Prognostication of fuel consumption for Massey Ferguson tractor (MF 285) by artificial neural network based modeling approach.

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

1- PhD student, Department of Agricultural Machinery, University of Basrah, Basrah, Iraq.

2- Faculty member, Department of Agricultural Machinery Engineering, College of Agriculture and Natural Resources, University of Tehran, Karaj, Iran .

* Corresponding author's email: rmardani@ut.ac.ir

Abstract

Due to the ascending significance of energy in the world, prognostication and optimization of Fuel Consumption (FC) in agricultural works is merit to consideration. Therefore, performance model for evolving parameters of tractors and implements are essential for farm machinery, operators and manufacturers alike. A conventional tillage system which included a moldboard plow with three furrows was used for collecting data from MF285 Massey Ferguson tractor. Field experiments were carried out in the experimental farm of Agricultural Engineering Department of Tehran University, Karaj province, Iran, which had loamy soil texture. The objective of this study was to assess the predictive capability of several configurations of ANNs for performance evaluating of tractor in parameter of fuel consumption. To predict performance parameters, ANN models with back-propagation algorithm were developed using a MATLAB software with different topologies and training algorithms. 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. 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. The obtained results promoted that the neural network can be able to learn the relationships between the input variables and fuel consumption of tractor, reliable.

Keywords: TFC, AFC, SFC, Artificial neural network.

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Introduction

Off-road vehicles especially agricultural wheeled machines are of major sources of energy consumption due to their massive size and complex soil-wheel interaction that forms stochastic tire deflection and soil deformation (Taghavifar and Mardani, 2013). Fuel consumption (FC) is directly related to the energy requirements of agricultural tasks and may be reduced by properly understanding of how the tractor power is distributed. An improvement in tractor performance will result in a diminished amount of depleted fuel for a certain operation and thereby leads to both environmental and financial benefits. Ability to anticipate the performance of tractors during field operations has been of great interest to scientists, manufacturers, and users in order to optimize the total operation (Grisso et al., 2006). Hence predicting tractor FC can lead to more appropriate decisions on tractor management. Several studies have been developed for predicting FC in diverse sections in agricultural operations which uses power like draught, tillage implements, tire resistance and etc. (Al-Janobi, 2000; Sahu and Raheman, 2006; Serrano et al., 2003, 2007).

The modeling techniques used in mechanization processes are quite important to provide an accurate and sustainable use of power resources. In recent years Artificial Neural Network approach has demonstrate to be effective as an exciting alternative method concerning complex system. Since agricultural systems and technologies are quite complex and uncertain, several researchers focused on neural network method for modeling of different component of agricultural systems (Zarifneshat et al., 2012; Çay et al., 2013; Khoshnevisan et al., 2013; Young et al., 2013; Safa and Samarasinghe, 2013). 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). 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. Taghavifar and Mardani (2014) used a feed-forward ANN (artificial neural network) with standard BP (back propagation) algorithm to construct a supervised representation to predict the energy efficiency indices of driven wheels. It was deduced, in view of the statistical performance criteria (i.e. MSE (mean squared error) and R^2), that a supervised ANN with 3-8-10-2 topology and Levenberg-Marquardt training algorithm represented the optimal model.

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. Çay et al. (2013) investigated the use of ANN (artificial neural networks) modeling to predict break specific fuel consumption, exhaust emissions that are carbon monoxide and unburned hydrocarbon, and air fuel ratio of a spark ignition engine which operates with methanol and gasoline. Quasi-Newton back propagation (BFGS) and LM algorithms were used for modeling.

The aim of this study was to assess the predictive capability of several configurations of ANNs for performance evaluation of tractor in fuel consumption.

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 (rpm)	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/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

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 expression 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:

$$TFC = \frac{fc}{T} \tag{1}$$

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:

$$AFC = \frac{10 \times TFC}{V_a \times W} \tag{2}$$

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:

$$SFC = \frac{TFC}{P_{db}} \tag{3}$$

where P_{db} is drawbar power (kW)

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

$$P_{db} = NT \times V_a \tag{4}$$

NT is net traction (kN) and V_a is actual velocity (m/sec).

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 was conducted against known loads by a hydraulic loading device from INSTRON (Model 4486).

ANN model design

In this research to predict fuel consumption of tractor Massey Ferguson 285, the ANN model with back-propagation algorithm has been 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 available data are usually divided into three randomly selected subsets which include: (I) 70% of the dataset for training, (II) 15% for model validation and (III) 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 the number of hidden layers and also the 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 the networks performance. Also, the functions of tangent hyperbolic conversion, sigmoid and linear motion function among layers were used. The ANN system applied for these prediction models have six inputs and a single output. These inputs were tillage depth, forward speed, engine speed, tire inflation pressure, moisture content and cone index. The outputs of each model was temporal fuel consumption, area-specific fuel consumption and specific fuel consumption. 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.

$$xn = 2\frac{xr - xr,min}{xr,max - xr,min} - 1 \quad (5)$$

Where xn denotes normalized input variable, xr is the raw input variable, and xr, min and xr, max denote the minimum and maximum of the input variable.

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:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(x_i - \hat{x}_i)^2 \quad (6)$$

$$R^2 = \frac{[\sum_{i=1}^{N}(\hat{x}_i - \bar{\hat{x}})(x_i - \bar{x})]^2}{[\sum_{i=1}^{N}(\hat{x}_i - \bar{\hat{x}})^2 \times \sum_{i=1}^{N}(x_i - \bar{x})^2} \quad (7)$$

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

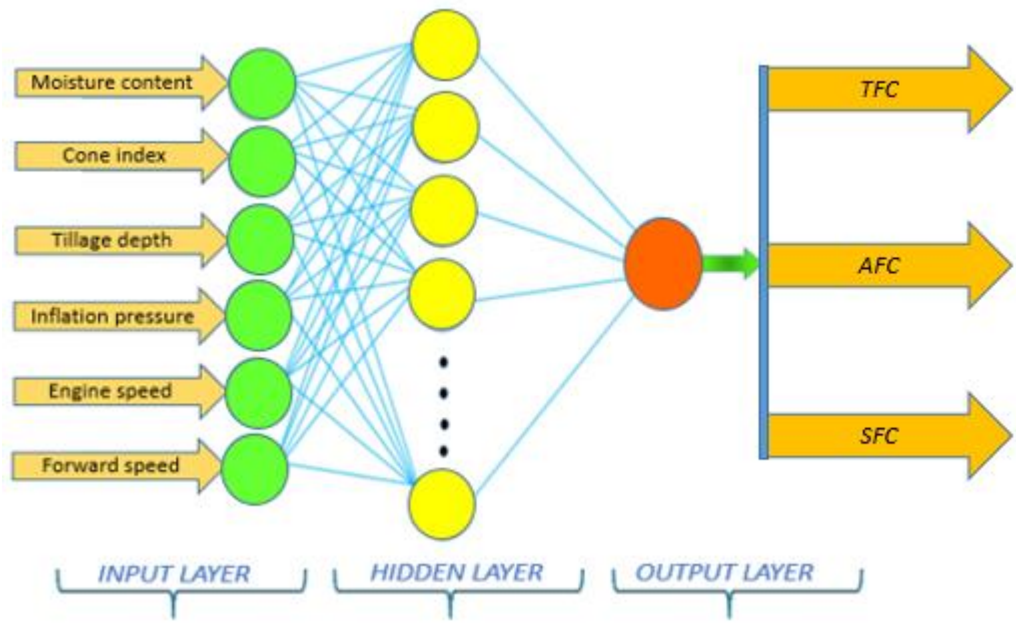

Fig. 1. Schematic architecture of the used ANN

Results and discussion

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

Fuel consumption

Three parameters of TFC, AFC and SFC were modeled using ANNs. Table 4 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 5 and Table 6). 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. Fig. 2, Fig. 3 and Fig. 4 show results of regression analysis for TFC, AFC and SFC, respectively. 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 4. 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	-	-	-

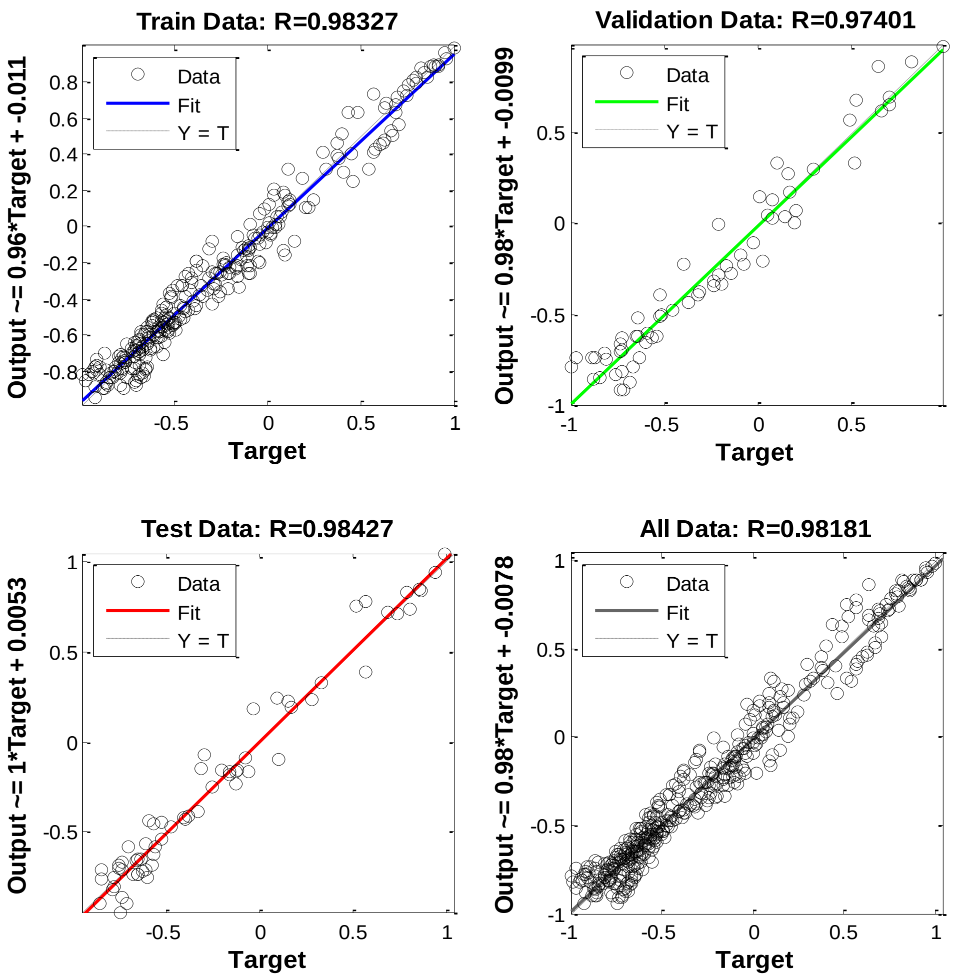

Fig. 2. Regression result of developed ANN for TFC parameter using Levenberg-Marquardt training algorithm.

Table 5. 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

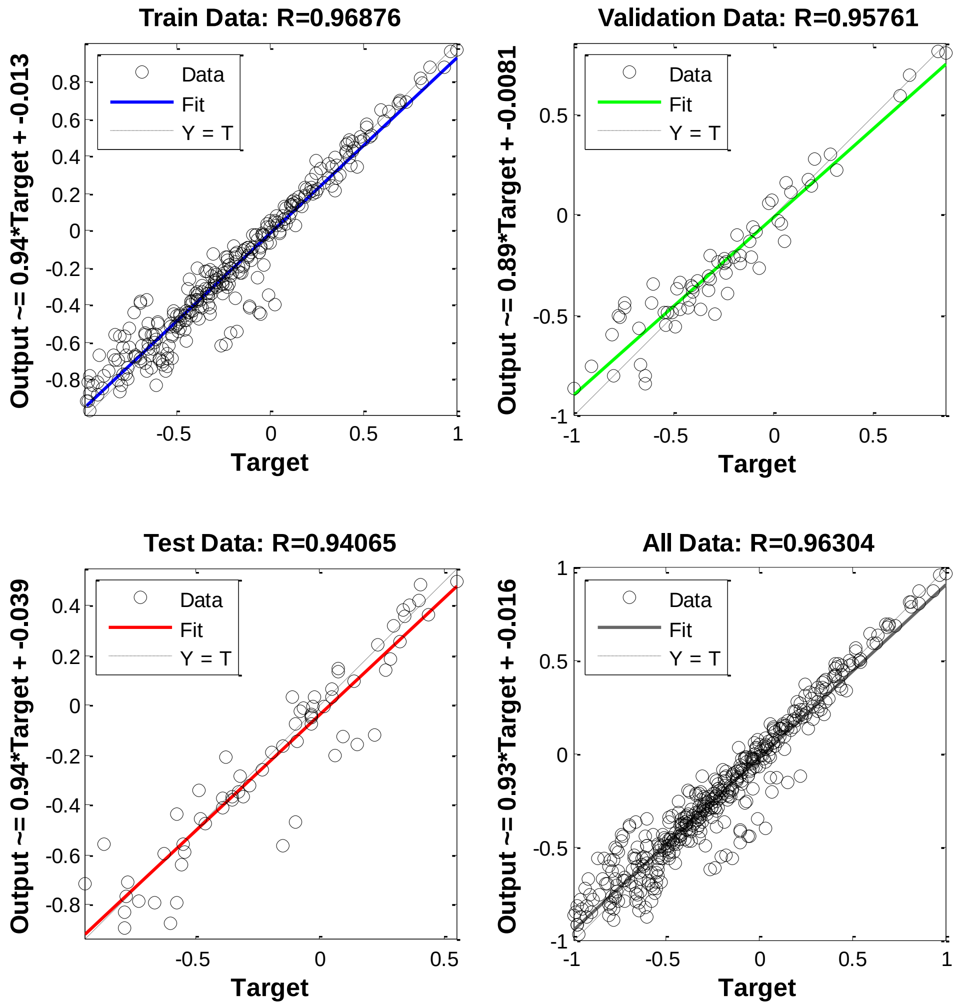

Fig. 3. Regression result of the best ANN for AFC by Levenberg-Marquardt training algorithm

Table 6. 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	-	-	-

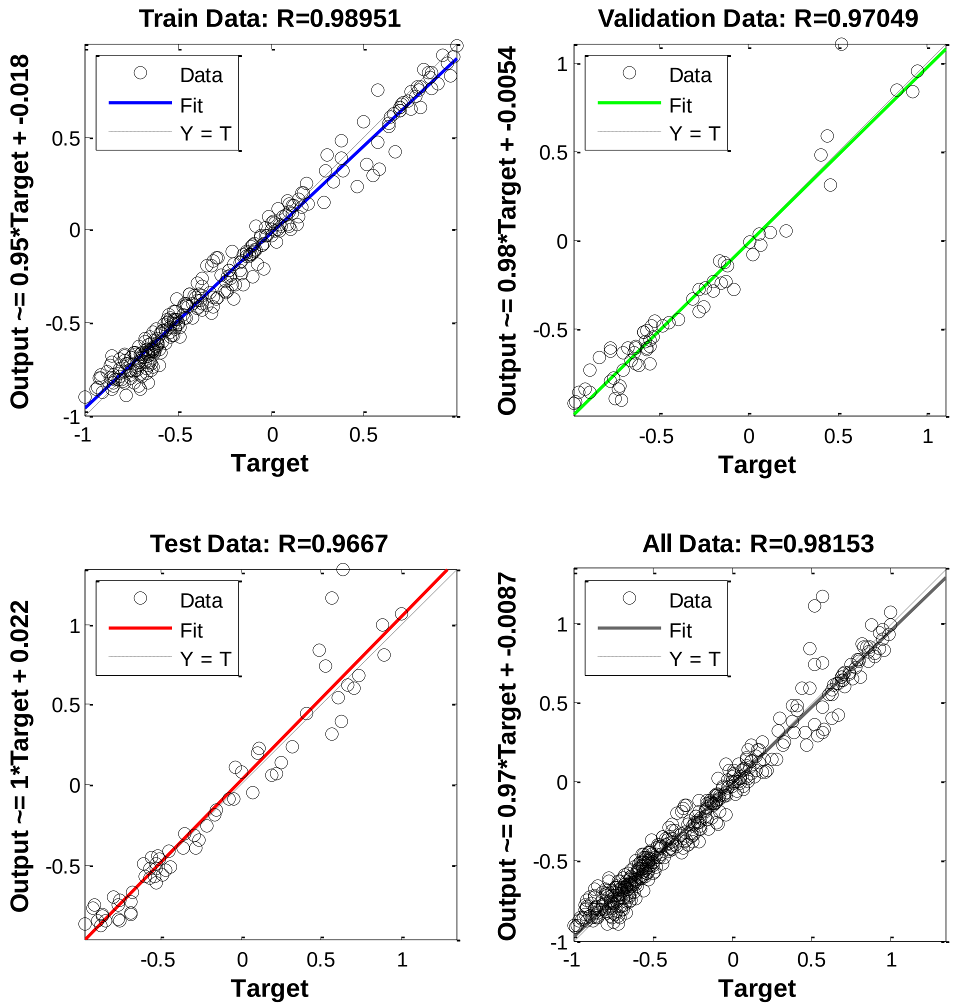

Fig. 4. Output of 6-10-1 structure model for SFC using Levenberg-Marquardt training algorithm

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 for TFC, AFC and SFC, 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 fuel consumption of tractor because of fast, accurate and reliable results, effectively.

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