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ARTIFICIAL NEURAL NETWORK MODEL FOR PREDICTING DRAFT AND ENERGY REQUIREMENTS OF A DISK PLOW

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ABSTRACT

In this study, artificial neural network (ANN) model was developed for predicting draft and energy requirements of a disk plow. The ANN model utilizes ten input parameters: plowing depth and speed, sand content, silt content, clay content, soil moisture content, disk diameter and angle, tilt angle and soil density. The model provides the draft, unit draft and energy requirements of disk plows as the predicted output. The ANN model was trained based on data from literature and tested on actual data from field experiments. The architecture of the ANN model consisted of one hidden layer with 8 nodes. Standard backpropagation-based algorithm was used to train the network. The results showed that correlation coefficients for testing points were 0.934, 0.933 and 0.915 for draft, unit draft and energy requirements, respectively. The promising results obtained indicate that the newly developed ANN model can be considered as a practical and reliable tool for predicting disk plow performance criteria under wide range of conditions. Using the network weights obtained from the ANN model, new formulations were presented for the calculation of draft, unit draft and energy requirements. Furthermore, as an added benefit, these formulations can be implemented with any programming language or spreadsheet program making them an attractive choice for routine analyses.

Key words: Artificial neural network, disk plow, draft, unit draft, energy requirement.

INTRODUCTION

Tillage is the mechanical manipulation of the soil by disturbing its original structure in the plow layer in order to promote tilth i.e. desired soil physical condition in relation to plant growth (Karmakar, 2005). The disk plow has always been the basic tillage implement on the farm. It is still useful and widely employed for primary tillage of virgin, stony and wet soils, cut through crop residues and roll over the roots (Boydas and Turgut, 2007). Disk plows have disks inclined to the rear for additional penetration (Vozka, 2007). The angle of attachment of the disk to the direction of travel is called the disk angle (Vozka, 2007). Another angle is the tilt angle of the disk. It is the slant (tilt) backward of the disk from the vertical (Bukhari *et al.*, 1992). The disk angles vary from 42° to 45° and the tilt angles vary from 15° to 25°. The disk diameters are commonly between 60 and 70 cm.

Performance efficiency of the tillage process is measured in terms of draft or input energy (Gill and Vanden Berg, 1967). The availability of data on the draft requirement of tillage implements is also an important factor while selecting suitable tillage implements for a particular farm situation. The factors affecting forces on disk plow include type of soil, the bearing of disk, scraper type, tilt angle, disk angle, forward speed, depth, width of cut, soil density and others as reported by many studies (Sommer *et al.*, 1983; Godwin *et al.*, 1987; Panigrahi *et al.*, 1990; Bukhari *et al.*, 1992; Morad, 1992; Shirin *et al.*,1993; Manian *et al*, 2000; Ismail, 2002; Abu–Hamdeh and Reeder, 2003; Mamkagh, 2009; Osman *et al.*,2011). At smaller disk angles, the draft tends to increase because of greater contact area between the furrow wall and the convex (rear) side of the disk.

Collecting draft data under wide range of field conditions is a tedious and time-consuming job. Therefore, draft prediction models are required to predict the draft of tillage implements such as the disk plow under different soil and operating conditions (Roul *et al.*, 2009). Further, mathematical solutions of soil-tool interaction based on empirical and semi-empirical models may be help tool for designers and researchers in the field of tillage implements (Karmakar, 2005).

The literature studies have shown that the relationship between the dependent and independent variables affecting performance parameters of a disk plow was modeled by regression analysis as reported by Ismail (2002) or by dimensional analysis as reported by Olatunji (2011). Recently, Karmakar (2005) reported that artificial neural networks (ANNs) have been used as possible approach to solve problems in the area of soil-tool interaction. It is noteworthy that there is a growing interest in modelling draft and energy requirements of tillage implements using ANN due to complexity and unavailable analytical models for all tillage implements. On the other hand, there is a shortage in empirical and analytical models for predicting draft force of disk plows due to the inherent characteristics of input factors, especially disk geometry. To overcome the problems related to analytical and empirical draft models, attempts have been made to develop ANN models for predicting the draft requirement of tillage implements from soil conditions, tool geometry and working conditions.

Several authors found ANN predictions for draft, pull and energy requirements of tillage implements to be an effective tool, as shown in studies by Hassan and Tohmaz (1995), Tohmaz and Hassan (1995), Kushwaha and Zhang (1997), Zhang and Kushawaha (1999), Al-Janobi *et al.* (2001), Aboukarima *et al.* (2003), El Awady *et al.* (2003), Aboukarima (2004), Aboukarima and Saad (2006), El Awady *et al.* (2004), Aboukarima (2007), Roul *et al.* (2009), Al-Janobi *et al.* (2010), Aboukarima (2013) and Saleh and Aly (2013).

Rahman *et al.* (2011) developed an ANN model to predict energy requirement of a tillage tool from the laboratory data. The ANN model was trained and tested with soil moisture content, plowing depths, and forward operating speeds as input parameters. The measured energy requirement for a tillage tool in silty clay loam soil was used as output parameter. Their results showed that the variation of measured and predicted energy requirement was small.

The literature studies have shown that empirical models can be useful alternative and practical tool for predicting both draft and energy requirement of tillage implement under different conditions. Therefore, the objective of this study was to develop, evaluate and validate a new ANN model to predict draft, unit draft and energy requirements of a disk plow. Several common and readily available factors were used as inputs to the ANN. Using these inputs, the ANN was trained based on literature data and later validated with data from field experiments.

MATERIALS AND METHODS

a) Field experiment site and procedure: The field test was carried out at Heef Alqahtani farm, Riyadh, Saudi Arabia which is 468.97 m above sea level and lies on longitude 47.14° East and latitude 24.33° North. The purpose of the field experiment was to determine draft force for disk plow to acquire data for developing and testing the ANN model. The soil at the site was loam sandy. Average soil density and soil moisture content were 1.84 g/cm^3 and 5.8 %db, respectively. All laboratory and field tests were conducted according to the recommendation of the Regional network for Agricultural machinery (RNAM, 1983).

Cone index values were obtained by taking penetrometer readings over the plowing depth. The cone used was of ASAE standard with a 30° cone angle and a diameter of 12.83 mm. Table 1 shows soil characteristics at the site. Disk plow (Nardi, mounted category II, weight 362 kg, Italy), model MF 38, serial No. TDPE48/D, with 3 disks with 36 cm disk diameter and distance between disks was 60 cm, the disk angle and tilt angle were measured and the angles set at 45° and 16°, respectively, were used in the experiment. The disk plow was hitched to a Fendt tractor model 306 LSA. The auxiliary tractor was Fendt tractor model 312LSA. Three plowing speeds were obtained by changing gears of the tractor.

An experimental block 60 m long by 3 m wide was used for each treatment. A small block of approximately 10 m long by 3 m wide in the beginning of each tested block was used to enable the tractor and plow to reach the required plowing speed and plowing depth. The depth of cut was measured with a steel tape from the bottom of the furrow to the surface level of the soil at eleven randomly selected places. The horizontal force (draft) was measured using a load cell (model Omega with capacity 0-10,000 lb) using the method described in (PAES, 2001). The draft was recorded within the distance of 60 m. The plowing speed was calculated by measuring of distance of five turns of the tractor rear wheel with time. On the same field, the plow was lifted out the ground and the rear tractor was pulled to record the idle draft force. The difference gave the draft of the implement. Raw data of the field tests are presented in Table 2.

b) Data Collection: Available draft data of disk plows in the literature, which directly related to the subject, were collected from (Bukhari *et al.*, 1992; Olatunji, 2011; Abu-Hamdeh and Reeder, 2003; Kheiralla *et al.*, 2004; Al-Janobi and Al-Suhaibani, 1998; Makki and Mohamed, 2008; El-Shazly *et al.*, 2008; Vozka, 2007). The above mentioned studies performed field or laboratory experiments using different disk plows in soils having different moistures, bulk densities and textures with different changeable working conditions and disk geometries. Collected data set consisted of 130 data points. Table 3 lists the summary statistics for the inputs used for training and testing the developed ANN model. Table 4 lists the corresponding statistics for the outputs.

Table 1. Mean characteristics of the soil at the site of the experiment.

	Unit	Value
Sand	(%)	83.2
Silt	(%)	9.8
Clay	(%)	7.0
Soil bulk density at depth (0-25 cm)	(g/cm^3)	1.52
Soil moisture content at depth (0-25 cm)	(% db)	6.44
Cone index at depth (0-25 cm)	(kPa)	1517

Table 2. Raw data of the field tests during plowing with disk plow.

Distance of five turns of the tractor rear wheel	Time of five turns of the tractor rear wheel	Plowing speed	Draft	Plowing depth
(m)	(sec)	(km/h)	(kN)	(cm)
24.35	60.65	1.45	5.09	23
22.97	36.43	2.27	5.43	23
28.50	36.17	2.84	5.86	23

c) Calculation of energy and unit draft: The width of cut (w, cm) may be adjusted on standard disk plows by changing the angle of the disks with respect to forward motion (Dumitru, 2009). In this study, actual width of cut (w) of a disk can be expressed as (Alam, 1989):

$$w = \frac{2\cos}{\cos\sim}\sqrt{d\left(D\cos\sim - d\right)} \quad .(1)$$

where β is disk angle (°), α is tilt angle (°), D is disk diameter (cm), d is plowing depth (cm). The total plowing width (W, cm) is calculated as:

$$W = N \times w \quad . (2)$$

where N is the number of disks on the plow. The tillage energy was calculated according to Smith (1993) as follows:

$$Energy(kW.h/ha/disk) = \frac{(F,kN/disk)\times(V,km/h)\times(1000,m/km)}{(3600,sec/h)\times(EFC,ha/h)} \quad (3)$$

where F is draft force and V is plowing speed. Field efficiency is the most frequently used factor in determining the effective field capacity (Lar *et al.*, 2011). Thus, in this study, the effective field capacity (EFC) was calculated according to the following equation:

$$EFC\ (ha/h) = TFC\ (ha/h) \times ¦ \quad \ldots (4)$$

where η is the field efficiency and for tillage primary it was ranged from 70 to 85% (Powell, 2000). In this study, η was assumed to be 0.8. Further, TFC denotes theoretical field capacity and was calculated according to the following equation:

$$TFC\ (ha/h) = \frac{(W,m)\times(V,km/h)\times 1000}{(10000, m^2/ha)} \quad \ldots (5)$$

Unit draft (UD) is calculated according to the following equation:

$$UD\ (N/cm^2/disk) = \frac{F, N/disk}{d, cm \times W, cm} \quad \ldots (6)$$

Table 3. Statistics for the inputs used in training and testing the ANN model.

Statistic	Plowing depth	Plowing speed	Soil moisture content	Disk angle	Tilt angle	Sand	Silt	Clay	Disk diameter	Soil density
	(cm)	(km/h)	(%db)	(°)	(°)	(%)	(%)	(%)	(cm)	(g/cm^3)
Mean	16.06	4.27	16.57	45	20	55.08	16.79	28.14	63	1.44
Standard deviation	3.95	1.97	6.66	2.83	2.34	28.41	16.04	19.22	4.77	0.15
Kurtosis	-0.85	1.64	-0.51	6.79	-0.93	-1.50	-0.30	-1.17	0.15	-1.34
Skewness	-0.44	1.34	0.37	2.58	0.05	-0.13	1.19	0.18	-1.29	0.32
Minimum	6.70	1.20	4.90	40.00	15.00	9.00	4.00	4.55	53.00	1.22
Maximum	23.40	10.00	28.00	55.00	25.00	90.85	48.00	70.00	66.00	1.67
Count	130	130	130	130	130	130	130	130	130	130

Table 4. Statistics for the targets (outputs) used in training and testing the ANN model.

Statistics	Draft	Unit draft	Energy
	(N/disk)	($N/cm^2/disk$)	(kW.h/ha/disk)
Mean	3828.95	2.48	12.88
Standard deviation	2033.12	1.60	7.02
Kurtosis	-1.07	0.53	-0.85
Skewness	0.52	1.08	0.53
Minimum	920.00	0.46	3.04
Maximum	8000.00	8.02	29.81
Count	130	130	130

d) ANN Background: ANNs are considered as artificial intelligence modelling techniques. They have a highly interconnected structure that aims to mimic the connectivity of brain cells. ANN consists of a large number of processing elements called neurons, which are arranged in different layers in the network: an input layer, an output layer and one or more hidden layers (Kumar and Singh, 2008). The basic working mechanism of a neuron is shown in Figure 1, where the neuron in the network receives input signals, processes them and sends an output signal (Haykin, 1999). Each neuron is connected with at least one other neuron and each connection is represented by a real number called a weight. The weights are adjusted iteratively so that the network attempts to produce the desired output (Safa *et al.*, 2009). Mathematically, this can be represented as (Haykin, 1999):

$$y_k = f\left(\sum_{k=1}^{n} w_k x_k + b_k\right) \quad \ldots (7)$$

where w_k represents the weight vector, x_k is the input vector (k = 1, 2..., m), b_k is the bias, f is the transfer function, and y_k is the output. The logistic sigmoid transfer (activation) function was chosen and it is defined for any variable S as:

$$f(S) = \frac{1}{\left(1 + e^{-S}\right)} \quad \ldots (8)$$

One of the well-known advantages of ANN is that the ANN has the ability to learn from the sample set, which is called training set, in an iterative learning process. Once the architecture of network is defined, a learning algorithm is used to search for the weights that produce the desired output with minimal error. Back-propagation neural networks represent a supervised learning method, requiring a large set of complete records, including the target (output) variables. As each observation from the training set is processed through the network, an output value is produced from output nodes. These values are then compared to the actual values of the target variables for this training set observation and the errors are calculated at each step of the algorithm (Kumar and Singh, 2008).

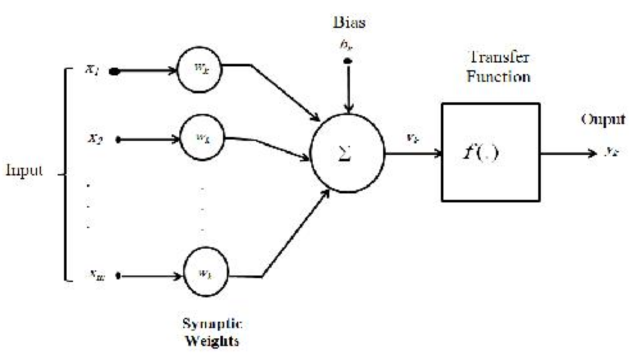

Figure 1. Structure of ANN (Haykin, 1999).

Feed forward ANNs are currently being used in a variety of applications with great success. Their first main advantage is that they do not require a user-specified problem solving algorithm (as is the case with classic programming) but instead they “learn” from examples, much like human beings. Their second main advantage is that they possess inherent generalization ability, when trained properly. This means that they can identify and respond to patterns that are similar but not identical to the ones with which they have been trained (Anantachar *et al.*, 2010).

e) Disk plow performance modeling with ANN: In the present work, the ANN model with standard back-propagation algorithm was developed using a commercially available software Qnet 2000 (Vesta Services, 2000). The ANN developed in the present study was characterized by three layers: an input layer, one hidden layer and an output layer. Input vectors and the corresponding target vectors are used to train the network until it can approximate a function which associates input vectors with specific output vectors. The inputs to the ANN model in this study were plowing depth, plowing speed, sand content, silt content, clay content, soil moisture content, disk diameter, disk angle, tilt angle and soil density. The outputs of the ANN were draft, unit draft and energy requirement of disk plows.

The data set (a total of 130) were randomized and were used in training and 22 points were randomly selected by an in-built algorithm in the software for the testing set. The test points provide an independent measure of how well the network can be expected to perform on data not used to train it. Prior to their use in the ANN model, the input and the output values were normalized between 0.15 and 0.85 according to the following equation:

$$T = \frac{(t - t_{\min})}{(t_{\max} - t_{\min})} \times (0.85 - 0.15) + 0.15 \quad \ldots (9)$$

where *t* is the original values of input and output parameters, *T* is the normalized value; t_{max} and t_{min} are the maximum and minimum values of the input and the output parameters, respectively.

Three and four layers ANN structures were investigated and the number of neuron in the hidden layers was also varied. Further, different values of the learning coefficient and the momentum factor, different transfer functions were used in training the network. The best ANN structure and optimal values of the network parameters were obtained on the basis of lowest error on training data by trial and error. The final learning rate was 0.05, a momentum factor of 0.8, logistic function (sigmoid transfer function) of neuron activation, 100,000 training cycles were used. These configurations gave a training error of 0.024. Root mean square error (RMSE) during training is shown in Figure 2. Table 5 presents network statistics from Qnet software.

Using the weights obtained from the trained ANN model, new formulations were presented in Appendix (A) for the calculation of draft, unit draft and energy requirements of a disk plow. These formulations can be employed with any programming language or spreadsheet program (Ahmed *et al*., 2012), thus facilitating their use in routine analysis.

f) Determination of errors in disk plow performance: The accuracy of ANN predictions was evaluated using different error statistics as follows:

$$MAE = \frac{1}{N_t} \times \sum_{i=1}^{i=N_t} \left| E_{iobs} - E_{ipre} \right| \quad \ldots (10)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{i=N_t} \left(E_{i\,obs} - E_{i\,pre} \right)^2}{N_t}} \quad (11)$$

where E_{iobs} and E_{ipre} are observed and predicted values, N_t is the number of data points, MAE is the mean absolute error and RMSE is the root mean square error. In addition, the coefficient of determination (R^2) was selected to measure the linear correlation between the observed and the predicted values. The optimal coefficient of determination value is unity.

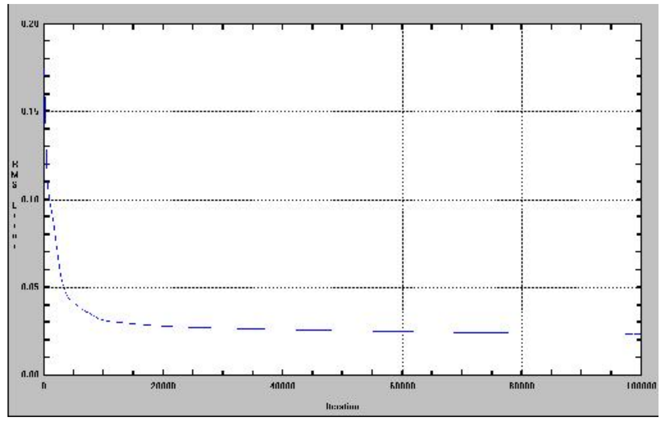

Figure 2. Root mean square error (RMSE) during training process.

Table 5.Network statistics from Qnet software.

Output node	Standard deviation	Bias	Maximum error	Correlation coefficient
Training data				
Draft (N/disk)	282.136	-2.261	1226.592	0.990
Unit draft (N/cm^2/disk)	0.210	-0.003	1.202	0.991
Energy requirement (kW.h/ha/disk)	0.867	-0.001	4.336	0.992
Testing data				
Draft (N/disk)	794.456	-0.997	2029.314	0.934
Unit draft (N/cm^2/disk)	0.583	0.016	1.797	0.933
Energy requirement (kW.h/ha/disk)	2.793	-0.175	7.229	0.915

RESULTS AND DISCUSSION

In this study, ANN model has been developed with 10 neurons in the input layer (plowing depth, plowing speed, sand content, silt content, clay content, soil moisture content, disk diameter, disk angle, tilt angle and soil density), 8 neurons in the hidden layer and 3 neurons in the output layer for the prediction of draft, unit draft and energy requirements of disk plows. Error criteria such as R^2, RMSE and MAE of training and testing phases are given in Table 6. For training phase, the coefficient of determination (R^2), the root mean square error (RMSE) and the mean absolute error (MAE) were 0.983, 0.21 N/cm^2/disk and 0.137 N/cm^2/disk, respectively for unit draft. For the testing set, the corresponding values were 0.8713, 0.584 N/cm^2/disk and 0.394 N/cm^2/disk, respectively for unit draft.

Figures 3 through 5 show the relationships and coefficients of determination between the observed and the predicted values of draft, unit draft and energy requirements, respectively, using ANN model during testing phase. From these figures, it is clear that the

Table 6. Error criteria during training and testing process of ANN model.

Performance parameters	RMSE		MAE		R^2	
	Training	Testing	Training	Testing	Training	Testing
Draft (N/disk)	282.136	794.456	187.171	567.845	0.9803	0.8733
Unit draft (N/cm^2/disk)	0.210	0.584	0.137	0.394	0.9830	0.8713
Energy requirement (kW.h/ha/disk)	0.867	2.793	0.587	1.910	0.9846	0.8374

points, during the testing process, were not uniformly scattered around the regression lines and coefficients of determination (R^2) was 0.8733.,0.8713 and 0.8374, respectively as illustrated in Figures (3) through (5).

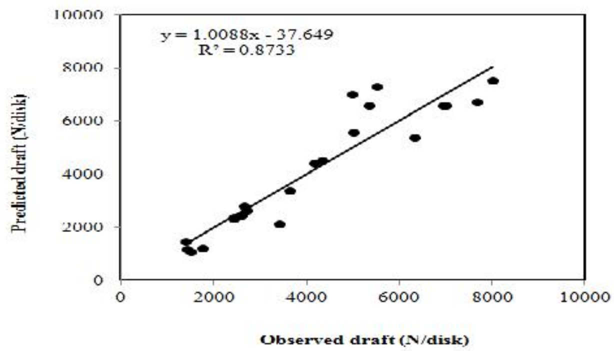

Figure 3. Comparison of the observed draft data and the results obtained from the developed ANN model during testing phase.

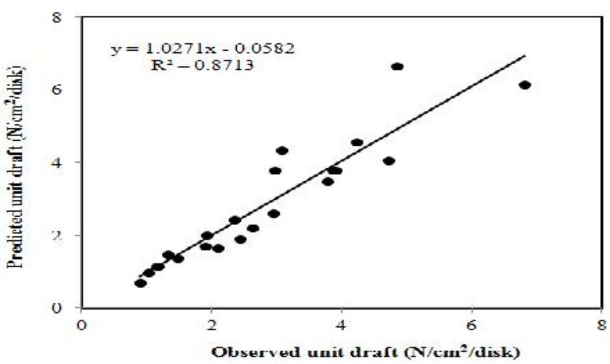

Figure 4. Comparison of the observed unit draft data and the results obtained from the developed ANN model during testing phase.

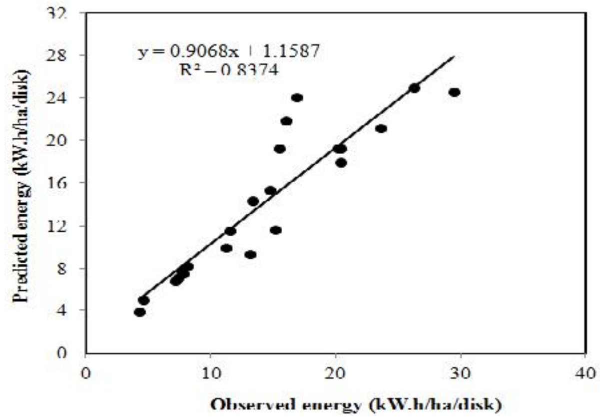

Figure 5. Comparison of the observed energy requirements data and the results obtained from the developed ANN model during testing phase.

The Qn*et al*gorithm computed the contribution percent which indicates how the change in each input changes the output prediction. The contribution percentage of the ten input variables to the outputs was calculated using the developed ANN model and results are illustrated in Figure 6 for draft, unit draft and energy requirements. This figure can be used to ascertain the relative contributions (and importance) of each of the ten input parameters. As evident from Figure 6, the input parameter with the largest contribution is the soil moisture content. This input parameter contributes about 23.44%, 17.36%, and 18.49%, respectively, for the predicted output obtained for draft, unit draft and energy requirements of disk plows by the developed ANN model.

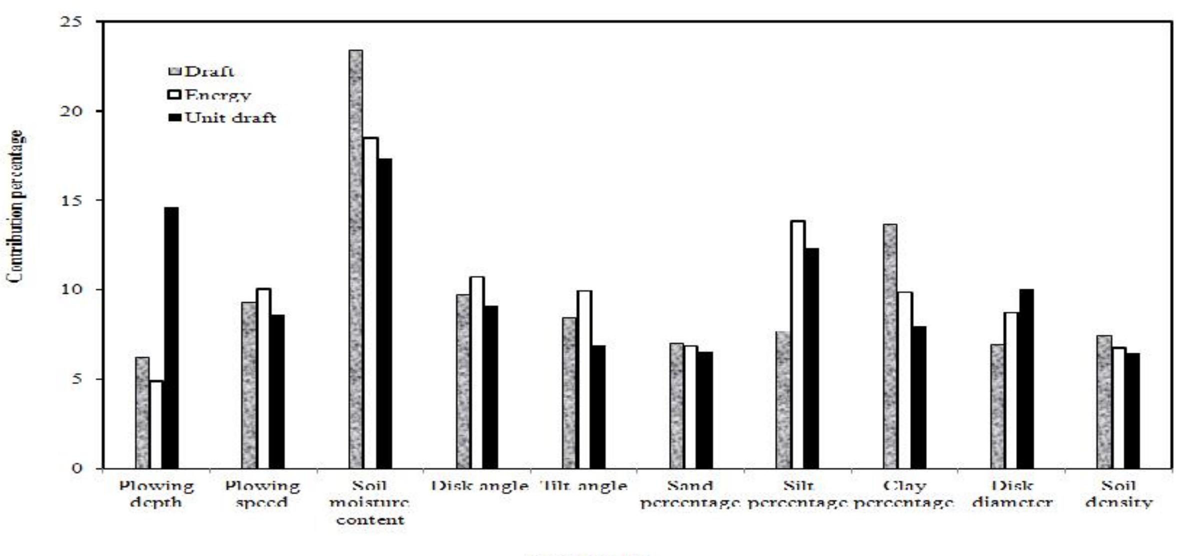

Figure 6. Contribution percentage of 10 independent variables used in the 10-8-3 ANN model for prediction of draft, unit draft and energy requirements of disk plows.

To validate the developed ANN model, the field experiments data were tested with the newly developed ANN model to predict draft, unit draft and energy requirements of disk plows. Figure 7 depicts the relationship between plowing speed vs. field and predicted values of draft of a disk plow. It is clear that the predicted pattern behaves as field pattern (i.e. increasing plowing speed results in increasing draft force of a disk plow). However, the coefficient of determination (R^2) as shown in Figure 8 between the actual data from the field experiment and the predicted values from the developed ANN model of draft of a disk plow was 0.983 which indicates accurate prediction of such draft.

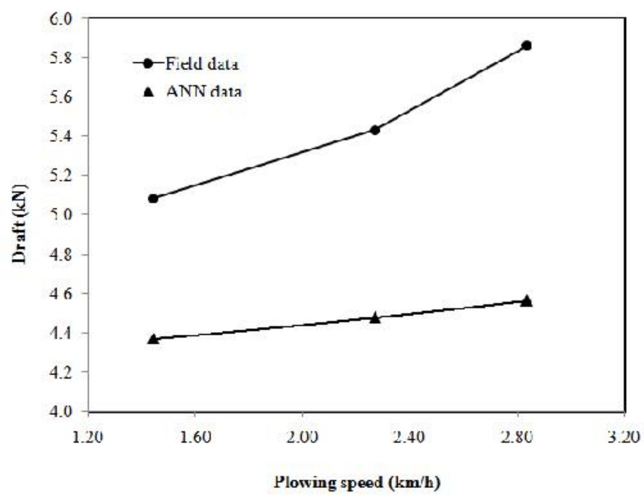

Figure 7. The relationship between plowing speed and actual (field data) and predicted values (ANN data) of draft of a disk plow.

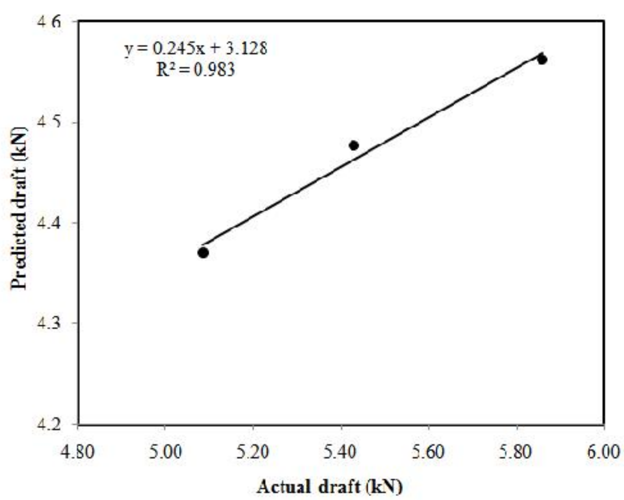

Figure 8. The relationships and coefficient of determination between the actual data from field experiments and the predicted values from the developed ANN model of draft of a disk plow.

Conclusion: ANN model was developed for the prediction of the performance parameters (draft, unit draft and required energy) of the disk plow. The appropriate architecture of the neural network was 10-8-3. Based on the results, the ANN model appears capable of providing accurate predictions of the disk plow's performance.

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Appendex (A): The following equations were used to predict draft, unit draft and energy requirements of a disk plow based on training ANN model:

Step 1: Normalizing the original input variables as follows:

$$X1 = \frac{(plowing\ depth, cm - 6.7)(0.85 - 0.15)}{(23.4 - 6.7)} + 0.15 \quad (1\text{-a})$$

$$X2 = \frac{(plowing\ \ speed, km/h - 1.2)(0.85 - 0.15)}{(10 - 1.2)} + 0.15 \quad (2\text{-a})$$

$$X3 = \frac{(soil\ \ moisture\ \ content, \%db - 4.9)(0.85 - 0.15)}{(28 - 4.9)} + 0.15 \quad (3\text{-a})$$

$$X4 = \frac{(disk\ \ angle, deg - 40)(0.85 - 0.15)}{(55 - 40)} + 0.15 \quad (4\text{-a})$$

$$X5 = \frac{(tilt\ \ angle\ ,deg\ - 15)(0.85 - 0.15)}{(25 - 15)} + 0.15 \quad (5\text{-a})$$

$$X6 = \frac{(sand,\%\ - 9)(0.85 - 0.15)}{(9 - 90.85)} + 0.15 \quad (6\text{-a})$$

$$X7 = \frac{(silt,\%\ - 4)(0.85 - 0.15)}{(48 - 4)} + 0.15 \quad (7\text{-a})$$

$$X8 = \frac{(clay,\%\ - 4.55)(0.85 - 0.15)}{(70 - 4.55)} + 0.15 \quad (8\text{-a})$$

$$X9 = \frac{(disk\ \ diamter, cm\ - 53)(0.85 - 0.15)}{(66 - 53)} + 0.15 \quad (9\text{-a})$$

$$X10 = \frac{(soil\ density, g/cm^3 - 1.22)(0.85 - 0.15)}{(1.67 - 1.22)} + 0.15 \quad (10\text{-a})$$

Step 2: Computing the sum of input signals as follows:

$$S1 = 4.53477 \times X1 - 0.75385 \times X2 - 1.77923 \times X3 + 0.99338 \times X4 + 0.11624 \times X5 + 0.72312 \times X6 + 1.58034 \times X7 - 1.86913 \times X8 + 0.56911 \times X9 - 0.7777 \times X10 + 0.07058 \quad (11\text{-a})$$

S2 = 1.29241 × X1-3.72518× X2-2.00173× X3-2.43304× X4-0.59781× X5 +0.08449× X6+11.764× X7-6.33366× X8+3.65165× X9+0.15948× X10+1.11317 (12-a)

S3 =-3.78579 × X1+1.77576× X2-3.54675× X3+2.64683× X4-0.4012× X5 +4.91284× X6+3.37597× X7-5.77836× X8+4.94561× X9+3.91233× X10+2.17369 (13-a)

S4 =-8.4977 × X1+0.03672× X2+3.07942× X3+4.40313× X4-1.43636× X5 +2.44895× X6-4.30954× X7-2.75231× X8-0.86524× X9+2.13487× X10-1.78055 (14-a)

S5 = -6.68797 × X1-3.91512× X2+6.04788× X3-4.75146× X4+4.58142× X5-3.20143× X6+3.69376× X7-1.56236× X8+0.18374× X9+4.09594× X10-2.18106 (15-a)

S6 = 1.15637 × X1-4.15588× X2-6.69301× X3-0.85919× X4+0.99635× X5+2.2503× X6+3.42382× X7+1.29259× X8-3.69893× X9+2.54745× X10+4.80934 (16-a)

S7 =7.88082 × X1+4.88983× X2-2.53565× X3-0.7717× X4-2.47017× X5+1.28793× X6+2.80806× X7+1.7806× X8-3.07712× X9-5.17897× X10+4.20017 (17-a)

S8 = -0.20168 × X1-1.18723× X2-3.04539× X3+5.17473× X4-2.79665× X5-2.69427× X6+7.44874× X7+6.32273× X8-2.58356× X9-2.38491× X10+6.07816 (18-a)

Step 3: Applying the sigmoid transfer function on the sum of input signals as follows:

$$F1 = \frac{1}{1+e^{-S1}} \tag{19-a}$$

$$F2 = \frac{1}{1+e^{-S2}} \tag{20-a}$$

$$F3 = \frac{1}{1+e^{-S3}} \tag{21-a}$$

$$F4 = \frac{1}{1+e^{-S4}} \tag{22-a}$$

SW (23-a)

$$F6 = \frac{1}{1+e^{-S6}} \tag{24-a}$$

$$F7 = \frac{1}{1+e^{-S7}} \tag{25-a}$$

$$F8 = \frac{1}{1+e^{-S8}} \tag{26-a}$$

Step 4: Computing the sum of hidden signals as follows:

Y1 (draft) = 5.63398× F1+0.30404× F2-4.1785× F3 +3.3589× F4 +3.91471× F5-4.56049× F6 +5.38933× F7-6.52522× F8 +2.43098 (27-a)

Y2 (unit draft) = 0.28639× F1-1.91125× F2-2.15524× F3 +4.21995× F4 +2.25171× F5+0.32243× F6 +4.4789× F7-2.75628× F8 -0.0659 (28-a)

Y3 (energy) = 4.12207× F1-3.3706× F2-4.17134× F3 +3.98389× F4 +3.69056× F5-0.11032× F6 +5.43425× F7-4.98536× F8 +1.36836 (29-a)

Step 5: Computing the normalized output signals as follows:

$$Y11\,(draft\ normalized) = \frac{1}{1+e^{-Y1}} \tag{30-a}$$

$$Y22\,(unit\ draft\ normalized) = \frac{1}{1+e^{-Y2}} \tag{31-a}$$

$$Y33\,(energy\ normalized) = \frac{1}{1+e^{-Y3}} \tag{32-a}$$

Step 6: Denormalizing the output signals as follows:

$$Draft\ \ (N/disk) = \frac{(Y11-0.15)(8000-920)}{(0.85-0.15)} + 920 \tag{33-a}$$

$$Unit\ \ Draft\ \ (N/cm^{2}/disk) = \frac{(Y22-0.15)(8.02-0.46)}{(0.85-0.15)} + 0.46 \tag{34-a}$$

$$Energy\ \ (kW.h/ha/d\ isk) = \frac{(Y33-0.15)(29.81-3.04)}{(0.85-0.15)} + 3.04 \tag{35-a}$$

Example: Predict draft (N/disk) of a disk plow, plowing speed was 7.85 km/h, plowing depth was 10 cm in soil having 79% sand, 10% clay and 11% sill. Disk diameter was 66 cm, disk angle was 45°, tilt angle was 22°, the soil moisture content was 9.5 % (d.b) and the soil density was 1.58 g/cm^3.

The solution: By applying equations in Appendix (A), the following results are obtained:

Equations (1-a through 10-a)		Equations (11-a through 18-a)		Equations (19-a through 26-a)		Equation (27-a)	Equation (30-a)
X1=	0.288323	S1=	1.303293	F1=	0.786389	Y1=-0.87506	Y11 =0.294203
X2=	0.678818	S2=	2.098369	F2=	0.890745		
X3=	0.289394	S3=	12.357357	F3=	0.999996		
X4=	0.383333	S4=	-1.631855	F4=	0.163576		
X5=	0.640000	S5=	-2.598592	F5=	0.069229		
X6=	0.748656	S6=	2.206447	F6=	0.900827		
X7=	0.261364	S7=	2.957571	F7=	0.95062		
X8=	0.208289	S8=	1.883960	F8=	0.868065		
X9=	0.850000						
X10=	0.710000						

Then by applying equation (33-a), the draft value is obtained and equals to 2378.51 N/disk. The observed draft was 2433.33 N/disk. So, the error was (2433.33-2378.51)/2433.33*100 =2.25%.