Simulation of draft force of winged share tillage tool using artificial neural network model

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Abstract: An artificial neural network (ANN) model, with a back propagation learning algorithm, was developed to predict draft requirements of two winged share tillage tools in a loam soil. The input parameters to the 3–7–1 ANN model were; share width, working depth and operating speed. The output from the network was the draft requirement of each tillage tool. The developed model predicted the draft requirements of the winged share tillage tools with a mean relative error of 0.56 and mean square errors of 0.049, when compared to measured draft values. This result indicates that the ANN model had successfully learnt from the training data set to enable correct interpolation and could be used as an alternative tool for modeling soil-tool interaction under specific experimental conditions and soil types.

Keywords: artificial neural network; soil-tool interaction; share width; working depth; operating speed; draft

Citation: Akbarnia, A., A. Mohammadi , F. Farhani, and R. Alimardani. 2014. Simulation of draft force of winged share tillage tool using artificial neural network model. Agric Eng Int: CIGR Journal, 16(4): 57-65.

1 Introduction

The draft of tillage implements plays an effective role in design of more efficient tillage tools. The knowledge of traction performance of tillage implements is an important factor when matching suitable tillage implements for a particular field condition. However, collecting draft data under various field conditions is an expensive and time¬consuming work. Thus, prediction of tillage tools forces is of importance to designers and operators of cultivation equipment to achieve the best results when implementing size matching of the tractor power.

Accepted date: 2014-09-01 **Received date:** 2014-11-05

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The effects of design parameters such as geometric shape and working parameters of implements on soil-tool interaction have been studied by researchers using empirical and semi-empirical methods (Desbiolles et al., 1997; Desbiolles et al., 1999; Desbiolles and Godwin, 2000; Hettiaratchi, 1997; Kheiralla et al., 2004; O'Dogherty et al., 1996; Wheeler and Godwin, 1996).

Agricultural systems, such as soil-tool interaction, consist of several variables and often unknown properties, and hence, they can be considered as ill-defined systems. Prediction and simulation of agricultural systems using traditional analytical methods is quite difficult because of the existence of complex and uncertain situations, time varying parameters and many unknown factors. Thus, modeling of soil-tillage tool relationship requires the use of a more effective approach compared to traditional methods. Under variable conditions of soil, a learning algorithm such as a neural network may succeed in simulating the behavior of soil-tillage tool interaction.

In recent years, Some researchers have used various techniques in artificial intelligence (AI) methods such as artificial neural networks(ANNs) in order to predict the effects of some input parameters (for example operating depth and speed of tillage tool) on output parameters (for example draft and vertical force of tillage tool) to evaluate soil-machine or soil-tillage tool interactions. Zhang and Kushwaha (1999) used a Radial Basis Function (RBF) neural network to predict draft requirements of narrow blades using operating speed, tools and soil types as input parameters. They reported that the developed neural network model had good ability for the draft prediction within the range of input parameters. Choi et al. (2000) developed a time lagged recurrent neural network (TLRNN) to predict dynamic draft of three kinds of tillage tools using tool shapes, shearing force and cone index of soil as input parameters. They concluded that an ANN model could be a promising modeling approach for simulating dynamic draft. Al-Janobi et al. (2001) developed a multi-layer perceptron (MLP) network with error back propagation (BP) learning algorithm to predict specific draft of a chisel plow, an offset disc harrow, a mouldboard plow and a disc plow using soil properties, tillage implements, plowing depths and forward operating speeds as input parameters and the specific draft as output parameter. They used a 4–24–12-1 ANN model with a sigmoid transfer functions in hidden layers. Their results showed that the variation of the measured and the specific draft was small with a correlation coefficient of 0.987 and the MSE between measured and predicted specific draft was 0.1445. Alimardani et al. (2009) developed a prediction model based on a MLP network with BP learning algorithm and gradient descent with momentum, Lavenberg-Marquardt and scaled conjugated gradient training algorithms using travel speed of tractor, tillage depth, soil parameters and physical properties (percentage of sand and clay, soil electrical conductivity, soil moisture content, cone index) as input parameters in order to predict draft force and tillage energy. They reported that the Lavenberg-Marquardt algorithm, with a high accuracy of prediction (95.8%) and more accurate simulation (97.6%), was the best algorithm. They reported a correlation coefficient (R2) of 0.996 in network training and a correlation coefficient of 0.987 in network testing between actual data and obtained data from ANN.

Artificial neural networks (ANNs) are computational tools that have found extensive application in simulating agricultural systems such as soil-tool interaction. They are information processing systems whose structure and functionality are modeled after the nervous system, especially the brain. An artificial neural network consists of three categories of layers: namely input, hidden, and output layers. The three layers are linked through connections whose weights are modified during training to minimize the error between the network output and the actual output. The trained network can then make decisions, perform mapping association, or generalize within the range of the input variables. One of the main advantages of ANNs compared to traditional methods lies in their ability to specify relation between non-uniform input variables and an output variable in uncertain dynamic processes.

The main objective of the present study was to develop an artificial neural network model (ANN), with a back propagation learning algorithm, to predict draft requirements of two winged share tillage tools in a loam soil. The input parameters to the 3–7–1 ANN model were; share width, working depth and operating speed. The output from the network was the draft requirement of each tillage tool. The predicted draft requirements of the winged share tillage tools were compared with measured draft values to validate the developed ANN model.

2 Materials and methods

2.1 Experiments

Two winged share tillage tools were used in this study. They consisted of a leg, with a chisel at the bottom, wings attached to both sides of the leg and two flanges for linking tillage tool to implement toolbar. To test the potential use of neural network for the draft force prediction, the input variables included widths of 440 mm and 660 mm, working depths of 150, 200, 250 and 300 mm and working speeds of 1.5 m s^{-1}, 3 m s^{-1} and 6 m s^{-1}. These variables were used to predict the draft force requirement of winged share tillage tool as the output variable.

An overview of the winged share used in this study is shown in Figure 1. The geometrical specifications of the winged shares are given in Table 1.

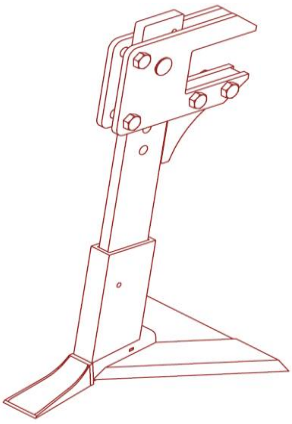

Figure 1 Winged share with leading chisel

Table 1 Geometrical specification of winged share tillage tools

	Narrow share	Wide share
Wing width	440 mm	660 mm
Chisel width	50 mm	60 mm
Wing rake angle	40 degree	40 degree
Chisel rake angle	30 degree	30 degree
Leg height	600 mm	650 mm
Leg width	20 mm	30 mm

Experiments were conducted using facilities at *Soil Dynamics Laboratory*, Agricultural Engineering Research Institute (AERI), Karaj, Iran. The facilities consist of an indoor soil bin of 27 m length, 1.7 m width and 1 m depth, a soil processing trolley with a leveling blade and compaction roller, a power transmission system and force measuring equipment.

The soil bin was filled with a 1 m thick layer of loam soil according to the USDA soil textural classification as shown in Figure 2.

Figure 2 Soil bin facility filled with a 1 m thick layer of loam soil

The soil processing trolley was used for processing and compacting soil in order to achieve uniform soil condition as desired for test-run throughout the soil bed. Before each test-run, three random soil samples (diameter 50 mm, length 50 mm) were taken for measuring initial soil moisture content and dry bulk density at 4 depth ranges (150, 200, 250 and 300 mm) based on working depth and then mean values were calculated. To determine the cohesion and the angle of internal friction of the soil, the direct shear test method was used (McKeys, 1985). Some physical and mechanical properties of soil are shown in Table 2.

In order to determine the draft requirement of the winged shares, a factorial experiment based on completely randomized design (CRD) with four working depths (150, 200, 250 and 300 mm) and three working speeds (1.5 m s^{-1}, 3 m s^{-1} and 6 m s^{-1}) were conducted for two winged share tillage tools (440 and 660 mm). Each treatment was replicated three times. Therefore, a total of 72 ($4\times3\times2\times3$) test-runs were performed. The force measuring equipment included a tillage tool dynamometer (comprising an Extended Octagonal Ring Transducer (EORT)) and a data acquisition system (Godwin, 1975), which was mounted on a tractor (MF 399) as shown in Figure 3.

Table 2 Physical and mechanical properties of loam soil used in this study

Parameter	Mean value
Soil composition	-
Sand (0.05-2.0 mm)	33.28 %
Silt (0.002-0.05 mm)	45.84 %
Clay (<0.002 mm)	20.88 %
Moisture content	13.23 %
Bulk density (db)	1.41 g/cm^3
Cohesion	41 kPa
Angle of internal friction	35 degree
Penetration resistance	1500 kPa

Figure 3 Force measuring equipment used in this study

2.2 ANN Development

For modeling the relations between inputs (namely working depth of winged share, operating speed and share width) and output (draft force), the neural network toolbox from MATLAB 7.10 was used. Input and output parameters determined the number of neurons in the input and output layer of the network, respectively. The number of neurons in the hidden layer was usually set at less than twice the number of neurons in the input layer (Roul et al., 2009). In order to develop the final network for this application, several fully connected architectures were experimented and at last a 3-7-1 ANN model was selected, as it was more accurate in simulating soil-tillage tool interaction. A 3-7-1 network refers to three input nodes, one hidden layer with seven nodes and one output node. The hidden and output layers have a sigmoid transfer function in neural network model and the learning rule was gradient descent. The schematic architecture of the used ANN is shown in Figure 4.

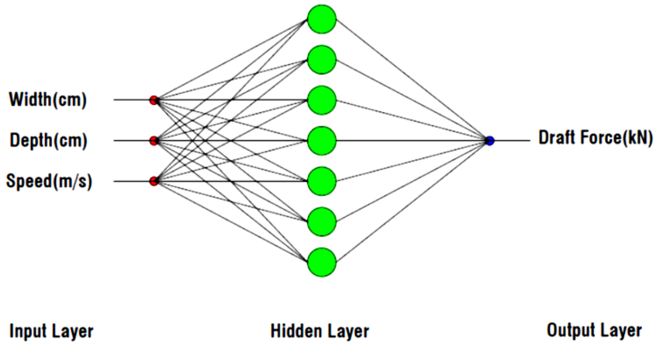

Figure 4 Architecture of the developed ANN for draft force prediction

The output of each neuron is usually a function of the total weighted sum of its inputs, presented by the following relationship (Medsker, 1994).

$$O_{k,i} = \frac{1}{\left(1+e^{\left(-WS_{k,i}+b_{k,i}\right)}\right)};-WS_{k,i} = \sum_{j=1}^{N} W_{(j,i)} O_{(k-1,j)} \tag{1}$$

Where:

$O_{k,i}$= Output of neuron *i* in layer (k)

$O_{k-1,j}$=Output of neuron *j* in layer (k-1)

$b_{k,i}$=A bias term associated with neuron *i* in layer (k)

k=Layer number

i=Node number in layer (k)

j=Node number in layer (k-1)

N=Number of nodes in layer (k-1)

$W_{j,i}$= Weight of the connection between node j in yer (k-1) and node i in layer (k)

$WS_{k,i}$= Weighted sum of inputs for node i in layer (k)

A total of 72 sets of draft data were used in the present study. Out of this, 54 sets (namely 75% of the total data) were used for training the feed-forward BP neural network and 18 sets (namely remained 25% of total data) were used for validation of the developed neural network.

2.3 ANN Validation

After the completion of the training, the final adjusted connection weights were fixed and the model was validated using a new set of data, which was not used during the training. In order to determine ANN prediction accuracy, the relative error (ε) and root mean square of error (MSE) were used as following:

$$\varepsilon\% = \frac{\sum_{i=1}^{n}\left|\frac{(y_p)_i - (y_{ex})_i}{(y_{ex})_i}\right|}{n}\times 100 \tag{2}$$

$$MSE = \frac{\sum_{i=1}^{n}\left((y_p)_i - (y_{ex})_i\right)^2}{n} \tag{3}$$

where n is the number of observations, y_p is the predicted draft and y_{ex} is the measured draft.

3 Results and discussion

The results of analysis of variance (ANOVA), performed to investigate the effects of input parameters on output parameter variation, are shown in Table 3. For each winged share the results showed that working speed, operating depth and share width affected the draft force of share significantly at 5% level of probability ($p < 0.05$). Greater working depths and widths provide more reaction force of soil at the interface. Moreover, higher operating speeds result in increase in the draft force because of increased acceleration of disturbed soil and sliding resistance on tillage tool surface (Spoor, 1969). It has been reported that the draft forces on implements increase significantly with speed and the relationship varies from linear to quadratic (Grisso et al, 1994). Earlier studies show that draft was increased in all implements with increase tillage depth and forward speed (Al-Suhaibani and Al-Janobi, 1997; Taniguchi et al., 1999).

The interaction between the width and depth was also statistically significant at 5% level of probability ($p < 0.05$). Mean values of draft force versus working depth at different levels of other input variables are shown in Figure 5.

The draft force varied from 1.10 to 6.13 kN. The greatest value of draft force was obtained at working depth of 30 cm and working speed of 6 m s^{-1}. A decrease of 33% in share width caused an approximately 43% decrease in the draft force. A plot of the selected ANN training performance in terms of error against epochs is shown in Figure 6.

Table 3 Analysis of variance of the test variables effects on the draft force

Source	Sum of squares	df	Mean square	F	Sig.
Treatment	131.847^{a}	23	5.732	29.420	0.000
Width	52.617	1	52.617	270.041**	0.000
Velocity	7.823	2	3.911	20.074**	0.000
Depth	59.877	3	19.959	102.435**	0.000
Width*velocity	0.262	2	0.131	0.672^{ns}	0.515
Width*depth	9.927	3	3.309	16.983**	0.000
Velocity*depth	0.983	6	0.164	0.841^{ns}	0.545
Width*velocity*depth	0.358	6	0.060	0.306^{ns}	0.931
Error	9.353	48	0.195		
Total	141.199	71			

^{a}: R Squared = 0.934 (Adjusted R Squared = 0.902)

*: significant at 5%

**: significant at 1%

^{ns}: not significant

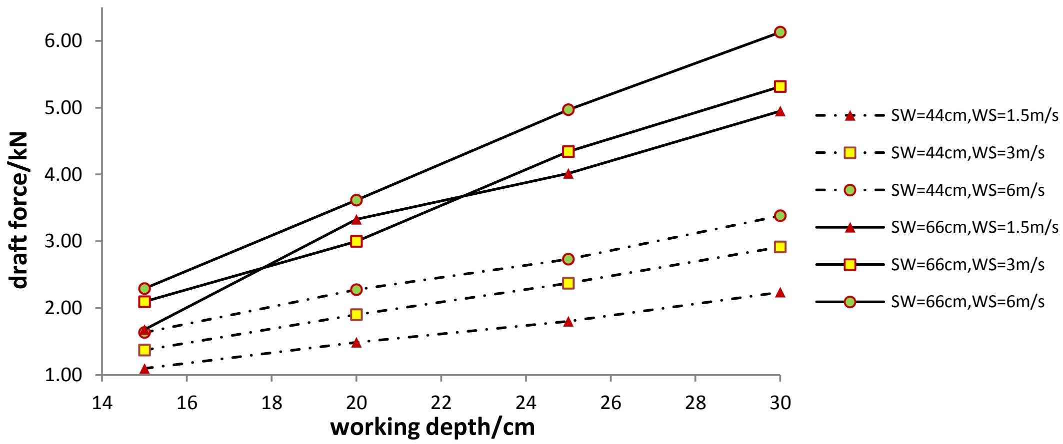

Figure 5 Measured values of draft force versus working depth

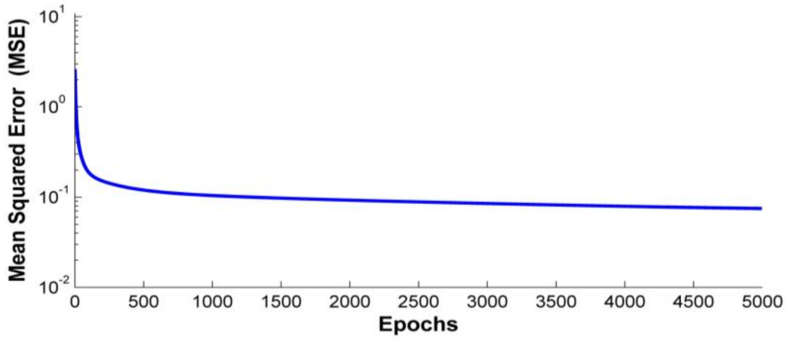

Figure 6 Trend of MSE against epochs for trained networks

The best result was achieved at 5000 epochs, which gave minimum mean squared errors (MSE) equal to 0.078 during the training process.

The results of ANN implementation for prediction of inputs-output relations are shown in Figure 7 and Figure 8 for two winged shares. These surfaces were extracted from the simulation of trained network.

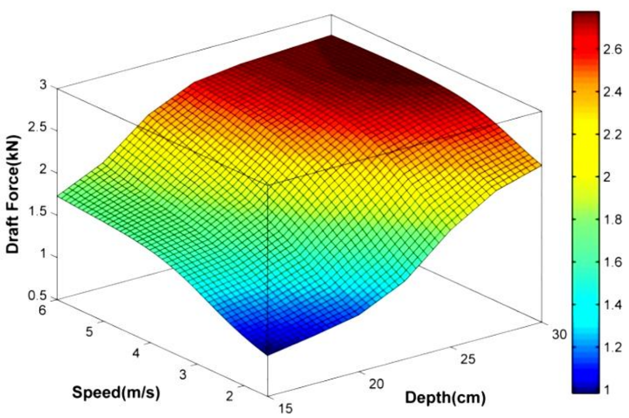

Figure 7 Evaluation surface of ANN for narrow share (44 cm)

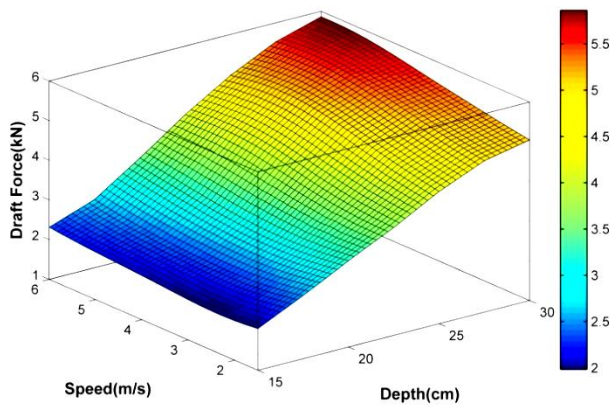

Figure 8 Evaluation surface of ANN for wide share (66 cm)

According to the ANN simulation, the effect of working depth on draft force variation was more significant than operating speed for two winged shares as shown in Figure 7 and Figure 8. After training the ANN model using train data set and according to levels of input parameters, correlation analysis was done between measured and predicted values of draft force for train and all data sets. As shown in Figure 9 and Figure 10 the variation of the measured and the predicted draft force was small with a correlation coefficient of 0.98 and 0.95, respectively, for train and all data sets. The mean relative error and mean squared errors between measured and predicted values were 6.56% and 0.049, respectively. These results indicate that the ANN model had successfully learnt from the training data set to enable correct interpolation.

Al-Hamed et al. (2013) developed an artificial neural network (ANN) model for predicting draft and energy requirements of a disk plow. Their results showed that correlation coefficients for testing points were 0.934, 0.933 and 0.915 for draft, unit draft and energy requirements, respectively. Saleh and Ayman (2013) trained an ANN model in order to predict plowing performance of simple multi-flat plate plowing tines using the error back propagation learning algorithm. The ANN model results showed a good agreement with the corresponding experimental data where the relative error is found in the order of ±2%.

The correlations between measured and predicted values of draft force in different working conditions for the training and all data sets are shown in Figure 9 and Figure 10, respectively. The small variation between the predicted and measured values confirmed the reliability of the network in predicting the draft requirement of these winged share tillage tools in a loam soil. However, more studies are required for other sizes of winged share tillage tool and soil conditions to make it a generalized ANN model.

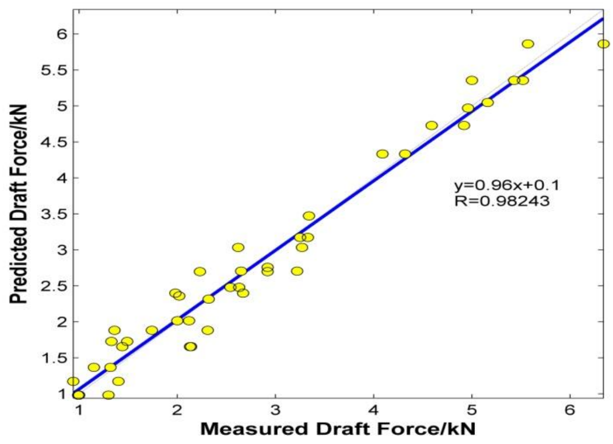

Figure 9 Correlation between measured and predicted values of draft force in train data set

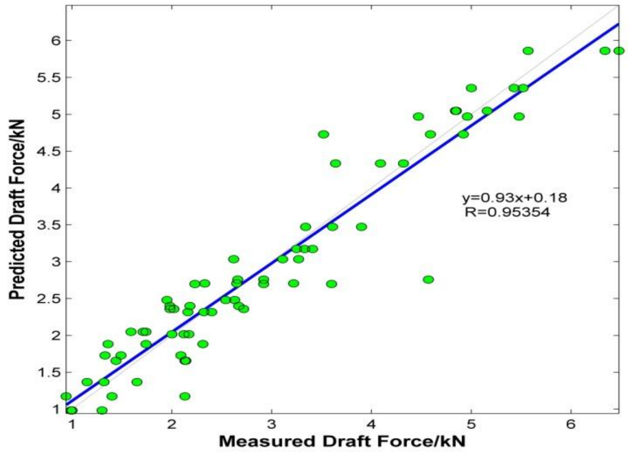

Figure 10 Correlation between measured and predicted values of draft force in all data sets

4 Conclusions

Based on the results of this study, the following specific conclusions can be made:

- A 3–7–1 neural network is capable of predicting draft requirement of winged share tillage tools in loam soil under varying operating conditions as indicated by high R (0.95), low MSE (0.049) and low ε% (6.56%).
- The small difference between the measured and predicted draft values over the range of test variables implies that the multilayer feed-forward neural network with BP algorithm and gradient descent learning rule was able to suitably model complex soil–tool interaction under the selected experimental conditions. Further work is required to demonstrate the generalized value of this ANN model for the similar tillage implements operating in other soil conditions.
- This system can be compared with other AI methods such as FIS (Fuzzy Inference System) and ANFIS (Adaptive Neuro-Fuzzy Inference System) method in order to achieve the best method to simulate soil-tillage tool interaction under different operating and soil conditions.

Nomenclature

Latin symbols

$b_{k,i}$	a bias term associated with neuron *i* in layer (k)
$O_{k,i}$	output of neuron *i* in layer (k)
$O_{k-1,i}$	output of neuron *j* in layer (k-1)

R	correlation coefficient
$W_{j,i}$	weight of the connection between node *j* in layer (k-1) and node *i* in layer (k)
$WS_{k,i}$	weighted sum of inputs for node *i* in layer (k)
y_{ex}	measured draft
y_p	predicted draft

Greek symbols

ε	relative error

Subscripts

i	Node number in layer (k)
j	node number in layer (k-1)
k	layer number
N	number of nodes in layer (k-1)
n	number of observations

Abbreviations

ANN	artificial neural network
ANOVA	analysis of variance
BP	back propagation
CRD	completely randomized design
EORT	extended octagonal ring transducer
MLP	multi layer perceptron
MSE	mean square of errors

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