawbar efficiency. To estimate the performance parameters, ANN models with back propagation algorithms with different topologies and training algorithms were developed using MATLAB software. As a result of their study, they confirmed that the ANN can learn the relationships between the input variables of the tractor and the performance parameters very well.

The performance of the driven tire varies according to the structural and operational properties and the ground properties on which it works. In terms of affecting the performance, factors such as controlling these changes during the study, time and economic cost, measurement precision can be a problem. Today, ANN, is commonly used to eliminate these negative situations [18].

In this study, we aimed to determine the reliability of estimating the specific fuel consumption by using ANN instead of long and costly testing approaches. In the study, the effects of four different axle loads, three different tire pressures and four different drawbar forces on the specific fuel consumption of the tractor were determined. In addition, specific fuel consumption prediction was made using ANN. The results obtained from the experiment were compared with the results obtained from the ANN.

2. Material and Method

This study was carried out at the Tractor Draft Force Experiment Track of the Agricultural Tools and Machinery Test Center Directorate (TAMTEST) affiliated to the Ministry of Agriculture and Forestry of the Republic of Turkey. The experimental track consists of a concrete floor approximately 400 m long. On the runway, there is the Draw Test Tunnel, which is a 65 m long and 4 m wide flat, closed section designed not to be affected by atmospheric conditions. The test tunnel is shown in Figure 1. During the testing, measurements were taken in this closed section of the runway. In order to increase the adhesion of the tires along the draw test tunnel, the surface of the concrete floor was processed.

Fig. 1. Drawbar test tunnel

In the research, Türk Tractor and Agricultural Machinery Inc. NEWHOLLAND TD 60D-2WD brand tractor produced by the company was used. The tractor used in the experiment was previously tested by the Test Center according to the "OECD Standard Code for the Official Test of Agricultural Tractors" and was used in the study after the test report was prepared. Some values of the tractor are given in Tables 1 and 2.

Table 1. Some values of the tractor used in the experiment [19]

	Group or Ratio	Total ratio (Engine/driving wheel)		Rated feed rate at 2500 min^{-1} rate motor speed * (km/h)	
		FORWARD	REAR	FORWARD	REAR
1	SLOW I	366.666	366.669	1.71	1.71
2		237.980	237.269	2.63	2.64
3		175.000	174.476	3.58	3.59
4		122.163	121.798	5.13	5.15
1	SLOW II	156.987	156.518	3.99	4.00
2		101.891	101.586	6.15	6.17
3		74.926	74.702	8.37	8.39
4		52.304	52.148	11.98	12.02
1	SLOW III	66.682	66.483	9.40	9.43
2		43.279	43.150	14.48	14.52
3		31.826	31.730	19.69	19.75
4		22.217	22.150	28.21	28.30

* Rear wheel radius is calculated based on r = 665 mm. (ISO 4251/1-1998)

Table 2. Features of the tractor used in the experiment [19].

Tractor	
Maximum Torque (Nm), (1500 min^{-1})	219
Total weight (kg)	2566
Front Axle Weight (kg)	836
Rear Axle Weight (kg)	1730
Wheelbase (mm)	2175

The specially designed towing trolley used in the study is shown in Figure 2. The front part of the towing car, called the control cabin consisting of two parts as operator part and control part. In the operator part, there is the compartment where the laptop computer is placed, the converter and the potentiometer connected to the generator right next to it. In the control part, there are equipment such as steering, brake pedal, three-stage gear lever and fuel meter. The electrical need of the electrically operated systems in the towing car is provided by 2 batteries.

The ground height of the tractor's drawbar hook and the drawbar tie bar are kept at the same level in order to make a comparable measurement on the dynamometer. The height of the drawbar pin lower point from the ground is set at 275 mm. This value is the same as the height of the tractor's drawbar from the ground. There is a fuel tank mounted at the top of the rear of the tow truck cab and four cooling towers at the rear.

The excess electricity generated in the generator during the tests is converted into heat in the resistance wires in the cooling towers and thrown into the atmosphere. A generator connected to the powertrain of the drawbar is used to load the work tractor. The movement provided by the tractor in the wheel of the tow truck is transmitted to the differential and loading (braking) is performed.

In order not to cause damage to the generator, the speed of the movement can be changed in three stages in the gearbox in order to prevent damage to the generator at high speeds.

Fig. 2. Front and rear view of the tow truck used in the experiment

In order to measure the fuel consumption, the fuel pump inlet of the tractor's fuel tank was removed and connected to the fuel tank in the tow truck with the fuel hose. During the tests, fuel was filled from the fuel tank in the towing trolley to the measuring cup of unit volume. Figure 3 shows the fuel metering unit located in the tow truck. With the help of the time counter in the control cabin, the fuel consumption time (**t**) in the measuring cup was determined. Thus, hourly fuel consumption (**B**) values were calculated by Eq (1).

$$B_e = \frac{90}{(t/1{,}026)} \quad (l/h) \tag{1}$$

Fig. 3. View of the fuel metering unit in the tow truck

Using the hourly fuel consumption determined by the above equation and the effective engine power (**P_e**) calculated by the draft package program according to the test conditions, the specific fuel consumption (**b_e**) was calculated with the Eq (2) [2]:

$$b_e = \frac{B_e}{P_e} * 1000 \quad \text{(g/kWh)} \tag{2}$$

Experiments were carried out at three levels, with driving tire inner pressures (**P**) of 160 kPa, 120 kPa and 80 kPa. Dynamic axle loads (**W**); standard weight (1796 daN) was determined as 280 kg, 480 kg and 680 kg in addition to this weight. Four different drawbar forces of 2000 daN, 1500 daN, 1000 daN and 500 daN were applied at each stage of the experiment. Since the drawbar measuring system allows the drawbar force to be controlled, the drawbar force is taken as a controlled variable.

At the adjusted tire pressure and axle load, the tire circumference was measured and entered into the towing program. Working speeds in agricultural activities were taken into account as the tractor progress speed, and the II-3 gear stage was selected. This gear stage corresponds to a forward speed of approximately 7.5 km/h. Tractor's characteristics, working gear stage and engine/PTO ratio are entered into the drafting program, and these values are taken from the tractor's test report. Until the tractor came to operating temperature and gave stable values, 7 to 8 laps were made on the track and then tests were started. Some power calculations were made using the power take-off power curve of the trial tractor given in Figure 4.

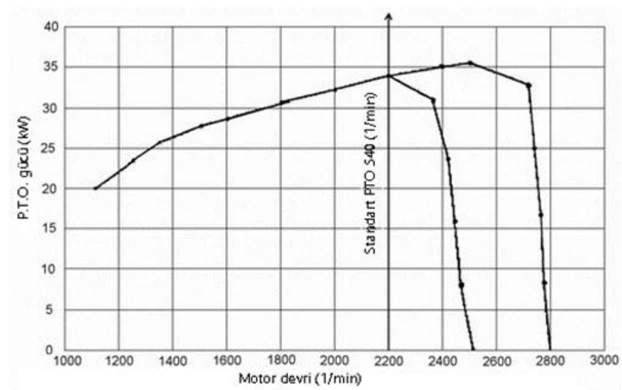

Fig. 4. PTO power curve of the tested tractor [19].

At the predetermined gear level and at full throttle, the tractor is loaded manually at the predetermined drawbar force values with the help of the potentiometer located on the drawbar. Experiments were made with 3 replications.

Analysis of variance was applied to determine the effects on skidding, drawbar efficiency and specific fuel consumption values on the controlled variables of axle load, tire inner pressure and traction force used in the study. If the results obtained are significant, LSD (Least Significant Difference) tests were then performed in order to determine which factors caused to this outcome [20].

In this study, the ANN model, whose model structure is given in Figure 5, was used for the prediction of specific fuel consumption. Of the 48 data obtained from the experiments for specific fuel consumption, 80% were used for training and the remaining 20% for testing. There are many parameters in ANN that affect the accuracy of the result such as the number of neurons in the hidden layer, training algorithm, activation function, learning coefficient, momentum coefficient. In order to find the best performing ANN model, the most suitable structure was searched by trying the number of neurons in the hidden layer, activation function and training algorithms. Logarithmic sigmoid function (logsig) and tangent hyperbolic sigmoid function (tansig) were used as activation functions. The number of neurons in the hidden layer was changed from 1 to 10 step by step, and various training algorithms (trainbfg, trainlm, trainingdx, etc.) were tried sequentially. Thus, the best network structure was tried to be obtained by changing the number of neurons in the hidden layer, training algorithms and activation functions.

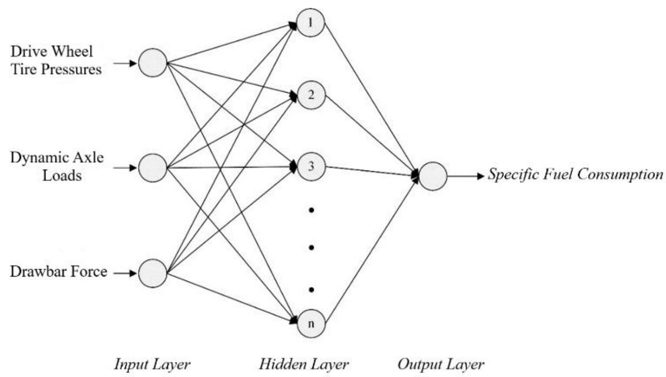

Fig. 5. ANN model used to estimate specific fuel consumption

Mean absolute error (MAE) and root mean square error (RMSE) error values were used to determine the performance values. The mathematical expressions of these error values are shown in Eq (3) and Eq (4), respectively [25].

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|Y_i - Z_i| \tag{3}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_i - Z_i)^2} \tag{4}$$

where Y_i represents the actual value, and Z_i represents the estimated value obtained by ANN.

3. Results

By increasing the rear axle load in the experiments, the contact surface of the driven tires with the ground also increased and the adhesion of the tires to the ground was improved. As a result, the drawbar efficiency was increased. These findings suggest that the rear axle load of the tractor should be increased in agricultural activities that require high traction force.

By reducing the tire pressure, the surface area of the tire in contact with the ground increased. Accordingly, as a result of the increased grip force, the traction efficiency increased and the specific fuel consumption decreased. This also suggests that the increased tire contact surface area should be preferred in agricultural activities as it reduces soil compaction. However, as a result of reducing the tire pressure below a certain value, it affects the tire life negatively due to the increase in the contact surface of the tires with the road and the deterioration of the carcass structure.

With the increase in the drawbar force, the specific fuel consumption decreased. In cases where high traction force is required, the tire pressures of the tractor should be reduced. If the slippage is above 10-15%, the tractor's rear axle load (AL) should be increased and the slippage value should be kept at the desired level. If these conditions are met, the specific fuel consumption is expected to be at the lowest level.

As seen in Figure 6, the lowest specific fuel consumption values are obtained by increasing the drawbar force. In terms of reduction in specific fuel consumption, it is seen that the specific fuel consumption decreases rapidly when the drawbar force is increased up to 1500 daN, while the amount decreases after 1500 daN. Similarly, increasing the axle load of the driving wheels caused an increase in the holding force, and as a result, the specific fuel consumption was improved.

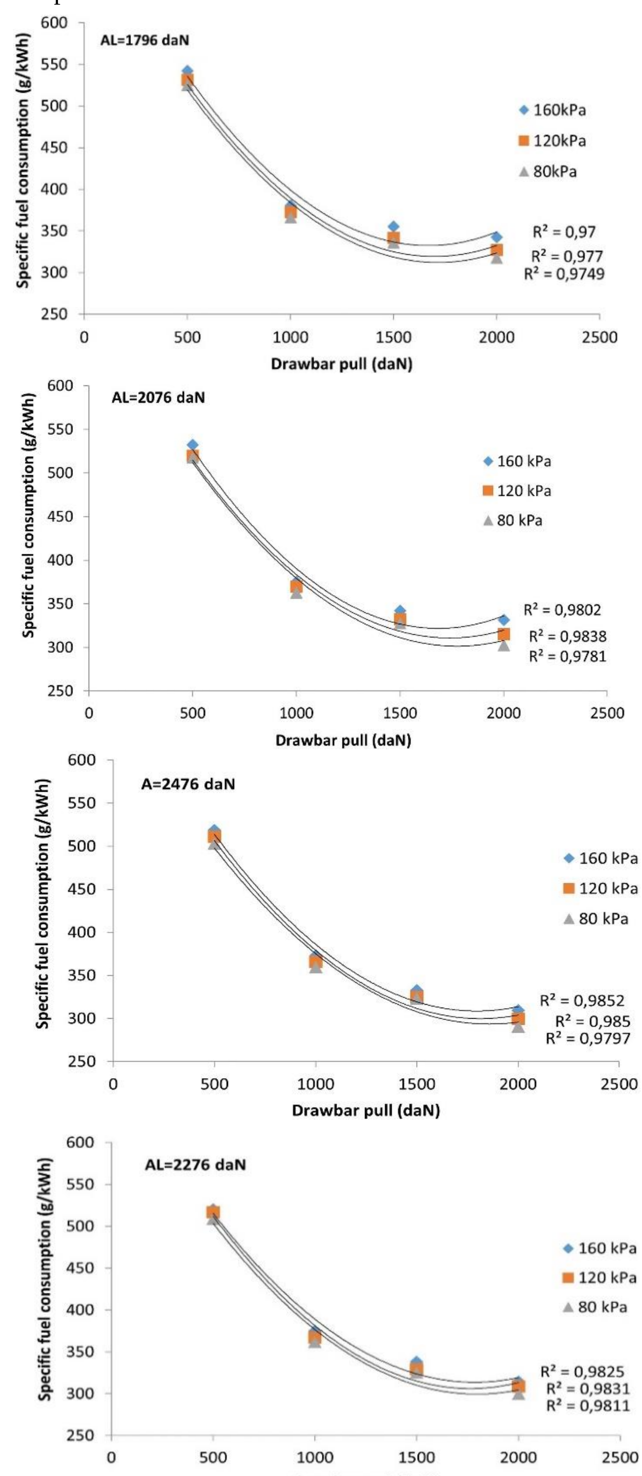

Fig. 6. Specific fuel consumption changes depending on the drawbar force

Moreover, it is seen that the specific fuel consumption increases with the increase in the internal pressures of the driving wheels. While the change in specific fuel consumption was 5% and 4% as a result of increasing the axle load at high tire inner pressure value and at low tire inner pressure value, respectively.

Despite the 38% increase in the axle load, a 3.5% decrease occurred in the specific fuel consumption values. Specific fuel consumption values increased due to increased tire inner pressure. Specific fuel consumption increased by 1.03% due to a 100% increase in tire pressure. The highest specific fuel consumption value was recorded as 542.1 g/kWh at 1796 daN axle load, 500 daN traction force and 160 kPa tire internal pressure. The lowest specific fuel consumption value was obtained as 290.7 g/kWh at 2476 daN axle load, 2000 daN traction force and 80 kPa tire inner pressure.

The outputs of each ANN model, which was found by trial and error method using the network structure in Figure 5, were recorded in Excel and the results were compared. Table 3 shows the lowest error values obtained according to different network models. Based on the inputs, the best network model is "Structure_3". The most successful ANN model for specific fuel consumption prediction was obtained when the training algorithm was "Bayesian regularization backpropagation" (trainbr), the hidden layer activation function was "tangent sigmoid function" (tansig) and the number of neurons in the hidden layer was "7". Figure 7 shows the graph showing the error values of different ANN models in Table 3.

The graph showing the actual and estimated values of the test data obtained as a result of the best ANN structure is given in Figure 8. As can be seen from the figure, it is seen that the actual values and the predicted values overlap.

Table 3. The lowest error values obtained for each network model

ANN Structure	Learning Method	Hidden Layer Activation Function	Number of hidden layer neurons	MAE	RMSE
Structure 1	trainbfg	tansig	10	0,006608	0,008671
Structure 2	trainbfg	logsig	3	0,006509	0,007964
Structure 3	*trainbr*	*tansig*	*7*	*0,005331*	*0,007551*
Structure 4	trainbr	logsig	4	0,006162	0,007771
Structure 5	traincgb	tansig	5	0,006392	0,007844
Structure 6	traincgb	logsig	4	0,007685	0,009518
Structure 7	traincgf	tansig	3	0,009525	0,011021
Structure 8	traincgf	logsig	7	0,009407	0,012482
Structure 9	traingda	tansig	7	0,029881	0,0353
Structure 10	traingda	logsig	1	0,037552	0,047587
Structure 11	traingdx	tansig	3	0,01304	0,016084
Structure 12	traingdx	logsig	2	0,017734	0,027863
Structure 13	trainlm	tansig	3	0,006597	0,008188
Structure 14	trainlm	logsig	5	0,005945	0,007849
Structure 15	trainoss	tansig	3	0,008919	0,01199
Structure 16	trainoss	logsig	1	0,015112	0,022216
Structure 17	trainr	tansig	6	0,015113	0,018269
Structure 18	trainr	logsig	9	0,10142	0,14067
Structure 19	trainrp	tansig	4	0,00818	0,010429
Structure 20	trainrp	logsig	5	0,006429	0,007671

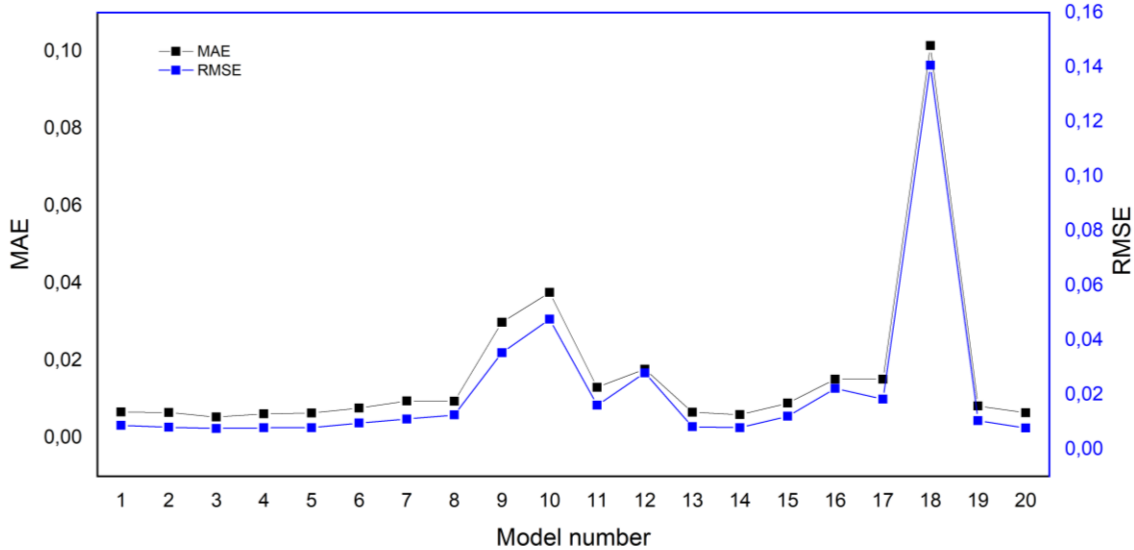

Fig. 7. Error values obtained from different ANN models

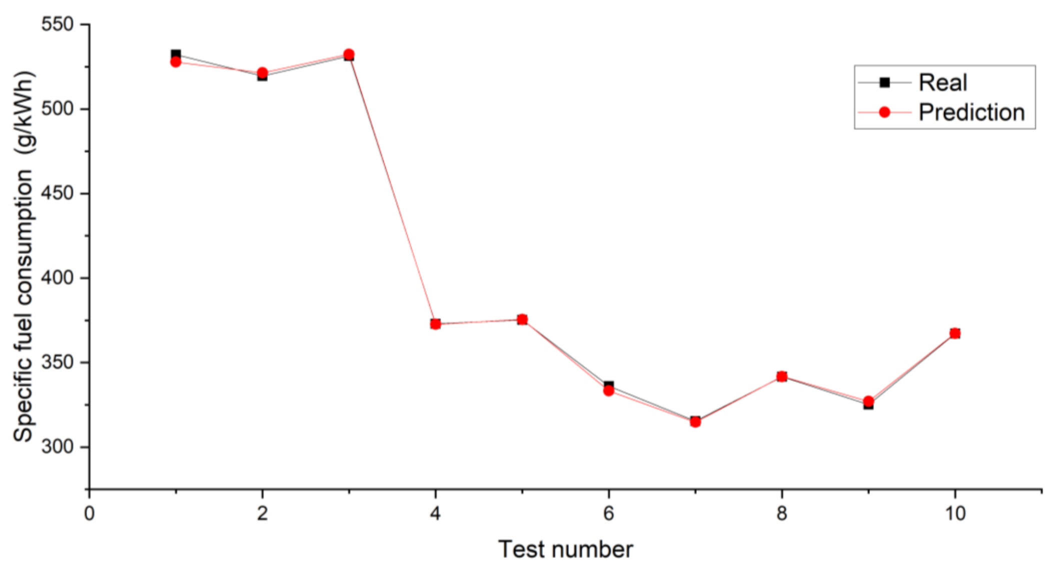

Fig. 8. Real and predicted test data

4. Conclusion

In this study, specific fuel consumption prediction was made using ANN. By changing the learning algorithms, activation functions and hidden layer neuron numbers in ANN, the most successful network model was determined by trial-and-error method. The most successful network model was obtained in the case when the number of neurons in the hidden layer was "7", the transfer function of the hidden layer was "tansig", and the training algorithm was "trainbr". The MAE and RMSE error values obtained in the prediction of specific fuel consumption with this model were calculated as 0.005331 and 0.007551, respectively. The most successful ANN model determined made a high-accuracy prediction in finding the specific fuel consumption even in a small data set.

Experimental studies to determine engine performance (torque, power, fuel consumption, exhaust temperature, etc.) in internal combustion engines are complex, time-consuming and costly. It also requires special tools. To overcome these difficulties, ANN can be used to estimate performance parameters in internal combustion engines [21, 18, 22, 23]. It is thought that a well-trained ANN model provides fast and consistent results and makes it an easy-to-use tool in preliminary studies for such engineering problems [24]. In the new generation tractors produced today, the operator should be able to see the traction force, skid values and specific fuel consumption values obtained from the tractor during operation on the driver panel. Thus, an economical and efficient operation will be ensured.

Acknowledgment

The data used in this study is based on the master's thesis titled "The Effect of Some Factors on Draft Performance in Tractors" made in the Department of Machine Education, Institute of Science and Technology, Selcuk University [26].

Nomenclature

t	: time (s)
B_e	: hourly fuel consumption (l/h)
b_e	: specific fuel consumption (g/kWh)
P_e	: effective engine power (kW)
P	: tire inner pressures (kPa)
W	: dynamic axle load (daN)
AL	: rear axle load
ANN	: artificial neural networks
MAE	: mean absolute error
RMSE	: root mean square error
Y_i	: actual value
Z_i	: estimated value
WD	: wheel drive
PTO	: power take-off
LSD	: least significant difference

Conflict of Interest Statement

The authors declare that there is no conflict of interest in the study.

CRediT Author Statement

Hanifi Küçüksariyildiz: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources, Visualization, Writing - original draft, Writing - review & editing
Kazım Çarman: Formal analysis, Methodology, Project administration, Supervision, Validation.
Kadir Sabanci: Data curation, Formal analysis, Methodology, Software, Visualization, Writing - review & editing

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