Artificial neural network based modeling of tractor performance at different field conditions

Salim Almaliki[1], Reza Alimardani[2*], Mahmoud Omid[2]

(1.Department of Agricultural Machinery, University of Basrah, Basrah, Iraq.
2.Department of Agricultural Machinery Engineering, College of Agriculture and Natural Resources, University of Tehran, Karaj, Iran)

Abstract: Application of tractors in farming is undeniable as a power supply. Therefore, performance model for evolving parameters of tractors and implements are essential for farm machinery, operators and manufacturers alike. The objective of this study was to assess the predictive capability of several configurations of ANNs for performance evaluating of tractor in parameters of drawbar power, fuel consumption, rolling resistance and tractive efficiency. A conventional tillage system which included a moldboard plow with three furrows was used for collecting data from MF285 Massey Ferguson tractor. To predict performance parameters, ANN models with back-propagation algorithm were developed using the MATLAB software with different topologies and training algorithms. For drawbar power, the best result was obtained by the ANN with 6-7-1 topology and Bayesian regulation training algorithm with R2 of 0.995 and MSE of 0.00024. The ANN model with 6-7-1 structure and Levenberg-Marquardt training algorithm had the best performance with R2 of 0.969 and MSE of 0.13427 for TFC prediction. The 6-8-1 topology shows the best power for prediction of AFC with R2 and MSE of 0.885 and 0.01348, respectively. Also, the 6-10-1 structure yielded the best performance for prediction of SFC with R2 of 0.935 and MSE of 0.012756. The obtained result showed that the 6-7-1 structured ANN with Levenberg-Marquardt training algorithm represents a good prediction of TE with R2 equal to 0.989 and MSE of 0.001327. The obtained results confirmed that the neural network can be able to learn the relationships between the input variables and performance parameters of tractor, very well.

Keywords: artificial neural network, tractive efficiency, rolling resistance, drawbar power, fuel consumption.

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1 Introduction

The great increase in agricultural productivity over the last century can be related to mechanization, particularly the development of the tractors. The main function of tractors is to be interfaced with implements that provide power, tractive effort to move the implements through the field and control the implements. It is necessary that we have the proper understanding of how the tractor power can be used, and tractor-implement systems can be optimized. The proper field machines' operation is essential for any system to be reasonably profitable. Thus, efficient operation of farm tractors includes: (a) maximizing fuel efficiency of the engine and mechanical efficiency of the drive train, (b) maximizing attractive advantage of traction devices and (c) selecting an optimum travel speed for a given tractor-implement system (Grisso et al., 2008). Therefore, performance model for evolving parameters of tractors and implements are essential for farm machinery operators and manufacturers alike.

The modeling techniques used in mechanization processes are quite important to provide an accurate and sustainable use of power resources. One of the most popular techniques for modelling and forecasting behavior of nonlinear systems is soft computing. Soft computing technology is an interdisciplinary research field in computational science. At present, various

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***Corresponding author: Reza Alimardani,** Department of Agricultural Machinery Engineering, College of Agriculture and Natural Resources, University of Tehran, Karaj, Iran. Tel.: +989123332216. E-mail Address: rmardani@ut.ac.ir

techniques are being used in soft computing such as statistics, machine learning, neural network and fuzzy logic for exploratory data analysis (Carman, 2008). In recent years, the methods of artificial intelligence (AI) have widely been used in different areas including agricultural applications (Safa et al., 2009; Douik and Abdellaoui, 2008; Kashaninejad et al., 2009). The application of soft computing to AI is studied collectively by the emerging discipline of computational intelligence (CI) for example, artificial neural networks (ANN). These methods are inspired by the central nervous system, exploiting features such as high connectivity and parallel information processing, exactly like in the human brain (Arriagada et al., 2002). Several researchers focused on artificial intelligence for modeling of different component of agricultural systems (Cakmak and Yıldız, 2011; Zarifneshat et al., 2012; Çay et al., 2013; Aghbashlo et al., 2012; Khoshnevisan et al., 2013; Young et al., 2013; Safa and Samarasinghe, 2013). For example Aghbashlo et al. (2012) developed a supervised ANN and mathematical models for determining the exegetics performance of a spray drying process. They were concluded that the MLP (multilayer perceptron) ANN approach for exegetics prediction of spray drying process was capable of yielding good results and that could be considered as an attractive alternative to traditional regression models and other related statistical approaches. Cakmak and Yıldız (2011) used ANN to determine the drying rate of seedy grapes. Input parameters used for the ANN model were the moisture content, the hot air temperature and the hot airflow rate. The structure of the ANN model with one hidden layer was determined considering different neuron numbers at the hidden layer. Based on error analysis results, they concluded Levenberge Marquardt optimization technique was the most appropriate method for prediction capability of transient drying rates. Zarifneshat et al. (2012) applied ANN to predict apple's bruise volume. The network was trained using two learning algorithms: BB (Basic Backpropagation) and BDLRF (Backpropagation with Declining Learning Rate Factor). They reported that BDLRF algorithm yields a better performance than BB algorithm. Developments of prediction equations for tire tractive performance have been the focus of much research. Artificial Neural Networks (ANNs) have been accepted as a potentially useful tool for modeling complex non-linear systems and widely used for prediction (Nayak et al., 2004). Many researchers have reported the proper ability of ANN versus regression method such as study done by Rahimi and Abbaspour (2011). They used artificial neural network and stepwise multiple range regression methods for prediction of tractor fuel consumption. Their results showed that ANN provided better prediction accuracy compared to stepwise regression. Roul et al. (2009) successfully applied ANN representation predicting the draught requirement of tillage implements under varying operating and soil conditions.

A neural network is adjusted for a definite task such as model distinguishing and data classification during a training process. Extensive aptitude of this approach for accurate estimations of complicated regressions contributes more advantage compared to classical statistical techniques. Bietresato et al. (2015) assessed the predictive capability of several configurations of ANNs for evaluating indirectly performance (torque, BSFC) of diesel engines employed in agricultural tractors. The results showed the ANNs with the outlined characteristics proved to be useful and reliable tools for correlating EG temperature and rpms with torque and BSFC. Ekinci et al. (2015) used ANNs and two types of Support Vector Regression (SVR) models to predict the tractive efficiency. The results showed that the ANN model trained using Levenberge Marquardt algorithm has produced more accurate results.

The objective of this study was to assess the predictive capability of several configurations of ANNs for performance evaluating of tractor in parameters of drawbar power, fuel consumption, rolling resistance and tractive efficiency.

2 Materials and methods

2.1 Field experiments

In this research, a conventional tillage system which includes a moldboard plow with three furrows (width of mold board was 100 cm) was used for collecting data from Massey Ferguson tractor (Model MF285). The specifications of tractor showed in Table 1. The experiments were carried out in the field with different conditions using three engine speeds, four tractor forward speeds (as shown in Table 2), three depths of moldboard plow and three tire Inflation pressures, These parameters were used at two moisture contents and four cone indexes of soils as shown in Table 2. Table 3 shows the actual velocity of the tractor at different engine speed and gears.

Table 1 Specifications of Massey Ferguson MF285

Item	Parameters
Effective output, hp	75
Type of fuel	Diesel
Type of steering system	Mechanical- hydraulic
Transmission	Gears
Type of injector pump	Rotary
Firing order	1342
Fuel tank capacity, L	90
Lifting capacity, kg	2227
Rated engine speed, r/min	2000
Type of cooling system	Liquid-cooled
Front tires size, inch	12.4-24
Rear tires size, inch	18.4-30
Front Weight, kg	1420
Rear Weight, kg	1694
Total Weight, kg	3114
Ground clearance under drawbar, mm	38

Table 2 Input parameters used in experiments

Moisture content, %	Depth , cm	Inflation pressure, kPa	Engine speed, r/min	Cone index, kPa	Gear
6	10	50	1200	100	1st
23	15	100	1600	160	2nd
	20	150	2000	930	3rd
				1160	4th

Table 3 Velocities used in experiments (m/s)

Engine speed, r/min	Gear			
	1st	2nd	3rd	4th
1200	0.39	0.56	0.79	1.09
1600	0.48	0.67	0.95	1.28
2000	0.61	0.90	1.2	1.56

2.2 Calculation of parameters

2.2.1 Drawbar power

Drawbar power is obtained using the relation between draft and travel speed as Equation 1:

$$P_{db} = NT \times V_a \qquad (1)$$

where P_{db} is drawbar power (kW), NT is net traction (kN) and V_a is actual velocity (m/s).

2.2.2 Fuel consumption

The fuel amount required for each tillage operation was determined by two flow sensors: one for measuring input fuel to injector pump and another on returning fuel line to the tank.

In this research, the expressions of characteristics of fuel consumption of engine farm tractor are in three terms as; Temporal Fuel Consumption (TFC), Area-specific Fuel Consumption (AFC) and Specific Fuel Consumption (SFC).

TFC represents the amount of fuel consumed for the unit of time according to the following Equation 2:

$$TFC = \frac{fc}{T} \qquad (2)$$

Where fc is fuel consumption at taken time (L/h) and T is time taken (h).

AFC represents the amount of fuel consumed to cover an area of one hectare and is calculated according to the following Equation 3:

$$AFC = \frac{10 \times TFC}{V_a \times W} \qquad (3)$$

Where TFC is fuel consumption (L/h), W is implement working width (m) and V_a is actual velocity of the tractor (m/s).

SFC represents the amount of fuel consumed during a specified time on the basis of the drawbar power available at the drawbar, it is calculated as Equation 4:

$$SFC = \frac{TFC}{P_{db}} \tag{4}$$

2.2.3 Rolling resistance

Rolling resistance of the tractor was measured by a dummy tractor towing the test tractor through load cell connected to a digital load indicator. Rear tractor was kept in neutral position while the front tractor pulled the rear one. The reading of load indicator was noted from digital indicator at determined time interval. An average of four readings was considered in computing the force required to pull a tractor.

The drawbar load cell was an *S* shape (model: H3-C3-3.0 t-6B-D55 from Zemic with capacity of 30 kN) mounted between two tractors. The first one was a Massey Ferguson 285 as puller and the other one was Massey Ferguson 165 as auxiliary. The auxiliary tractor pulls the implement-mounted tractor with the latter in neutral gear but with the implement in the operating position. The force exerted by the implement is measured by a strain gauge Wheatstone bridge arrangement. Draft was recorded in the measured distance (20 m) as well as the time taken to traverse the distance. Calibrations of the load cell were conducted against known loads by a hydraulic loading device from INSTRON (Model 4486).

2.2.4 Tractive efficiency

Tractive efficiency (TE) is defined as; ability of tractor to transfer power from the axle input to the soil through wheels. TE depends on slip (set by ballast), soil conditions, tires and drive configurations and is calculated using Equation 5:

$$TE = \left(\frac{output\ \ power}{input\ \ power}\right) \times 100 = \left(\frac{drawbar\ \ power}{axele\ \ power}\right) \times 100 \tag{5}$$

2.3 ANN model design

In this study, to predict performance parameters, ANN models with back-propagation algorithm were developed using MATLAB software (Demuth and Beale, 1998). Generally, the ANN is characterized by three layers: an input layer, a hidden layer, and an output layer. The acquired data was usually divided into three randomly selected subsets which include: 70% of the dataset for training, 15% for model validation and 15% for testing. Seven different training algorithms of gradient descent with momentum (traingdm), Gradient descent with momentum and adaptive learning rate (traingdx), Bayesian regulation (trainbr), scaled conjugated gradient (trainscg), Resilient (trainrp), Gradient descent with adaptive learning rate (traingda) and Levenberg-Marquardt (trainlm) were used for network training. In general, there is not a specific method for defining number of hidden layers and also number of neurons in the hidden layer; so the number of neurons in the hidden layer was obtained by trial and error method. In this research, the number of hidden layers and neurons in the hidden layer (or layers) were chosen by comparing performance of the designed networks. Also, the functions of tangent hyperbolic conversion, sigmoid and linear motion function among layers were used. The ANN system applied for these prediction models had six inputs and a single output. The input vector included depth, forward speed, engine speed, inflation tire, moisture content and cone index of soil and the output of the ANNs were drawbar power, TFC, AFC, SFC, rolling resistance and TE. The schematic architecture of the used ANN is shown in Figure 1.

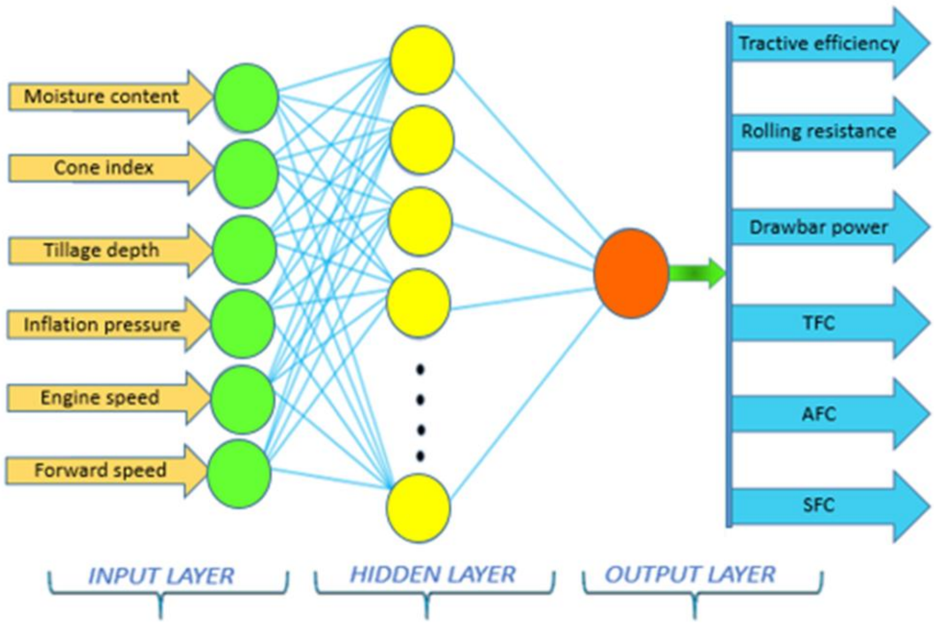

Figure 1 Schematic architecture of the used ANN

The input model consists of dendritic nodes similar to a biological cell that could be represented as a vector with N items X= (X1, X2,… , Xn); the summation of inputs multiplied by their corresponding weights could be represented by scalar quantity S. See Equation 6.

$$S = \sum_{n=1}^{n} Wn\, Xn \tag{6}$$

where W=(W1 ,W2 ,… ,WN) is the weight vector of associations among neurons. The S quantity is then inserted into a non-linear conversion function f, yielding the following output as Equation 7:

$$y = f(s) \tag{7}$$

Non-linear transfer function is usually represented as sigmoid functions and is defined via Equation 8:

$$f(s) = \frac{1}{1+e^{-s}} \tag{8}$$

The output of y can be as a result of the model or that of the next layer (in multilayer networks). In the design of an ANN, certain elements should be taken into account including type of input parameters.

Prior to the utilization of dataset for model development, the inputs and target output were normalized or scaled linearly between -1 and 1 in order to increase the accuracy, performance and speed of ANN.

To evaluate performance of developed models, various criteria were used to calculate errors. Mean square error (MSE) criterion which is a well-known standard error is often used as a criterion to compare error aspects in various models. Coefficient of determination (R^2) which is a method to calculate a standard error in estimating methods shows the normal difference of real data from the estimated data. The expressions for these statistical measures are given as Equation 9 and Equation 10:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(x_i - \hat{x}_i)^2 \tag{9}$$

$$R^2 = \frac{[\sum_{i=1}^{N}(\hat{x}_i - \bar{\hat{x}})(x_i - \bar{x})]^2}{[\sum_{i=1}^{N}(\hat{x}_i - \bar{\hat{x}})^2 \times \sum_{i=1}^{N}(x_i - \bar{x})^2} \tag{10}$$

where N is the number of test observation, x_i shows the value of the variable being modeled (observed data), $\hat{x}_i$ shows the value of variable modeled (predicted), and $\bar{x}$ is the mean value of the variable.

3 Results and discussion

In this research, a computer program has been developed under MATLAB software environment for designing of ANNs based models for prediction of tractor performance’s parameters. To evaluate the best fitting model, MSE and R^2 as index of network performance, were utilized.

3.1 Drawbar power

Table 4 shows result of ANN modeling using different training algorithms. As a whole, all training algorithm represented acceptable results. The best result was obtained by the ANN with 6-7-1 topology and Bayesian regulation training algorithm with R^2 of 0.995 and MSE of 0.00024. Figure 2 shows regression result of 6-7-1 ANN model in training, validation and test mode. The closeness between the predicted and actual values promoted the accuracy of the network in prognostication of the drawbar power. The results are in agreement with the result of ElWahed and Aboukarima (2007). They developed ANN model to predict drawbar pull of chisel plow using forward speed, plowing depth, nominal tractor power, rated plow width, soil texture index, initial soil moisture content and initial soil specific weight as independent variables. They reported the R^2 value of the developed model was more than 0.93.

Table 4 Optimum structure ANN models developed by different training algorithms

Training algorithm	Optimum topology	Epochs	MSE	R2
Trainbr	6-7-1	35	0.000245	0.995
Trainlm	6-6-1	49	0.000257	0.996
Trainrp	6-7-1	96	0.001153	0.988
Trainscg	6-9-1	78	0.001200	0.913
Traingda	6-1-1	100	0.002485	0.979
Traingdx	6-1-1	100	0.004366	0.955
Traingdm	6-6-1	100	0.033402	0.848

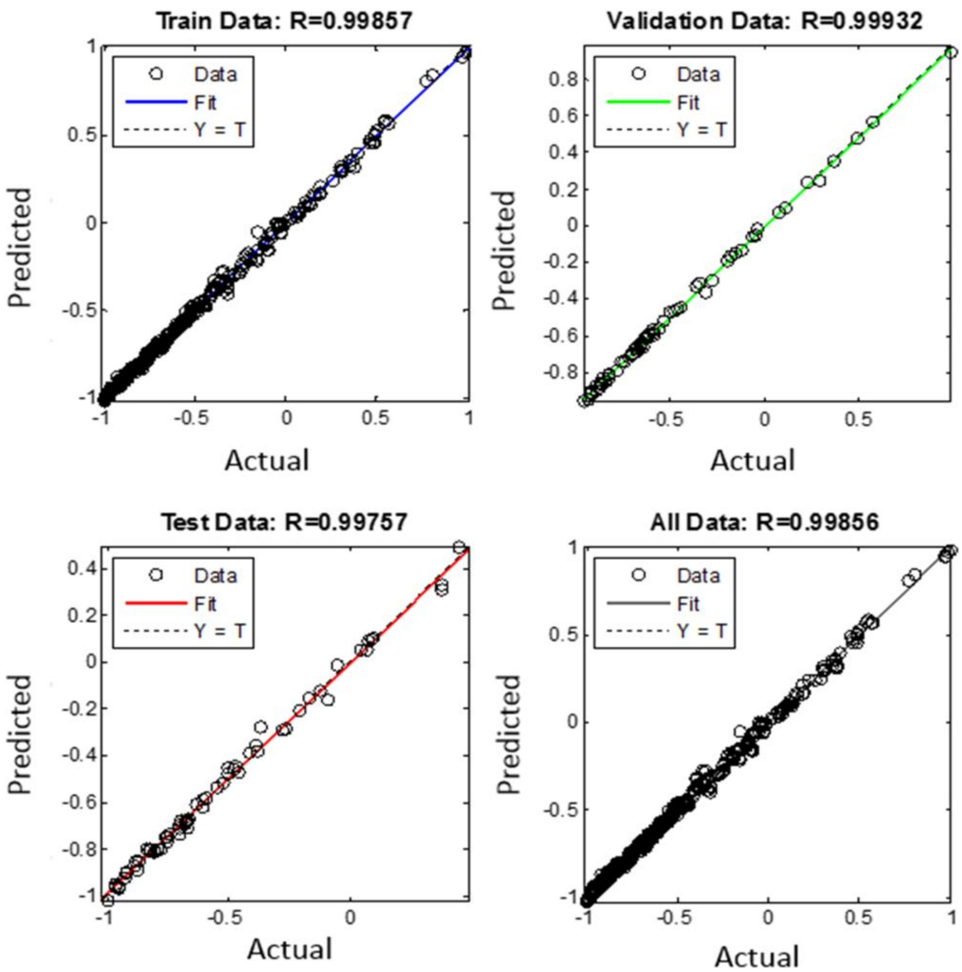

Figure 2 Output of the best ANN model for drawbar power prediction using Bayesian regulation training algorithm

3.2 Fuel consumption

Three parameters of TFC, AFC and SFC were modeled using ANNs. Table 5 represents different structures of ANNs. Results show that the ANN model with 6-7-1 structure and Levenberg-Marquardt training algorithm had the best performance with R^2 of 0.969 and MSE of 0.13427 for TFC prediction. Also for AFC and SFC, the Levenberg-Marquardt training algorithm yielded the best results (Table 6 and Table 7). The 6-8-1 topology shows the best power for prediction of AFC with R^2 and MSE of 0.885 and 0.01348, respectively. Also, the 6-10-1 structure yielded the best performance for prediction of SFC with R^2 of 0.935 and MSE of 0.012756. Gradient descent with momentum and adaptive learning rate (traingdx), gradient descent with momentum (traingdm), Gradient descent with momentum and adaptive learning rate (traingdx) and Bayesian regulation (trainbr) were not responded in predicting for TFC while Gradient descent with momentum and adaptive learning rate (traingdx), gradient descent with momentum (traingdm), Gradient descent with momentum and adaptive learning rate (traingdx) and Resilient (trainrp) were not responded in predicting for SFC. During training process some training algorithms caused the error not to decrease, so the process was diverging. As a result the algorithm marked as not responding method. The regression graphs represent the relationship between actual and predicted values of the ANN, in the training, validation and test sets that are illustrated in Figure 3, Figure 4 and Figure 5 for TFC, AFC and SFC, respectively. The closeness of the scattered data to the unity slope line is the representative of the satisfactory performance of the optimal model. Rahimi-Ajdadi and Abbaspour-Gilandeh (2011) obtained the same result in fuel consumption prediction of tractor. They assumed that fuel consumption to be a function of engine speed, throttle and load conditions, chassis type, total tested weight, drawbar and PTO power. They adopted Back propagation Artificial Neural Network (ANN) models with different training algorithms and reported that the highest performance was obtained for the network with two hidden layers each having 10 neurons which employed Levenberg–Marquardt training algorithm with R^2 of 0.986.

Table 5 Different networks structure to predict TFC

Training algorithm	**Optimum topology**	**Epochs**	**MSE**	**R2**
Trainlm	6-7-1	100	0.013427	0.969
Trainrp	6-8-1	76	0.042401	0.735
Trainscg	6-10-1	100	0.048406	0.604
Trainbr	Not responding	-	-	-
Traingdx	Not responding	-	-	-
Traingda	Not responding	-	-	-
Traingdm	Not responding	-	-	-

Table 6 Optimum models for AFC prediction

Training algorithm	Optimum topology	Epochs	MSE	R^2
Trainlm	6-8-1	100	0.01348	0.885
Trainscg	6-6-1	5	0.03156	0.682
Trainbr	6-4-1	80	0.03291	0.688
Trainrp	6-4-1	80	0.03291	0.688
Traingdx	6-9-1	100	0.03864	0.627
Traingda	6-8-1	99	0.04134	0.558
Traingdm	6-7-1	93	0.06187	0.511

Table 7 Optimum models for SFC prediction

Training algorithm	Optimum topology	Epochs	MSE	R^2
Trainlm	6-10-1	54	0.012756	0.935
Trainscg	6-6-1	65	0.043969	0.650
Trainbr	6-6-1	34	0.047281	0.617
Trainrp	Not responding	-	-	-
Traingdx	Not responding	-	-	-
Traingda	Not responding	-	-	-
Traingdm	Not responding	-	-	-

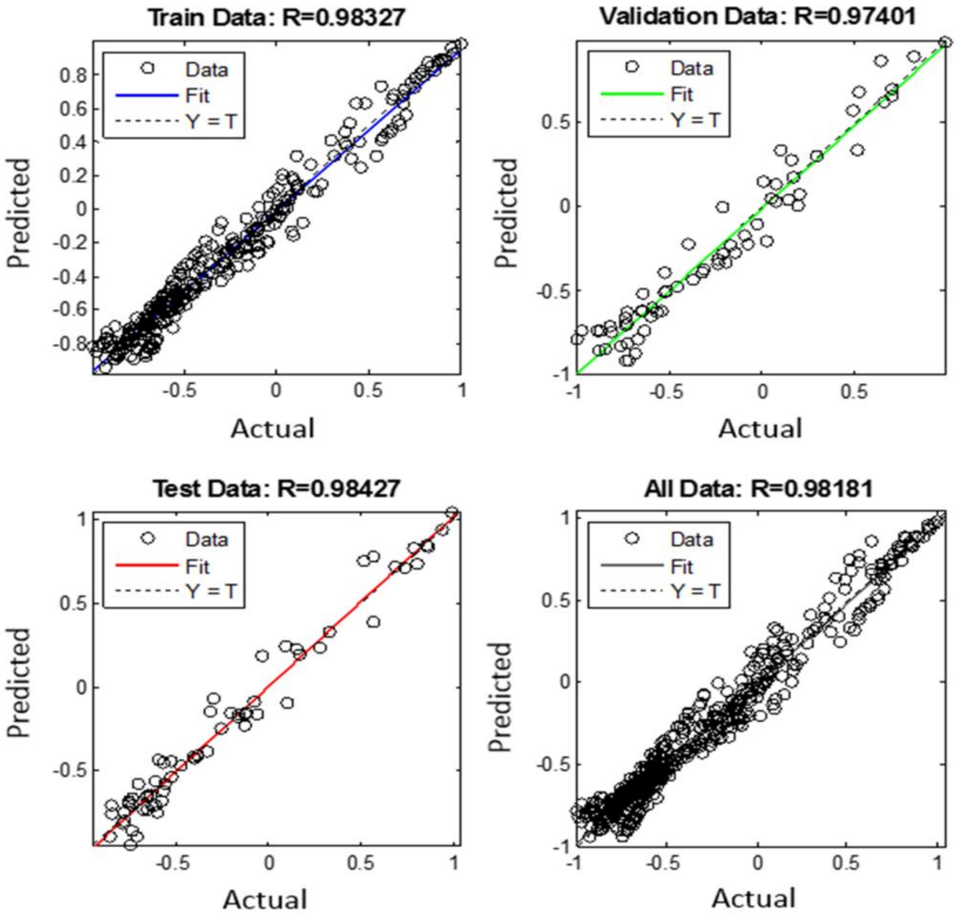

Figure 3 Regression result of developed ANN for TFC parameter using Levenberg-Marquardt training algorithm

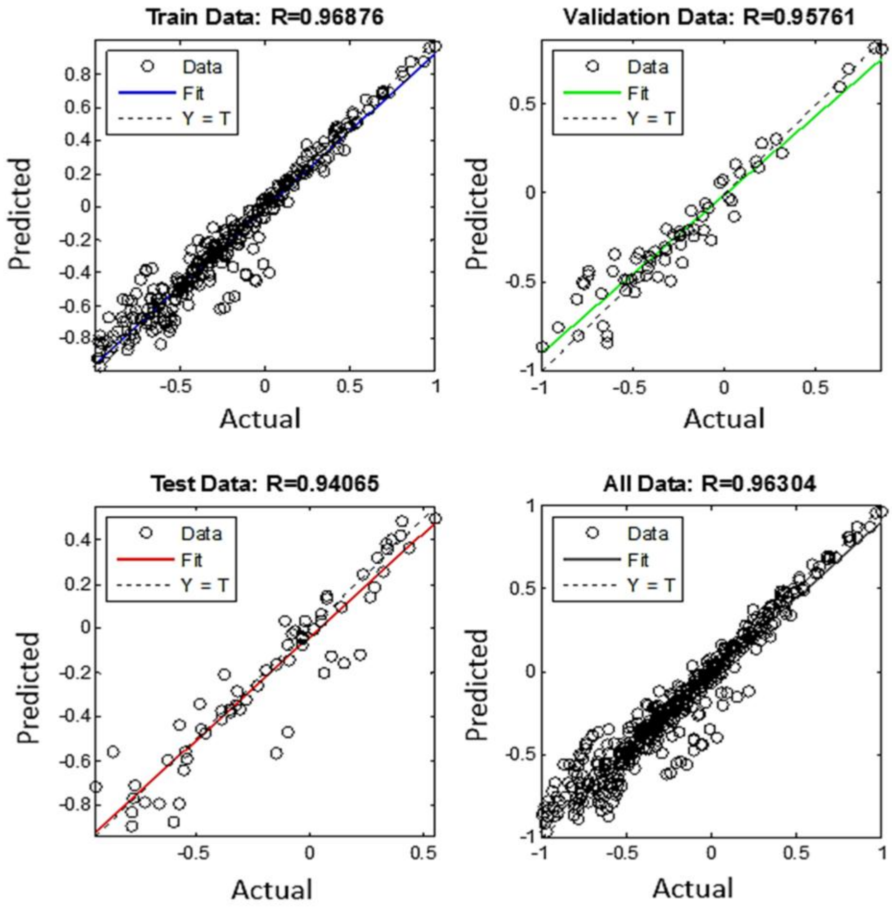

Figure 4 Regression result of the best ANN for AFC by Levenberg-Marquardt training algorithm

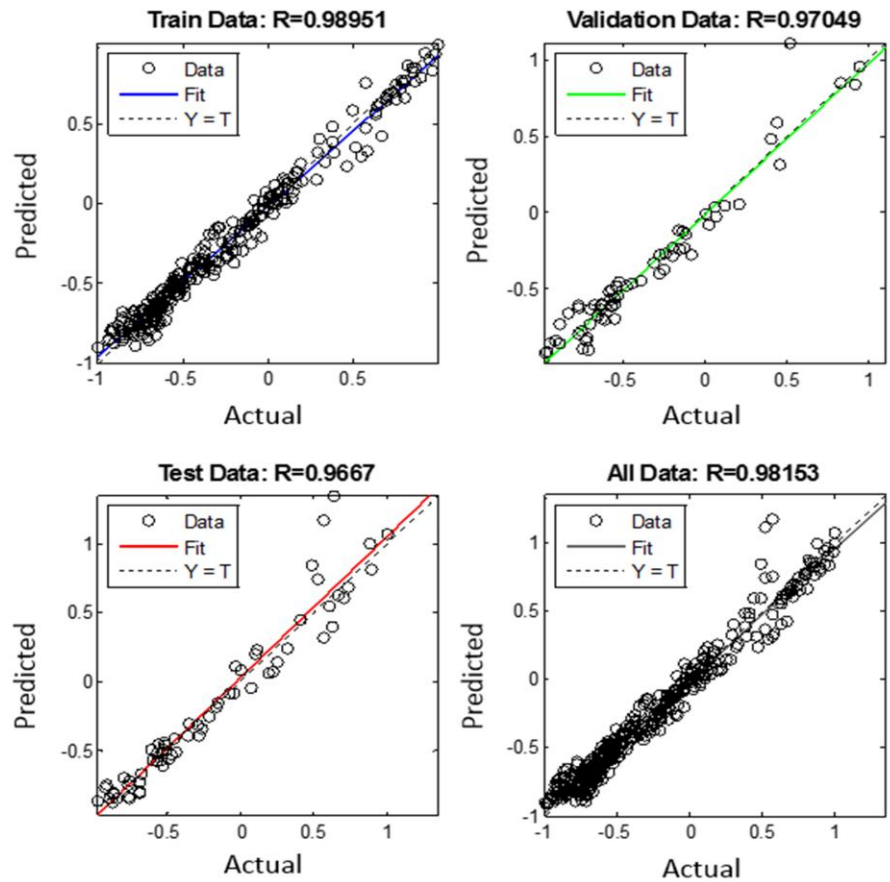

Figure 5 Output of 6-10-1 structure model for SFC using Levenberg-Marquardt training algorithm

3.3 Rolling resistance

As shown in Table 8, among adopted models, the ANNs with Bayesian regulation and Levenberg-Marquardt training algorithms had the best results. But Levenberg-Marquardt algorithm yield the least error (MSE= 0.000783) and reached to the minimum error at epoch 88, faster than Bayesian regulation (Epoch 96). Figure 6 illustrates the result of 6-10-1 structured analysis. The inconsiderable difference between the predicted and actual values corroborated the reliability of the network in predicting the rolling resistance. Taghavifar et al. (2013) reported the same results. They adopted a 3-10-1 feed-forward Artificial Neural Network (ANN) with back propagation (BP) learning algorithm to estimate the rolling resistance of wheel as affected by velocity, tire inflation pressure, and normal load acting on wheel inside the soil bin facility creating controlled condition for test run. The model represented MSE of 0.0257 and predicted relative error values with less than 10% and high R^2 equal to 0.9322 utilizing experimental output data obtained from single-wheel tester of soil bin facility.

Table 8 Different ANN structures for rolling resistance prediction

Training algorithm	Optimum topology	Epochs	MSE	R^2
Trainlm	6-10-1	88	0.000783	0.928
Trainbr	6-8-1	99	0.000880	0.940
Trainrp	6-7-1	96	0.001153	0.988
Trainscg	6-9-1	78	0.001200	0.913
Traingda	6-1-1	100	0.003740	0.947
Traingdx	6-1-1	79	0.004436	0.943
Traingdm	6-1-1	100	0.028810	0.894

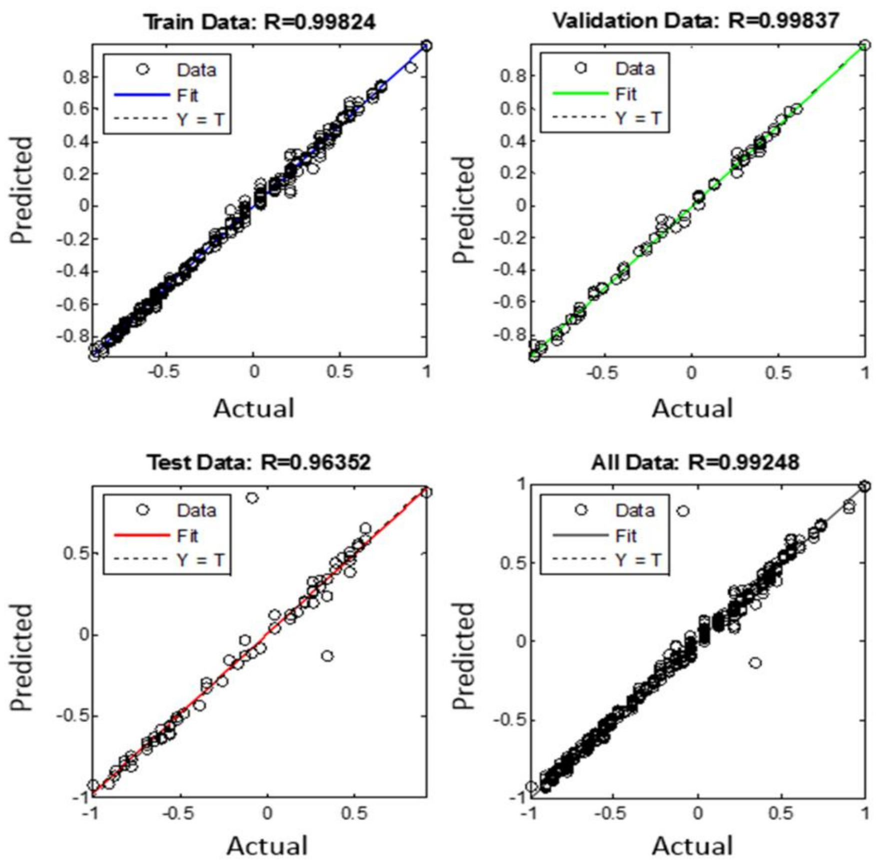

Figure 6 Result of regression analysis for rolling resistance predictor based 6-10-1 structure and Levenberg-Marquardt training algorithm

3.4 Tractive efficiency (TE)

To predict TE parameter of the tractor, ANNs with different topology and training algorithms were adapted. The obtained result showed that the 6-7-1 structured ANN with Levenberg-Marquardt training algorithm represents a good prediction of TE with R^2 equal to 0.989 and MSE of 0.001327 (Table 9). Figure 7 presents result of regression analysis for TE. The small variation between the predicted and measured values confirmed the reliability of the network in predicting the tractive efficiency. The similar result was reported by Taghavifar and Mardani (2014). They used neuro-fuzzy inference system (ANFIS) for TE prediction of agricultural tractor driving wheel. The input parameters were wheel load, velocity and slippage. They obtained MSE equal to 1.5676 and R^2 equal to 0.97 for TE. Çarman and Taner (2012) developed an ANN model with a back propagation learning algorithm to predict TE of a driver wheel in clay loam soil. They obtained mean relative error and R^2 equal to 1.33% and 0.999, respectively.

Table 9 Different ANN structures for TE

Training algorithm	Optimum topology	Epochs	MSE	R^2
Trainlm	6-7-1	18	0.001327	0.989
Trainbr	6-8-1	67	0.001580	0.964
Trainscg	6-5-1	98	0.003007	0.974
Trainrp	6-10-1	86	0.004411	0.962
Traingda	6-2-1	91	0.007423	0.953
Traingdx	6-8-1	100	0.009905	0.950
Traingdm	6-8-1	100	0.031309	0.774

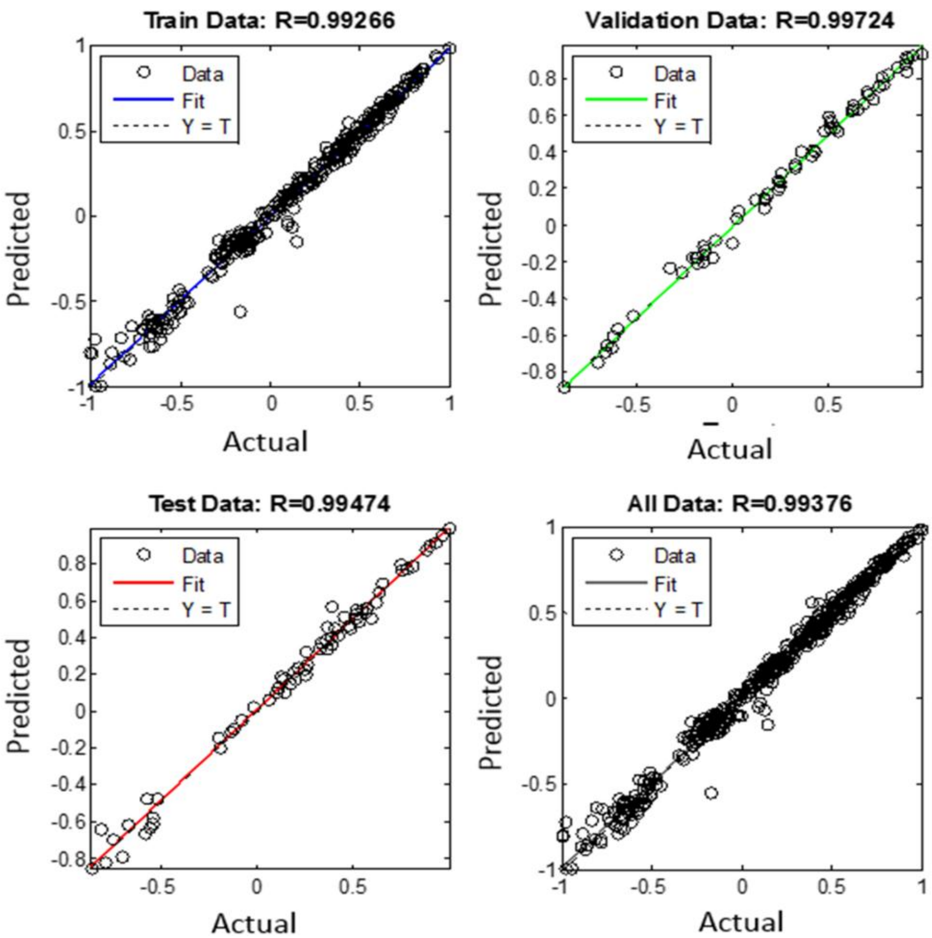

Figure 7 Regression result in TE prediction using 6-7-1 structured ANN model

4 Conclusion

This research represents ANN models for predicting tractor performance parameters. Back propagation neural networks with different training algorithms were examined. On the basis of statistical performance criteria of MSE and R^2, it was found that for drawbar power the ANN with Bayesian regulation training algorithm showed the best prediction power and for TFC, AFC SFC rolling resistance and TE, the ANNs with Levenberg–Marquardt training algorithm represented the best results. The obtained results confirmed that the neural network can be able to learn the relationships between the input variables and performance parameters of tractor, very well. Eventually, it can be claim that the ANN models can be suggested to predict performance of tractor because of fast, accurate and reliable results, effectively.

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References

ElWahed, A. and M. Aboukarima. 2007. Draft models of chisel plow based on simulation using artificial neural networks. *Misr Journal of Agricultural Engineering*, 24(1):42-61.

Aghbashlo, M., H. Mobli, S. Rafiee, and A. Madadlou. 2012 The use of artificial neural network to predict exegetic performance of a spray drying process: a preliminary study. *Computers & Electronics in Agriculture*, 88(2):32-43.

Arriagada, J., P. Olausson, and A. Selimovic. 2002 Artificial neural network simulator for SOFC performance prediction. *Journal of Power Sources*, 112(1):54-60.

Bietresato, M., A. Calcante, and, F. Mazzetto. 2015. A neural network approach for indirectly estimating farm tractors engine performances. *Fuel*, 143(2015):144-154.

Cakmak, G., and C. Yıldız. 2011. The prediction of seedy grape drying rate using a neural network method. *Computers & Electronics in Agriculture*, 75(1):132-138.

Carman, K. 2008. Prediction of soil compaction under pneumatic tires a using fuzzy logic approach. *Journal of Terramechanics*, 45(4):103-108.

Çarman, K., and A. Taner. 2012. Prediction of tire tractive performance by using artificial neural networks. *Mathematical and Computational Applications*, 17(3):182-192.

Çay, Y., I, Korkmaz, A, Çiçek, and F. Kara. 2013. Prediction of engine performance and exhaust emissions for gasoline and methanol using artificial neural network. *Energy*, 50(1):177-186.

Demuth, H., and M. Beale. 1998. Neural Network Toolbox for Use with Matlab the Mathworks Inc. January 1998.

Douik, A., and M. Abdellaoui. 2008. Cereal varieties classification using wavelet techniques combined to multi-layer neural networks. 16th Mediterranean Conference on Control and Automation, France, 1822-1827

Ekinci, S., K. Çarman, and H. Kahramanlı. 2015. Investigation and modeling of the tractive performance of radial tires Using off-road vehicles. *Energy*, 93:1953-1963.

Grisso, R. D., D. H. Vaughan, and G. T. Roberson. 2008. Fuel prediction for specific tractor models. *Applied Eng. Agric.*, 24(2008):423-428.

Kashaninejad, M., A. A. Dehghani, and M. Kashiri. 2009. Modeling of wheat soaking using two artificial neural networks (MLP and RBF) *Journal of Food Engineering*, 91(4):602-607.

Khoshnevisan, B., S. Rafiee, M. Omid, M. Yousefi, and M. Movahedi. 2013. Modeling of energy consumption and GHG (greenhouse gas) emissions in wheat production in Esfahan province of Iran using artificial neural networks. *Energy*, 52(1):333-338.

Nayak, P. C., K. P. Sudheer, D. M. Ragan, and K. S. Ramasastri, 2004. A neuro fuzzy computing technique for modeling hydrological time series. *Journal of Hydrology*, 29(1-2):52-66.

Rahimi, A. F., and G. Y. Abbaspour. 2011. Artificial neural network and stepwise multiple range regression methods for prediction of tractor fuel consumption. *Measurement*, 44(10):2104-2111.

Roul, A. K., H. Raheman, M. S. Pansare, and R. Machavaram. 2009. Predicting the draught requirement of tillage implements in sandy clay loam soil using an artificial neural network. *Biosystems Engineering*, 104(4):476-485.

Safa, M., S. Samarasinghe, and M. Mohsen, 2009. Modeling fuel consumption in wheat production using neural networks. In: Proceedings of the 18th world IMACS/MODSIM Congress, Australia; July 2009. Pp. 775-781

Safa, M., and S. Samarasinghe. 2013. Modelling fuel consumption in wheat production using artificial neural networks. *Energy*, 49(1):337-343.

Taghavifar, H., and A. Mardani. 2014. On the modeling of energy efficiency indices of agricultural tractor driving wheels applying adaptive neuro-fuzzy inference system. *Journal of Terramechanics*, 56:37-47.

Taghavifar, H., A. Mardani, H. Karim-Maslak, andH. Kalbkhani. 2013. Artificial Neural Network estimation of wheel rolling resistance in clay loam soil. *Applied Soft Computing*, 13(8):3544-3551.

Young, J. S., Y. P. Lin, and P. W. Shih. 2013. Neural network approach to gain scheduling for traction control of electrical vehicles. *Applied Mechanics and Materials*, 392:272-276.

Zarifneshat, S., A. Rohani, H. R. Ghassemzadeh, M. Sadeghi, E. Ahmadi, and M. Zarifneshat. 2012. Predictions of apple bruise volume using artificial neural network. *Computers & Electronics in Agriculture*, 82(1):75-86.