Modeling of tractive performance of Massey Ferguson tractor (MF 285) in different field conditions using artificial neural networks

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Abstract

Implementation of tractors in agriculture is Substantial as a power supply. Therefore, performance model for developing parameters of tractors and implements are major 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, 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 a 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 R^2 of 0.995 and MSE of 0.00024. The obtained result showed that the 6-7-1structred ANN with Levenberg-Marquardt training algorithm represents a good prediction of TE with R^2 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.

Introduction

The great increase in agricultural productivity over the last century can be related to mechanization, particularly the development of the tractor. 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. By properly understanding how the tractor power can be used, 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 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 indifferent 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(Arriagadaet 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 exergetic performance of a spray drying process. They were concluded that the MLP (multilayer perceptron) ANN approach for exergetic 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 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. Ekinci et al. (2015) used ANNs and two types of Support Vector Machine Regression (SVM) 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, rolling resistance and tractive efficiency.

Materials and methods

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 speed, 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 content 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.

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 (rpm)	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. The input parameters used in experiments

Moisture content	Depth(cm)	Inflation pressure (kPa)	Engine speed(Rp	Cone index(kPa)	Gear

(%)			m)		
6	10	50	1200	100	1
23	15	100	1600	160	2
	20	150	2000	930	3
				1160	4

Table 3. Measured velocity (m/sec)

Engine speed (rpm)	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

Calculation of parameters

Drawbar power

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

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

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

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-C3-3.0t-6B-D55 from Zemic with capacity of 30kN) mounted between two tractors. The first one was a Massey Fergusson 285 as puller and another one was Massey Fergusson 165 as towed. The force exerted by the implement was measured by a strain gauge Wheatstone bridge arrangement. The load cell was calibrated by means of a hydraulic loading calibration device (Model INSTRON).

Tractive Efficiency

Tractive efficiency (TE) is defined as; ability to transfer power from the axle to the drawbar through the tire and soil. TE depends on slip (set by ballast), soil conditions, tires and drive configurations and is calculated using Eq. 6:

$$TE = \left(\frac{output \quad power}{input \quad power}\right) \times 100 = \left(\frac{drawbar \quad power}{axele \quad power}\right) \times 100 \qquad (2)$$

ANN model design

In this study, to predict performance parameters, ANN models with back-propagation algorithm were developed using a 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 includes: 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) andLevenberg-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, rolling resistance and TE. The schematic architecture of the used ANN is shown in Fig.1.

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 that shows the normal difference of real data from the estimated data. The expressions for these statistical measures are given below:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(x_i - \hat{x}_i)^2 \tag{3}$$

$$R^2 = \frac{[\sum_{i=1}^{N}(\hat{x}_i - \bar{\hat{x}})(x_i - \bar{x})]^2}{[\sum_{i=1}^{N}(\hat{x}_i - \bar{\hat{x}})^2 \times \sum_{i=1}^{N}(x_i - \bar{x})^2} \tag{4}$$

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 by the model (predicted), and $\bar{x}$ is the mean value of the variable.

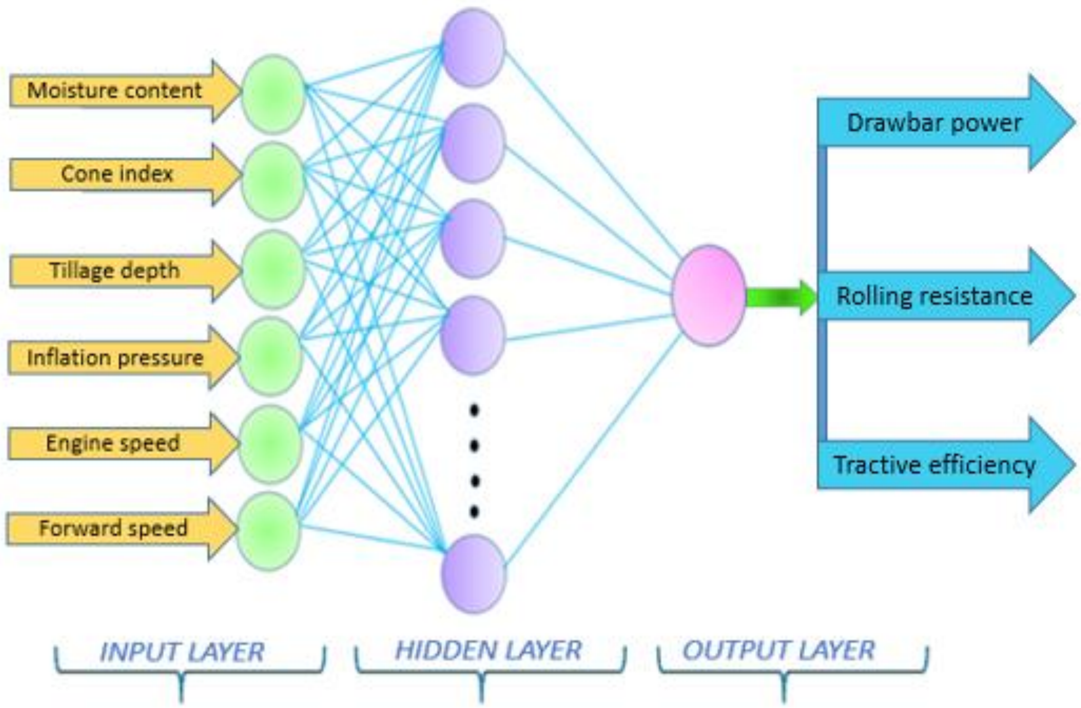

Fig.1. Schematic architecture of the used ANN

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.

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. Fig. 2 shows regression result of 6-7-1 ANN model in training, validation and test mode. The results are in agreement with result of Abd ElWahedand 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

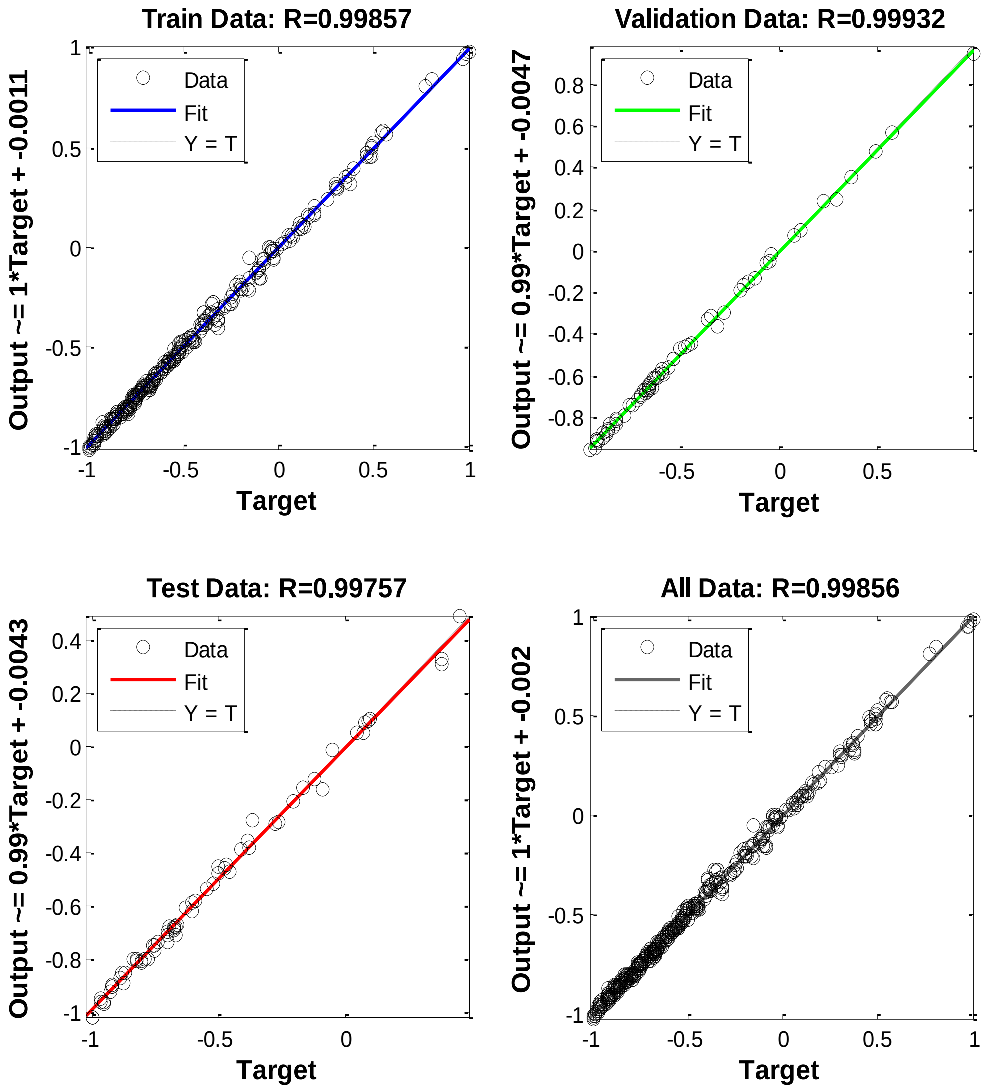

Fig.2. Output of the best ANN model for drawbar power prediction using Bayesian regulation training algorithm.

Rolling resistance

As shown in Table 5, 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= 0000783) and reached to the minimum error at epoch 88, faster than Bayesian regulation (Epoch 96). Fig. 3 illustrates result of 6-10-1 structured analysis. 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 highR^2 equal to 0.9322 utilizing experimental output data obtained from single-wheel tester of soil bin facility.

Table 5. 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

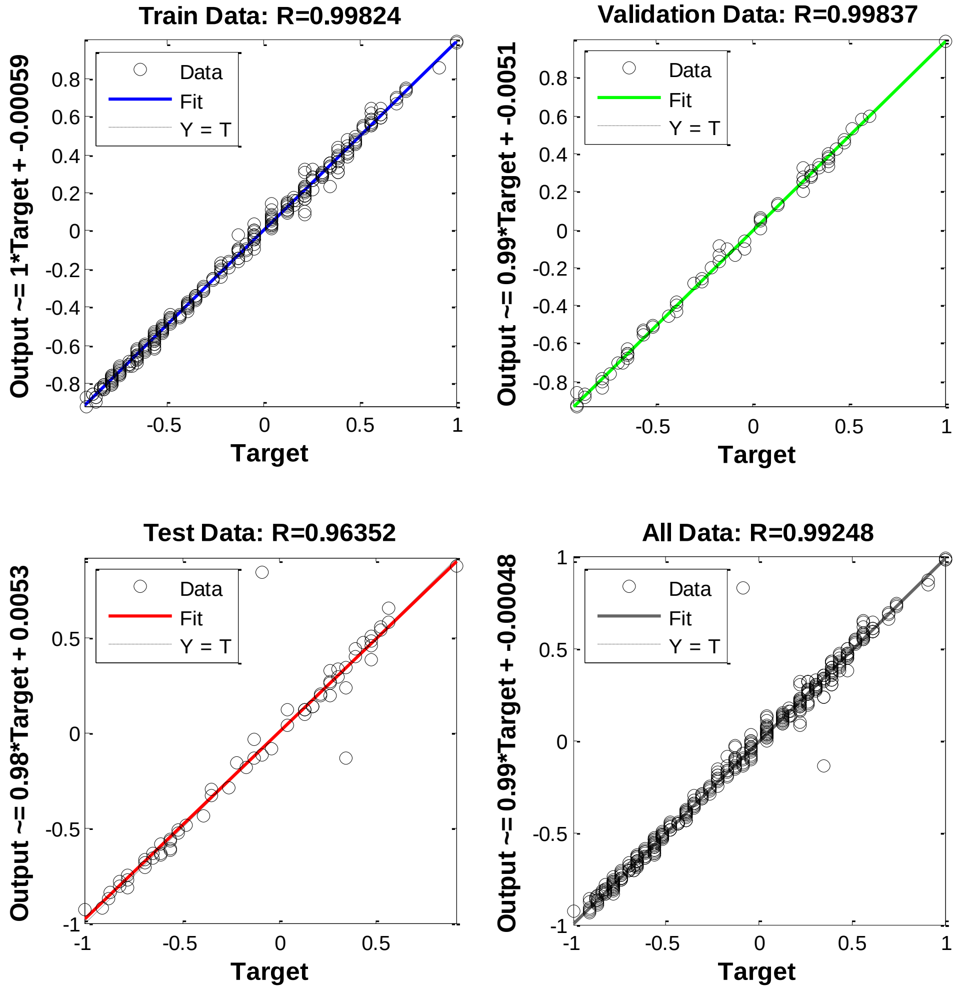

Fig.3. Result of regression analysis for rolling resistance predictor based 6-10-1 structure and Levenberg-Marquardt training algorithm

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 6-7-1structred 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 6). Fig. 4 presents result of regression analysis for TE. 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^2equal 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 6. 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

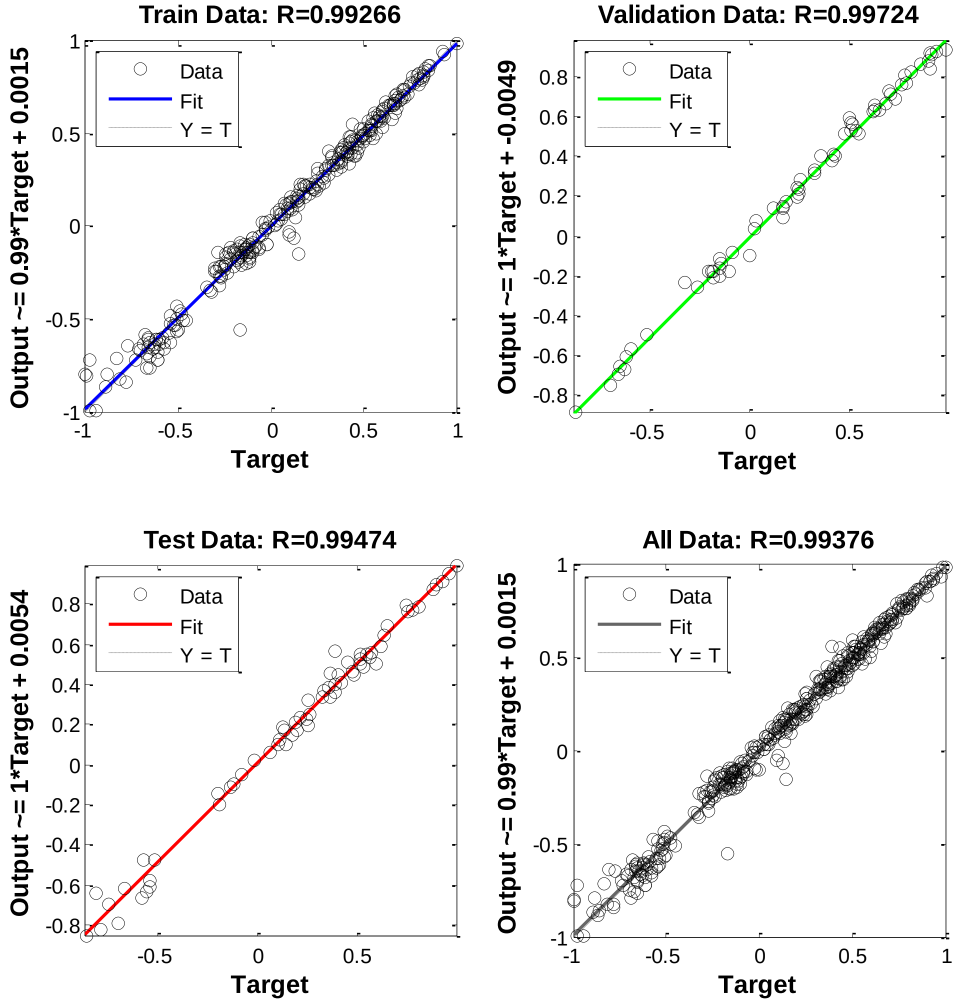

Fig.4. Regression result in TE prediction using 6-7-1 structured ANN model.

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 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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