Assessment of Different Indices Depicting Soil Texture for Predicting Chisel Plow Draft Using Neural Networks

Abd El Wahed M. Aboukarima [1] and Ahmed F. Saad [2]

ABSTRACT

The aim of the present study is to assessment of different indices depicting soil texture for predicting chisel plow draft using neural networks. So, six neural network models with different inputs and one output were trained using a backpropagation learning algorithm. The soil texture indices were formed by different combinations of soil fractions. Available data in literature, directly related to our subject, were collected. These data were observations of field experiments. The input parameters were soil fractions in different forms (soil texture index), plowing depth, rated plow width, forward speed, initial soil moisture content, initial soil bulk density and rated tractor power. The results showed that the neural network model with any soil texture index represented by soil fractions could predict chisel plow draft with reasonable accuracy. Correlation coefficients values between actual and predicted draft were higher than 0.80 for all neural network models. However, values of mean absolute percentage error were 11.027 % and 11.887 % during training and testing the developed neural network model which used soil fractions values to represent soil texture as separated inputs, respectively.

INTRODUCTION

Draft affects the energy requirement of tillage implements. It reflects the soil physical conditions and the degree of compaction of agricultural soils. For unique soil type, plowing speed and implement design, draft varies with soil bulk density, soil moisture content and plowing depth. These influencing factors are the main axis of interest of previous research, adapting field experiments to understand how these factors affect the draft of tillage implements (Mouazen and Ramon, 2002).

Instrumentation systems to determine energy requirements of tractor-implement system have been developed by agricultural machinery manufactures, universities and governmental agencies. These systems are generally complex and expensive. So, predicting is an important and effective factor in efficient planing. Accurate predicting tillage implements draft is of prime importance to enhance crop productivity and sustainable agriculture.

Several researches have attempted to model the draft requirements using linear and nonlinear regressions for unique soil type. These attempts produced many empirical equations to predict draft as dependent parameter and soil physical and working conditions as independent parameters. The draft empirical equations were ranged from simple to complex.

Michel et al. (1985) showed that the variation in power, energy and fuel consumption for primary tillage could be attributed to many variables including soil moisture, soil density and operation speed and depth. Chandon and Kushwaha (2002) mentioned that tillage energy is a function of the operating speed, working depth, tool characteristics and soil properties. However, soil moisture content, calcium carbonate, soil bulk density and soil fractions affected the penetration resistance (saad, 2003).

Dahab and Al-Hashem (2002) studied the effect of tractor power working on clay loam soil on drawbar pull. The results showed that the increase in tractor power had a highly significant effect on drawbar pull. Harriagn and Rotz (1995) mentioned that farm managers and consultants use draft or power data to match tractors with implements and to estimate fuel requirements. Grisso et al. (1996) reported that draft required during tillage is a function of soil properties, working depth, tool geometry, travel speed and width of the implement. It is an important parameter for measuring and evaluating implement performance for energy requirements.

In the field of tillage, Kushwaha and Chi (1991) showed that theoretical methods were developed, in recent years, for predicting soil forces during tillage operations. These methods can be divided into two categories: analytical and numerical. The analytical methods provided fairly simple equations to evaluate the soil forces on the tool. With the accessibility of computers, a numerical method was also developed to solve the soil-cutting problem. Finite element analysis provides flexibility of predicting soil forces for different blade shapes.

[1] Agric. Eng. Res. Inst., Agric. Res. Center
E-mail: aboukarima @maktoob.com.
[2] Soil and Water Sci. Dept., Faculty of Agric., Alexandria Univ.
Received Feb. 21,2006, Accepted June 12,2006.

Recently, using neural networks method in prediction has been applied in different agricultural engineering and soil science fields with great success. Neural networks have the advantage of making complex decisions based on the unbiased selection of the most important parameters from a large number of computing parameters. This is particularly important in the area of agricultural mechanization, where the principles governing machine performance are complex and not yet fully understood. The researcher is then able to explore various hypotheses in the most general terms, using the neural network as a tool to prioritize the relevant information.

The ability of artificial neural networks in prediction in the field of agricultural engineering and soil science was seen by different researchers (Aboukarima et al., 2003; El Awady et al., 2003; El Awady et al.,2004; Kushwaha and Zhang, 1997; Zhang and Kushawaha, 1999; Hassan and Tohmaz, 1995; Lentzscha et al., 2005; Kaul et al., 2005; Licznara and Nearingb, 2003; Parlak et al., 2006 and Merdun et al., 2005). Using neural networks method in prediction tillage implements draft or pull requirements showed great success as results of studies by Aboukarima (2004) and Al-Janobi et al. (2001). Howevere, Tohmaz and Hassan (1995) used a neural network to study the tractive performance of a rubber-tired skidder operating on soft organic soil and showed that good generalizaition of the pull-load relationships with data not used in network training. Ingleby and Crowe (2001) used a neural network for predicting organic matter content in Saskatchewan soils. Marcel and Leij (1998) used a neural network to predict soil water retention and soil hydraulic conductivity. Yang et al. (1997) estimated soil temperature using a neural network. All these studies were considered that a well-trained neural network model provided fast and consistent results, making it an easy-to-use tool in studies for such soil and agricultural engineering problems.

The objective of this study is to assessment of different indices depicting soil texture for predicting chisel plow draft using neural networks.

MATERIALS AND METHODS

Neural Network:

The neural network used in this study is the multilayer perceptron (MLP). Details about the MLP can be found in Haykin (1999). According to Dutot et al. (2003) a MLP consists of a multi-level neural network with a supervised training phase. The basic structure of an artificial neuron in a MLP is shown in Fig. (1). Basically, the neuron works by transferring the weighted sum of the input data through a nonlinear (transfer) function (e.g. sigmoid, hyperbolic tangent (tanh),...etc.) into the output of the neuron. The total MLP consists of a network of several neurons assembled in layers.

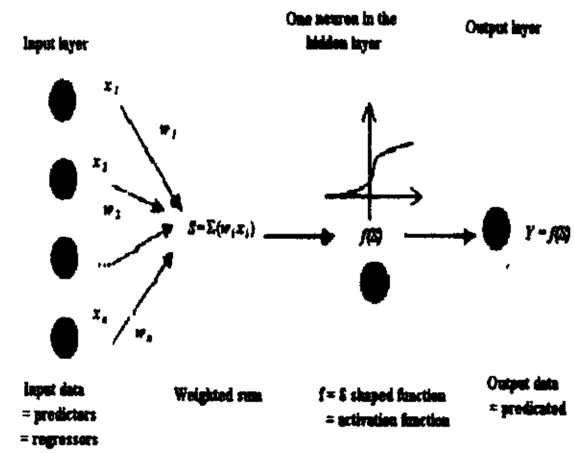

Fig. 1. Basic structure of an artificial neuron as shown in Dutot et al. (2003).

The neurons of a specific layer are generally all connected to the neurons of the following layer, Fig. (2). During a supervised training phase, relationships between the predictors (input data) and the predicated (output data) are computed within the MLP. During this procedure, differences between actual and predicted results are computed. These differences are used to derive the optimal connecting weight. In this phase, named the minimization phase of the differences between actual and predicted data, the optimization of the weights is set up according to a backpropagation procedure.

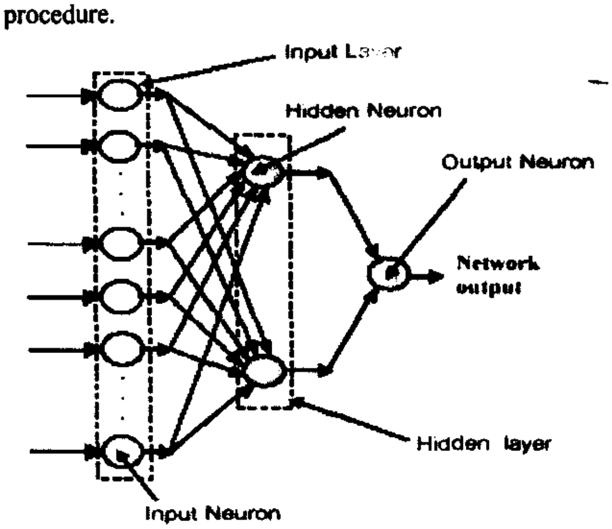

Fig. 2. Schematic artificial neural network of the multilayer perceptron.

Indeed, such a procedure is a convenient way of calculating the derivative of an error function with respect to the weights. In order to learn a given behavior in a stable way, each learning example is presented to the network several times. The final weights can then be used for the prediction of unknown rate constant of new molecules. In a statistical point of view, the MLP neural networks can be seen as multiple nonlinear regression methods:

$$Y = \sum_j w_j \left(f\left(\sum_i w_i x_i \right) \right) \quad \text{..............(1)}$$

Where Y is the neural network model output, f is a "S" shaped function, x_i are the input data and w_i and w_j are the parameters of the regression (i.e. the connecting weight) obtained by minimization of the error between actual and predicted values during the training phase.

An important feature of the MLP is its capability to model all the smooth functional relationships between predictors and predictions. This ability can be fulfilled with only one hidden layer in the MLP that consequently results in a very simple architecture. The optimization of both the nonlinear function and the geometry of the neural network were performed after many empirical trials. In the present study, the error function used is the delta rule. This rule determines the weights w_i by minimizing "E":

$$E = \frac{1}{2}\sum (F - Y)^2 \quad \text{............(2)}$$

where: F is actual observations and Y is the predicted values. Finally, these best weights are applied on unseen data that constitute the testing set. These results are used to quantify the quality of the neural network performance.

Representing Soil texture:

Altendorf et al. (1999) showed that to make any model more universal, a variable describing the soil fractions must be added to the input layer in neural network applications. By browsing through literature, different equations were formulated to represent soil fractions (sand, silt, and clay) in numeric values as soil texture index to be used in mathematical models. Elbanna (1990) mentioned that clay ratio (CR) could represent soil texture and it could be calculated as follows:

$$CR = \frac{C_a}{S_i + S_a} \quad \text{............(3)}$$

Where S_i, S_a and C_a are % of silt, sand, and clay fractions in soil, respectively. Oskoui and Harvey (1992) developed a formula to estimate soil texture index. They mentioned that soil texture index represents soil type better than clay ratio. The clay ratio only reflects the effect of clay content and, to a limited extent, the effect of sand content. It is insensitive to values of silt content. For example, 30% clay, 5% silt, and 65% sand has the same clay ratio as 30% clay, 65% silt, and 5% sand. These two soils have completely different physical properties. The soil texture index (CTI) could be calculated according to them as follows:

$$CTI = \frac{\log (S_i^{C_a})}{100} \quad \text{...........(4)}$$

Oskoui and Harvey (1992) showed that the CTI reflects the effects of all three of the soil fractions. The CTI produces unique numbers for every combination of sand, silt, and clay contents. The justification for choosing CTI is that the clay fraction influences cohesive properties by its virtue of chemical bond and using clay as an exponent reflects the relative importance of cohesion to friction. The silt fraction becomes more important in the absence of large amounts of clay fraction and its inclusion at the base of the power function reflects this relative importance.

Zein Eldin (1995) developed a formula to calculate soil texture index as follows:

$$CTI_z = \frac{\log (S_i^{C_a} + S_a)}{100} \quad \text{...........(5)}$$

It is remarked that the soil texture indices of Zein Eldin (1995) and Oskoui and Harvey (1992) are practically identical for all soil types. This is because the Eq. (4) of Oskoui and Harvey (1992) represents the sand fraction implicitly since the sum of sand, silt and clay contents is always constant.

Ismail (2002) found that there was a significant interaction between clay ratio (CR) and silt ratio (SR). He mentioned that this was a logic result because clay percent in the soil is not responsible only for soil resistance since soil contains high percentage of silt. Therefore, a modification was done to calculate this interaction and the soil texture index (CSI) could be calculated according him as follows:

$$CSI = \left[\frac{C_a}{S_a + S_i}\right] \times \left[\frac{S_i}{S_a + C_a}\right] \quad \text{.............(6)}$$

Also, the silt ratio (SR) as mentioned by Ismail (2002) was taken to represent soil texture and it could be calculated according him as follows:

$$SR = \left[\frac{S_i}{S_a + C_a} \right] \text{...........(7)}$$

On the other hand, Oskoui and Harvey (1992) and Ismail (2002) showed that the clay percent in the soil is not responsible only for soil resistance since soil contains high percentage of silt. So, in the present study , modified soil texture index (STI) was implemented to represent importance of silt content in soil and it could be obtained as follows:

$$STI = \frac{\log \left(C_a^{S_i} \right)}{100} \text{...........(8)}$$

Where S_i, S_a and C_a are % of silt, sand, and clay fractions in soil, respectively. Finally, soil fractions (sand, silt, and clay) are represented in numeric values in the input layer as separated values (its model named SSC) to represent soil texture. So, in the present study 6 neural network models are available.

Evaluation Criteria:

In most prediction situations, accuracy is treated as the over-riding criterion for selecting a predicting method. Makridakis et al. (1998) mentioned some standard statistical measures. If F_t is the actual observation for period t and Y_t is the prediction for the same period for n periods, then there will be n error terms, and the following standard statistical measures can be defined as follows: (a) root mean sequare error (RMSE). It measures standard deviation between observed and predicted data.

$$RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^{n} (F_t - Y_t)^2} \text{ ....(9)}$$

(b):To make comparisons, relative or percentage error measures must be defined as:

$$PE_t = \left(\frac{F_t - Y_t}{Y_t} \right) \times 100 \text{ ....(10)}$$

$$MPE = \frac{1}{n} \sum_{t=1}^{n} PE_t \text{ ....(11)}$$

$$MAPE = \frac{1}{n} \sum_{t=1}^{n} |PE_t| \text{ ....(12)}$$

Where PE_t is percentage error (%), MPE is mean percentage error (%), and MAPE is mean absolute percentage error (%). The correlation coefficient (r) between the actual and the predicted observations was also used as a criterion for comparison.

Collecting Required Data:

Available data in literatures, which directly related to our subject, are collected from (Abd El Maksoud, 1970; Nasr, 1985; El Sheikha, 1989; Idris, 1990; Obaia, 1991;

Table 1. Statistical parameters of collecting data that describe affecting input parameters used in developing neural network models for predicting chisel plow draft.

Input parameters			Units	Statistical parameters*			
				Average	Minimum	Maximum	Standard deviation
Rated tractor power+			(kW)	47.11	22.07	103.01	15.57
Rated plow width			(m)	1.75	1.00	3.10	0.24
Plowing depth			(cm)	16.58	8.00	26.00	4.30
Forward speed			(km/h)	3.46	0.94	7.20	1.10
Soil texture indices		CTI	(---)	0.540	0.026	0.842	0.254
Soil texture indices		CR	(---)	0.704	0.031	1.805	0.411
Soil texture indices		CSI	(---)	0.329	0.002	0.647	0.210
Soil texture indices		STI	(---)	0.441	0.022	0.706	0.208
Soil texture indices		SR	(---)	0.433	0.024	0.918	0.226
Soil texture indices	SSC	S_a	(%)	33.57	10.08	91.00	24.33
Soil texture indices	SSC	S_i	(%)	28.03	2.30	47.87	11.93
Soil texture indices	SSC	C_a	(%)	37.05	3.00	62.10	16.35
Initial soil moisture content			(%,d.b)	21.85	4.60	41.73	7.19
Initial soil bulk density			(g/cm^3)	1.36	0.90	1.83	0.17

* No. of observations = 1026.

+ According to tractor operator's manual.

Bahnas, 1999; Shaban, 1999 and Ghazy, 2000). All these studies executed field experiments under Egyptian conditions using different chisel plows (only one pass over the soil) in different Egyptian sites with different changeable working conditions. Collected data sets were 1026 data points. Table (1) shows some statistical parameters of collecting data that describe affecting input parameters used in developing neural network models for predicting chisel plow draft.

Developing Neural Network Models:

Using commercially available software, Qnet2000 (Vesta Services, 2000), implementation of multilayer perceptron with the backpropagation network in supervised manner was used to develop the neural network models. The neural network models input parameters are plowing depth, rated plow width, forward speed, soil texture index, initial soil moisture content, initial soil bulk density, and rated tractor power (according to tractor operator's manual). However, six neural network models were used, fixing training data set, number of hidden layers, number of neuron in every hidden layers, number of iterations, momentum factor, and learning rate and the changing input parameter is only values of soil fractions forms. The output is draft of the chisel plow. The data were normalized by the software. In the present study, the optimum structure of the neural network models is done using trial and error method. The optimum structure was based on minimizing the difference between the model output and the desired output using training data set (900 data points). Once the optimal structure with respect to the number of hidden layers, number of neurons in each hidden layer and learning runs was found, the performance of the neural network models was tested with testing data set (126 data points). The computed errors converged to a minimum value for predicted output at one hidden layer with 10 neurons. Also, the optimum configuration of the models is achieved at 10000 iteration. The hidden and the output layers have a sigmoid activation function. The learning rate and momentum factor were 0.01 and 0.8, respectively. Table (2) shows the definitions, training control values and training error for different neural network models. To validate the developed neural network models, another data were taken from Khadr (2004) and Aboukarima (2004). Validation input data are shown in Table (3) and they not used in training or testing phases.

Table 2.Definitions, training control values and training error for different neural network models.

Different items	Neural network models					
	CTI	CR	CSI	STI	SR	SSC
Network layers	3	3	3	3	3	3
Input neurons	7	7	7	7	7	9
Output neurons	1	1	1	1	1	1
Hidden neurons	10	10	10	10	10	10
Transfer function	Sigmoid	Sigmoid	Sigmoid	Sigmoid	Sigmoid	Sigmoid
Connections	80	80	80	80	80	100
Training patterns	900	900	900	900	900	900
Network size (Bytes)	92128	92128	92128	92128	92128	99740
Training mode	Standard	Standard	Standard	Standard	Standard	Standard
Maximum iteration	10000	10000	10000	10000	10000	10000
Learning rate	0.01	0.01	0.01	0.01	0.01	0.01
Momentum	0.8	0.8	0.8	0.8	0.8	0.8
Patterns per update	900	900	900	900	900	900
Training speed (CPS)	4724	4285	4726	4475	4964	5443
Training error	0.0507	0.0466	0.0483	0.0455	0.0474	0.0427

RESULTS AND DISCUSSION

Neural network with one hidden layer of 10 neurons was found to best model the relationship between the affecting parameters and draft of chisel plow. In all neural network models, the magnitude of training error was nearly constant and tends to be 0.0427 – 0.0507, Table (2). This trend could be due to that all data were normalized before training neural network models.

Table (4) illustrates comparisons of predictions using different neural network models during training and testing phases. With regard to the correlation coefficient, the neural network model which used seperated soil frictions (SSC model) gave nearly higher values of correlation coefficiens compared to other neural network models during training and testing phases.

Table 3. Validation input data for the developed neural network models for predicting chisel plow draft.

Rated tractor power	Rated plow width	Plowing depth	Forward speed	Sand	Silt	Clay	Initial soil moisture content	Initial soil bulk density	Data points
(kW)	(m)	(cm)	(km/h)	(%)	(%)	(%)	(%,d.b)	(g/cm^3)	(---)
				Data from Khadr (2004)					
80.93	1.75	14.92	3.20	15.60	20.40	64.00	19.80	1.15	1
80.93	1.75	14.87	3.56	15.60	20.40	64.00	19.80	1.15	2
80.93	1.75	14.80	3.70	15.60	20.40	64.00	19.80	1.15	3
80.93	1.75	14.00	4.70	15.60	20.40	64.00	19.80	1.15	4
80.93	1.75	13.40	6.90	15.60	20.40	64.00	19.80	1.15	5
				Data from Aboukarima (2004)					
80.93	1.75	17.00	2.50	28.50	17.70	53.70	17.42	1.35	6
80.93	1.75	17.00	3.40	28.50	17.70	53.70	17.42	1.35	7
80.93	1.75	17.00	4.80	28.50	17.70	53.70	17.42	1.35	8
80.93	1.75	18.00	2.40	28.50	17.70	53.70	17.55	1.30	9
80.93	1.75	18.00	3.50	28.50	17.70	53.70	17.55	1.30	10
80.93	1.75	18.00	5.10	28.50	17.70	53.70	17.55	1.30	11
80.93	1.75	18.00	2.50	28.50	17.70	53.70	20.02	1.38	12
80.93	1.75	18.00	3.20	28.50	17.70	53.70	20.02	1.38	13
80.93	1.75	18.00	5.10	28.50	17.70	53.70	20.02	1.38	14

Table 4. Evaluation criteria of predictive neural network models for chisel plow draft during training and testing phases.

Neural network models	MPE (%)		MAPE (%)		RMSE (kN)		Correlation coefficient ---	
	Training	Testing	Training	Testing	Training	Testing	Training	Testing
CTI	0.463	-6.780	11.826	14.328	2.658	2.957	0.862	0.802
CR	-2.072	-1.652	11.279	12.192	2.442	2.726	0.881	0.832
CSI	-2.756	-1.471	11.608	12.841	2.534	2.812	0.872	0.819
STI	-2.109	-2.646	11.297	12.399	2.387	2.617	0.887	0.845
SR	-2.222	-3.817	11.840	13.693	2.485	2.876	0.877	0.810
SSC	-4.893	-0.300	11.027	11.887	2.237	2.488	0.906	0.866

From Table (4), it is seen that the SSC neural network model gave less values of MAPE and RMSE during training and testing phases. Meanwhile, CTI neural network model gave positive value of MPE during training phase. However, as with the MPE is likely to be small since positive and negative PEs tend to offset one another. Hence, the MAPE is defined using absolute values of PE_t in Eq. (12). Fig. (3) shows comparisons of RMSE during training and testing phases for the six neural network models. It is seen that the SSC neural network model gave less value of RMSE during training and testing phases. RMSE measures the standard deviation of the errors.

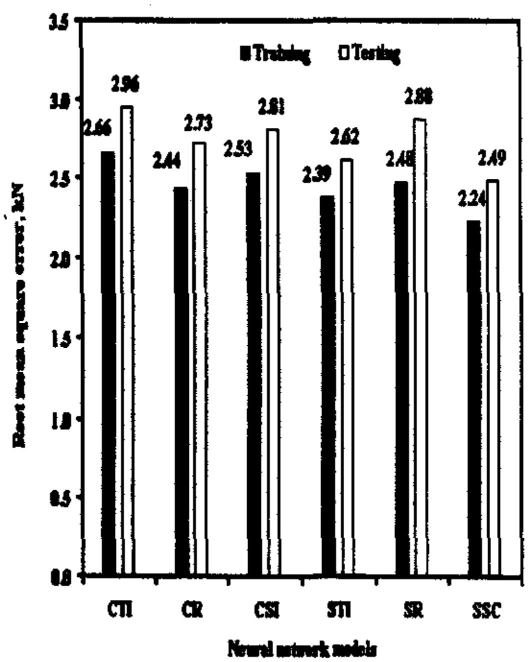

Fig. 3. Comparisons of RMSE during training and testing phases for the predictive neural network models.

Fig. (4) shows predicted versus actual draft using testing data with the six neural network models. Visual inspection of Fig. (4) indicates that the six neural network models follow the trends of the data relatively well. Also, scattering data show there is some tendency for the network to under- or overestimated chisel plow draft for all neural network models, however, data points were more widely dispersed about the ideal line (1:1). This greater dispersion corresponding to a relatively large testing RMSE values for the six neural network models.

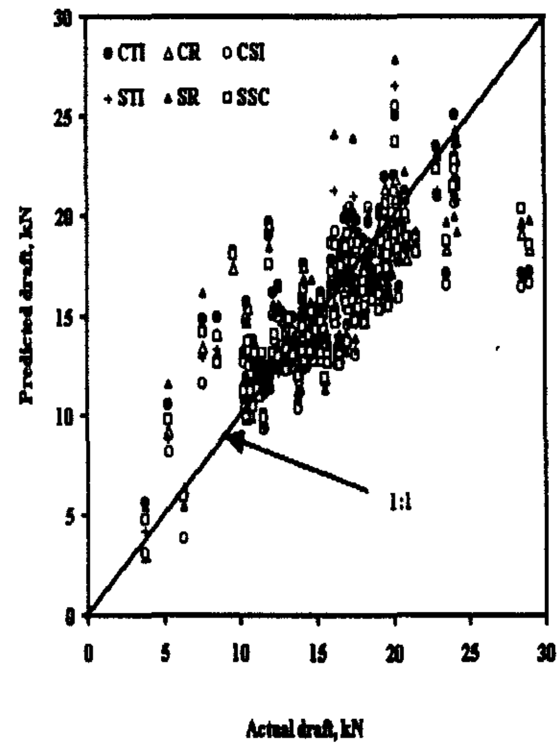

Fig. 4. Actual and predicted chisel plow draft (testing data) using six neural network models.

Overall, all neural network models provided good performance with any combination of soil fractions (i.e. soil texture index) as shown in Table (4). Little improvements in predictive accuracy may be possible through selection of inputs including separated soil frictions as RMSE value of SSC neural network model equals to 2.488 kN in testing phase compared to higher values of other neural network models of 2.957, 2.726, 2.812, 2.617 and 2.876 kN for CTI, CR, CSI, STI and SR neural network models, respectively. In general, the neural network model performs best when presented with data representing soil fractions as their separated values.

Table (5) shows actual chisel plow draft of validation data and percentage errors and MPE values when using six neural network models in predicting draft. It is seen from Table (5) that the SSC neural network model predicted chisel plow draft using validation data with reasonable accuracy, however, MPE value is -5.37 % compared to other values of MPE for CTI, CR, CSI, STI and SR neural network models for data from Khadr (2004).

Table 5. Actual chisel plow draft of validation data and percentage errors and MPE values when using six neural network models in predicting draft.

Actual chisel plow draft	Percentage errors (PE, %) using different neural network models						Data points
(kN)	CTI	CR	CSI	STI	SR	SSC	—
			Data from Khadr (2004)				
16.64	-25.30	-17.55	-6.55	27.82	20.19	1.14	1
16.72	-28.41	-23.50	-9.81	24.16	16.63	-2.75	2
17.21	-26.26	-22.43	-7.96	24.75	17.55	-1.51	3
17.30	-34.97	-36.36	-13.93	15.32	8.67	-12.49	4
20.23	-23.97	-32.38	6.18	15.72	8.21	-11.22	5
MPE, %	-27.78	-26.44	-6.41	21.56	14.25	-5.37	
			Data from Aboukarima (2004)				
12.23	-12.51	-7.11	7.60	15.62	11.37	12.02	6
13.28	-16.27	-19.88	1.51	7.53	5.65	3.54	7
14.77	-22.34	-36.09	-4.74	-3.59	-3.18	-9.00	8
11.20	-20.54	-12.50	4.82	12.95	3.30	7.77	9
12.59	-24.78	-26.69	-2.30	3.34	-3.02	-2.30	10
14.51	-30.60	-41.90	-8.41	-8.41	-11.72	-14.89	11
11.86	-8.26	-2.28	3.29	14.59	13.83	13.91	12
12.85	-10.19	-12.30	-0.86	8.79	10.35	7.78	13
15.48	-15.76	-32.88	-6.65	-4.01	1.49	-6.40	14
MPE, %	-17.92	-21.29	-0.64	5.20	3.12	1.38	

Table (6) shows the correlation coefficients between actual and predicted chisel plow draft using validation data, however, correlation coefficients are above 0.90. Higher values of correlation coefficients for data from Aboukarima (2004) (r = 0.99) compared to correlation coefficients values (r = 0.91 – 0.95) for data from Khadr (2004) are due to less deviations in draft data as depicted by MPE values, Table (5) Theses results show that the neural networks models offer the potential for better chisel plow draft predicts, which can lead to better management of the tractor-implement interaction with soil type.

Table 6. Correlation coefficients between actual and predicted chisel plow draft using validation data.

Source of data	Data points	Neural network models						
		CTI	CR	CSI	STI	SR	SSC	CTI
		Correlation coefficients (r)						
Khadr (2004)	From 1 to 5	0.91	0.93	0.94	0.94	0.95	0.95	0.91
Aboukarima (2004)	From 6 to 8	0.99	0.99	0.99	0.99	0.99	0.99	0.99
Aboukarima (2004)	From 9 to 11	0.99	0.99	0.99	0.99	0.99	0.99	0.99
Aboukarima (2004)	From 12 to 14	0.99	0.99	0.99	0.99	0.99	0.99	0.99

CONCLUSION

This study was undertaken to assessment of different indices depicting soil texture for predicting chisel plow draft using neural networks. The data needed were taken from pervious studies. To make the neural network model more universal, a variable describing the soil fractions (i.e. soil texture index) added to the input layer. Six forms of soil texture index were formulated to describe soil fractions. Training data set was the same for the six neural network models except that soil fractions form was changed. The developed neural network models were found to perform well in both training and testing for six soil fractions forms. Overall, all neural network models provided good performance with any combination of soil fractions. Little improvements in predictive accuracy may be possible through selection of inputs including separated soil frictions as RMSE value of SSC neural network model equals to 2.488 kN in testing phase compared to higher values of other neural network models of 2.957, 2.726, 2.812, 2.617 and 2.876 kN for CTI, CR, CSI, STI and SR neural network models, respectively. With regard to error criteria, any form could represent soil fractions during developing neural network model, but when soil fractions values were put as seprated inputs, they gave best results. Finally, the test of hypothesis using correlation coefficent and root mean square error indicated that the neural network predicts chisel plow draft with reasonable accuracy.

REFERENCES

Abd El Maksoud, S. E. (1970): Relation between soil physical characteristics and unit draft at different plough speeds and depths. Ph.D Thesis, Agric. Eng. Dept., Faculty of Agric., Cairo University.

Aboukarima, A.M. (2004): Artificial neural networks configuration for predicting performance of tillage implements under Egyptian conditions. Ph.D Thesis, Agric. Eng. Dept., Faculty of Agric., Ain Shams University.

Aboukarima, A.M.; M. N. El Awady; A. G.El Kabany and M. H.A. Kabeel (2003): Plows performance under Egyptian conditions depicted by artificial neural networks. Misr J. Ag. Eng., 20 (4): 919-936.

Al-Janobi, A.A.; A. M. Aboukarima and Kh. A. Ahmed (2001): Prediction of specific draft of different tillage implements using neural networks. Misr J. Ag. Eng., 18 (3): 669-714.

Altendorf, C.T.; R. L. Elliott; E.W. Stevens and M.L. Stone (1999): Development and validation of a neural network model for soil water content prediction with comparison to regression techniques. Trans. ASAE, 42(3):691-699.

Bahnas, O.T.S. (1999): Evaluation of some farm machinery under the Egyptian conditions. Ph.D Thesis, Agric. Mech. Dept., Faculty of Agric., Mansoura University.

Chandon, K. and R.L. Kushwaha (2002): Soil forces on deep tillage tools. The AIC 2002 Meeting CSAE/SCGR Program Saskatoon, Saskatchewan, July 14 - 17.

Dahab, M.H. and H.A.E. Al-Hashem (2002): Study on the effect of tractor power and speed on some field performance parameters working on a clay loam soil. J. Agric. Sci. Mansoura Univ., 27 (1): 573-582.

Dutot, A.-L.; J. Rude and B. Aumont (2003): Neural network method to estimate the aqueous rate constants for the OH reactions with organic compounds. Atmospheric Environment, 37:269–276.

El Awady, M. N.; A. G. El Kabany; M. H. A. Kabeel and A. M. Aboukarima (2003): Relative importance of variables affecting chisel-plow performance using neural networks. The 11th Conf. of Misr Soc. Ag. Eng., 15-16 October, Rice Mech. Center, Meet El Deeba, Kafer El Sheikh Governorate.

El Awady, M. N.; A. G. El Kabany; M. H. A. Kabeel and A. M. Aboukarima (2004): Predicting unit draft of tillage implements using statistical models and neural networks. The 12th Conf. of Misr Soc. Ag. Eng., 4-5 October, Alexandria Univ.: 139-249.

El Sheikha, M.A. (1989): A quick and effective method to prepare seedbed for Egyptian farms. Misr J. Ag. Eng., 16 (3): 213-223.

Elbanna, E. B. (1990): Effect of multiple wheel passes on soil properties and compaction. J. Agric. Sci. Mansoura Univ., 15(2): 274-289.

Ghazy, M.I.A. (2000): Soil mechanics and water. M.Sc Thesis, Agric. Mech. Dept., Faculty of Agric., Mansoura University.

Grisso, R.D.; M.Yasin and M.F. Kocher (1996): Tillage implement force operating in silty clay loam. Trans. ASAE, 39(6): 1977 – 1983.

Harrigan, T.M. and C.A. Rotz (1995): Draft relationships for tillage and seeding equipment. Applied Eng. in Agric., 11(6): 773 – 783.

Hassan, A.E. and A.S. Tohmaz (1995): Performance of skidder tires in swamps-comparison between statistical and neural network models. Trans. ASAE, 38 (5): 1545-1551.

Haykin, S. (1999): Neural networks, a comprehensive foundation, second edition. Prentice Hal: 2-235.

Idris, M.I.A. (1990): Actual and predicted power demands for ploughing operation under local conditions. M.Sc Thesis, Agric. Mech. Dept., Faculty of Agric., Tanta Univ., Kafer El Sheikh.

Ingleby, H. R. and T.G. Crowe (2001): Neural network models for predicting organic matter content in Saskatchewan soils. Can. Biosystems Eng., 43:7.1-7.5

Ismail, K.M. (2002): Statistical treatment of disk tool data for predicting soil draft. Misr J. Ag. Eng., 19 (2): 455-466.

Kaul, M.; R. L. Hill and C. Walthall (2005): Artificial neural networks for corn and soybean yield prediction. Agricultural Systems, 85: 1–18.

Khadr, Kh. A. A. (2004): Energy requirements for some seed-bed preparation implements under Egyptian conditions. The 12th Conf. of Misr Soc. Ag. Eng., 4-5 October, Alexandria Univ.:481-491.

Kushwaha, R.L. and L. Chi (1991): Finite element analysis of soil forces on tillage tools. Can. Agric. Eng., 33:39-45.

Kushwaha, R.L. and Z.X. Zhang (1997): Artificial neural networks modeling of soil-tool interaction. ASAE Paper No. 97-3067, ASAE, St. Joseph, Mich., USA:1-11.

Lentzscha, P.; R. Wielandb and S. Wirtha (2005): Application of multiple regression and neural network approaches for landscape-scale assessment of soil microbial biomass. Soil Biology & Biochemistry, 37:1577–1580.

Licznara, P. and M.A. Nearingb (2003): Artificial neural networks of soil erosion and runoff prediction at the plot scale. Catena, 51:89–114.

Makridakis,S. ; S.C. Wheelwright and R.J. Hyndman (1998): Forecasting: Methods and applications. 3rd Ed., John Wiley & Sons, Inc., N.Y: 642 p.

Marcel, G.S. and F. J. Leij (1998): Using neural networks to predict soil water retention and soil hydraulic conductivity. Soil & Tillage Res., (47): 37-42.

Merdun, H.,O. Cinar, R. Meral and, M. Apan (2005): Comparison of artificial neural network and regression pedotransfer functions for prediction of soil water retention and saturated hydraulic conductivity. Soil & Tillage Res., xxx (2005): xxx–xxx.

Michel, Jr, J.A.; K. J. Fornstrom and J. Borrelli (1985): Energy requirements of two tillage systems for irrigated sugarbeets, dry beans and corn. Trans. ASAE, 28 (6): 1731-1735.

Mouazen, A.M and H. Ramon (2002): A numerical-statistical hybrid modeling scheme for evaluation of draft requirements of a subsoiler cutting a sandy loam soil, as affected by moisture content, bulk density and depth. Soil & Tillage Res., 63 (3-4): 155-165.

Nasr, G. M. (1985): Study of the optimum tractor power requirement under Egyptian agricultural conditions. Ph.D Thesis, Agric. Eng. Dept., Faculty of Agric., Cairo University.

Obaia, A. R. A. (1991): Agricultural machinery selection based on tillage power requirements. M.Sc Thesis, Agric. Mech. Dept., Faculty of Agric., Mansoura University.

Oskoui, K.E. and S. J. Harvey (1992): Predicting cone index from soil physical properties and organic matter content. ASAE Paper No.92-1056, ASAE St. Joseph, Mich., USA:1-16.

Parlak, A.; Y. Islamoglu; H. Yasar and A. Egrisogut (2006): Application of artificial neural network to predict specific fuel consumption and exhaust temperature for a diesel engine. Applied Thermal Engineering, 26:824–828.

Saad, A.F. (2003): Pentetration resistance and soil water relations in calcareous soils. J. Agric. Sci. Mansoura Univ., 28(8): 6531-6537.

Shaban, A. O. (1999): Effects of some tillage systems and tractor performance on some soil properties and the production of some crops in the North Western coast of Egypt. M.Sc Thesis, Soil and Agric. Chem. Dept., Faculty of Agric. (Saba Bacha), Alex. University.

Tohmaz, A.S. and A.E. Hassan (1995): Application of artificial neural networks to skidder traction performancs. Journal of Terramechanics, 32 (3): 105-114.

Vesta Services, Inc. (2000): Qnet2000 Shareware, Vesta Services, Inc., 1001 Green Bay Rd, STE 196, Winnetka, IL 60093.

Yang, C.-C.; S.O. Prasher and G.R. Mehuys (1997): An artificial neural network to estimate soil temperature. Can. J. Soil Sci.,77:421-429.

Zein Eldin, A.M. (1995): Predicting soil bulk density from cone index data. Misr J. Agr. Eng., 12 (1): 179-194.

Zhang, Z. X. and R. L. Kushawaha (1999): Application of neural networks to simulate soil-tool interaction and soil behavior. Can. Agric. Eng., 41(2):119-125.

الملخص العربي

تقييم دلائل مختلفة تصف قوام التربة للتنبؤ بقوة شد المحراث الحفار مستخدمًا الشبكات العصبية

عبد الواحد محمد أبوكريمة [1] أحمد فريد سعد [2]

[1] معهد بحوث الهندسة الزراعية، مركز البحوث الزراعية

[2] قسم علوم الأراضي والمياه، كلية الزراعة، جامعة الإسكندرية

في هـــذه الدراسة تم تقييم دلائل مختلفة تصف قوام التربة للتنبؤ بقـــوة شـــد المحراث الحفار مستخدمًا الشبكات العصبية. تم ربط مكونـــات التربة من الرمل والطين والسلت بأشكال مختلفة لتكوين دلائل تصف قوام التربة. شملت المتغيرات المؤثرة في قوة الشد: عمق الحـــرث، عرض المحراث، قدرة الجرار المستخدم، السرعة الأمامية، دلـــيل قـــوام الـــتربة، المحتوى الرطوبي الابتدائي والكثافة الظاهرية الابتدائية للتربة.

أنشأت ستة شبكات عصبية باستخدام بيانات تجريبية حقلية تم تجمـــيعها مـــن دراسات سابقة في هذا المجال، وتم تحقيق النتائج من بـــيانات تجريبية حقلية لم تستخدم في التدريب أو الاختبار. وقد تم الحصـــول على نتائج تتوافق جيدًا مع القيم المشاهدة عند استخدام كل أشكال مكونات التربة (دلائل وصف قوام التربة) في التنبؤ بقوة شـــد المحـــراث الحفار، وكانت قيم معاملات الارتباط أكثر من ٨٠ % خلال مرحلتي التدريب والاختبار، مما يوضح إمكانية التنبؤ بقـــوة شد المحراث الحفار باستخدام نماذج الشبكة العصبية المقترحة بدقة مقبولة.

وعـــندما أنشأت شبكة عصبية واعتبرت مكونات التربة (الرمل والســـلت والطين) كمدخلات منفصلة بقيمها بالإضافة للمتغيرات الأخرى في هذه الدراسة أعطت أفضل النتائج على أساس أقل قيمة للجذر التربيعي للفرق بين مربع الأخطاء (RMSE) ومتوسط نسبة الخطأ المطلق (MAPE) خلال مراحل التدريب والاختبار والتحقق. حيـــث كانـــت قـــيمتي متوسط نسبة الخطأ المطلق خلال مرحلتي التدريـــب والاختـــبا+ر هما ١١,٠٢٧ % و ١١,٨٨٧% على الترتيب.