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DRAFT MODELS OF CHISEL PLOW BASED ON SIMULATION USING ARTIFICIAL NEURAL NETWORKS

Abd El Wahed M. Aboukarima*

ABSTRACT

In this research, draft data for chisel plows working with different soil conditions, rated plow widths and operational parameters were obtained with the help of simulation results using artificial neural networks. Whereas, polynomial draft models from regression analyses were formulated. The independent variables were forward speed, plowing depth, nominal tractor power, rated plow width, soil texture index, initial soil moisture content and initial soil specific weight. Effects of independent variables on simulated draft were in agreement with the published data in literatures for the chisel plow. Whereas, the coefficients of determination (R^2) were higher than 93%. Using the weights obtained from the trained neural network model, new formulations were presented for the calculation of draft of chisel plow. These formulations could be employed with any programming language or spreadsheet program for the estimation of draft of chisel plow.

INTRODUCTION

Draft of tillage implements reflects the soil physical conditions and the degree of soil compaction. For unique soil type, plowing speed and tool design, draft varies with bulk density, moisture content and plowing depth. These influencing factors were the main axis of interest of previous research, which adapted field experiments to understand how these factors affect the draft of tillage implements (Mouazen and Ramon, 2002). Instrumentation systems and field experiments are needed to determine draft of tractor-implement combination. This is time consuming and generally is complex and expensive work. So, simulation techniques are important and effective factors in efficient planning in such problems.

* Researcher, Agric. Eng. Res. Inst., Agric. Res. Center.

Mamman and Oni (2005) mentioned that draft of different plows varies with variations in soil conditions, tool design and operational parameters. Meanwhile, Zadeh (2006) reported that the amount of energy consumed during tillage operations depends on soil, tool and operating parameters.

Kheiralla et al. (2004) formulated polynomial draft models from orthogonal regression analyses based on linear and quadratic functions of travel speed and tillage depth. 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. Shebi et al. (1988) investigated the influence of tractor speed; tractor power and tractor tire inflation pressure with different tillage implements. They showed that measured drawbar pull was consistently higher than estimated drawbar pull. Also, travel reduction decreased from 11.2 to 3.5% while estimated drawbar pull increased from 0.72 to 1.42 kN when the tractor power was increased from 19 to 47 kW. 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. Mouazen and Ramon (2002) showed that soil moisture content, wet bulk density and tillage depth are important variables that affect draft.

Tong and Moayad (2006) found that from field experiments with a chisel plow the draft increased with increasing soil bulk density. Metwalli et al. (2002) showed that forward speed, plowing depth and inflation pressure had significant effect on draft during executing tillage in clay loam soil. Abo-Elnor et al. (2004) concluded that the blade cutting width had a significant effect on cutting forces so that the cutting forces increased but not in linear proportion as the cutting width increased. Dahab and Mutwalli (2002) reported that the traction force for chisel plow was higher in a soil of higher bulk density. Mouazen et al. (2003) showed that draft decreased with increasing moisture content. Al-Janobi et al. (2002) found that plowing depth and forward speed affect the horizontal force required to pull chisel plow.

Sahu and Raheman (2006) reported that the draft of the tillage implements was significantly affected by depth and speed of operation and with increase in depth and speed of operation, the draft of the combination tillage implements increased. This was because of the higher soil resistance and more volume of soil handled with increase in depth and higher force required to accomplish the soil acceleration with increase in speed of operation. By browsing in literatures, different forms of statistical and mathematical models for prediction of draft of different tillage implements were developed as results of Al-Janobi et al. (2000), Elbanna (1992), Al-Hamed and Aboukarima (2001) and Godwin and O'Dogherty (2007).

Artificial neural networks are a calculation technique originated from the structure and function of a human brain. The basic propriety of artificial neural networks is a possibility of less or more self-reliant investigation of the relationships between sets of inputs and corresponding sets of outputs through the determination of functional dependencies with any degree of complexity. It takes place in, so-called, network self-learning process, which is a gradual generalization of the information on a given phenomenon along with the investigation of particular real-time relationships among variables (Adamczyk et al., 2005). Artificial neural networks perform particularly well in the detection and incorporation of non-linear relationships and can be applied to a wide variety of fields such as Parlak et al. (2006) who used artificial neural network to predict specific fuel consumption for a diesel engine.

Many authors found a high effectiveness of artificial neural networks estimation of draft of tillage implements with great success, as results of studies by Aboukarima (2004), Aboukarima and Saad (2006), Aboukarima et al. (2003), Al-Janobi et al. (2001), El Awady et al. (2003), El Awady et al. (2004), El Awady et al. (2002), Kushwaha and Zhang (1997), Zhang and Kushawaha (1999), Tohmaz and Hassan (1995) and Hassan and Tohmaz (1995). All of these studies did not perform parametric study to show the trend and effect of individual variable on draft of tillage implement when the others were held. Occasionally, farm mechanization manager wants to know the magnitude of draft of a tillage implement at levels of separate forward speed, plowing depth, nominal tractor power, rated plow width, soil texture index, initial soil moisture content and initial soil specific weight. In these cases, numerous experiments are needed to get draft data and the cost is very high. So, simulation technique to generate draft data using artificial neural networks is useful in this case, because the results obtained depend on data performing in the actual field.

The aims of this research were:

(1) To obtain draft data of chisel plows working with different soil conditions, rated plow widths and operational parameters with the help of simulation results using artificial neural networks to formulate simple draft models from regression analyses.

(2) To introduce new formulations that can be employed with any programming language or spreadsheet program for the estimation of draft of chisel plow.

(3) To illustrate an example of how to predict draft of mechanization unit (chisel plow + tractor) using the developed formulations.

MATERIALS AND METHODS

Soil texture index developed by Aboukarima and Saad (2006) was used to represent soil type in this research. The soil texture index (*STI*) could be obtained as follows:

$$STI = \frac{log\ (C_a^{\ S_i})}{100} \tag{1}$$

Where S_i and C_a are % of silt and clay fractions in the soil, respectively. Meanwhile, the sand fraction is represented implicitly since the sum of sand, silt and clay contents is always constant.

Collecting required data:

Available data in literatures, which directly relate to the subject, are collected from (Abd El Maksoud, 1970; Nasr, 1985; El Sheikha, 1989; Idris, 1990; Obaia, 1991; Bahnas, 1999; Shaban, 1999, Ghazy, 2000, Khader, 2004 and Yaya, 2004). Also, the obtained data (80 data points) for chisel plow by the author were taken (the description of the field experiments was in Aboukarima et al., 2006). Whereas, these studies executed field experiments using different chisel plows (only one pass over the soil) in different sites having different moistures, bulk densities and textures with different changeable working conditions. Collected data set was consisted of 1121 data points. Table (1) shows some statistical parameters of collecting data that describe affecting input variables used in developing artificial neural network model for predicting draft of chisel plow.

Table (1): Statistical parameters* of collecting data.

Statistical parameters	Inputs							Output
	Nominal tractor power+	Rated plow width	Plowing depth	Forward speed	Soil texture index	Initial soil moisture content	Initial soil specific weight	Measured draft
	(kW)	(m)	(cm)	(km/h)	(---)	(%,d.b)	(kN/m^3)	(kN)
Average	49.71	1.75	16.43	3.47	0.434	21.41	13.53	16.39
Minimum	22.07	1.00	8.00	0.94	0.022	4.60	8.78	2.75
Maximum	103.01	3.10	26.00	7.20	0.781	41.73	17.95	39.46
Standard deviation	17.41	0.23	4.30	1.09	0.205	7.06	1.72	5.02
Coefficient of variation (%)	35.02	13.10	26.14	31.47	47.18	32.99	12.70	30.64

* No. of observations = 1121. + According to tractor operator's manual.

Structure and developing artificial neural network model:

Artificial neural networks consist of simple processing elements or 'neurons' linked with each other in a particular configuration, Fig. (1). Each neuron is a non-linear transducer of input signals. Input signals (*Xi*) are given weight coefficients (*Wi*), summed and transferred to a non-linear function of activation (transfer function, *F*) that forms an output signal (*Y*). 'Training' of the network then consists of the adjustment of the weight coefficients of input neuron signals. Values of the vector of input signals and the vector of desired output signals are presented to the network. Weight coefficients are chosen in such a way that the vector of predicted output signals maximally correspond to the vector of desired output signals.

The action of the neural network is determined not only by neuron properties and weights of connections between them, but also by net topology, i.e. the relative positions of neurons.

The development of a particular training algorithm, called the 'delta rule of error back propagation' has made multilayer feed forward networks the most popular type, Fig. (2).

Using commercially available software, Qnet2000 (Vesta Services, 2000), the artificial neural network used in the present study was characterized by the following parameters: feed-forward, back-propagation training algorithm, one hidden layer (5 hidden neurons), random choice of starting values of weights ranged from –1 to 1, constant learning coeffcient of 0.00729, momentum factor of 0.8, logistic function (sigmoid transfer function) of neuron activation, 200000 training cycles. These configurations gave training error of 0.040711. The choice of the artificial neural network type was done based on the results of preliminary investigations (data not included). The input layer of the model consisted of the nodes corresponding to the following variables: plowing depth, rated plow width, forward speed, soil texture index, initial soil moisture content, initial soil specific weight and nominal tractor power. The output layer (representing the variable that is being predicted) consisted of the one node related to draft, Fig. (2).

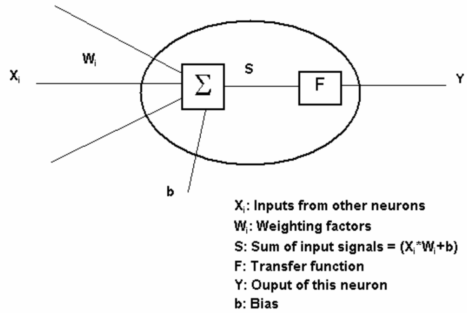

Fig. (1): Structure of a single neuron.

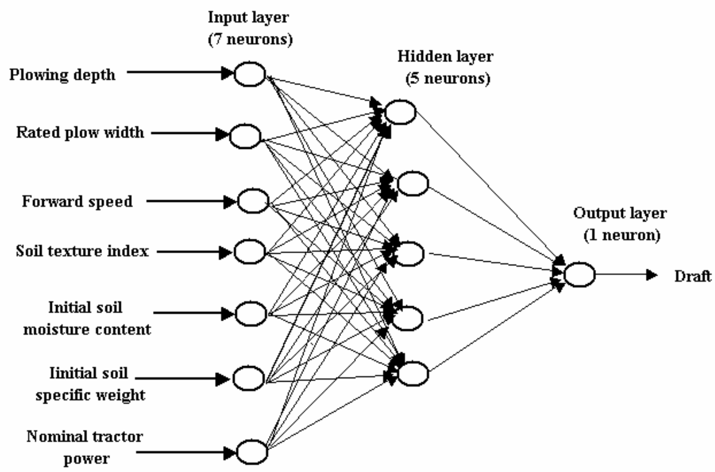

Fig. (2): Illustration of a three-layered neural network with one input layer, one hidden layer and one output layer.

The whole data set (1121 data points) was randomized and used for training the artificial neural network. Because the logistic function of neuron activation in the hidden layer was chosen, the input and output values were normalized between 0.15 and 0.85 prior to use with the model, according to the following formula:

$$X = X(t) = \frac{(t - t_{\min})}{(t_{\max} - t_{\min})} \times (0.85 - 0.15) + 0.15 \qquad (2)$$

Where t is the original values of input and output variables, X is normalized value and t_{max} and t_{min} are maximum and minimum values of input and output variables, Table (1). The final step in neural network activity is the denormalization of output.

The accuracy of artificial neural network predictions was evaluated using the different error statistics as follows:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{i=N} (Measured\ -\ Predicted\ )^2}{N}} \qquad (3)$$

$$MAE = \frac{1}{N} \times \sum_{i=1}^{i=N} \left| Measured\ -\ Predicted \right| \qquad (4)$$

$$D = 1 - \left[\frac{\sum_{i=1}^{i=N} (P_i' - O_i')^2}{\sum_{i=1}^{i=N} \left(|P_i'| + |O_i'| \right)^2} \right] \qquad (5)$$

Where *RMSE* is root mean square error and *MAE* is mean absolute error. *D* is index of agreement between measured (O_i) and predicted (P_i) values according to Willmott (1981), where $P_i' = P_i - \overline{O}$ and $O_i' = O_i - \overline{O}$, with $\overline{O}$ the mean measured value. The index, *D*, can be any value between 0 and 1, the nearer *D* is to 1 the better the agreement between measured and predicted values. In this research, parametric study showing the effects of forward speed, plowing depth, nominal tractor power, rated plow width, soil type, initial soil moisture content and initial soil specific weight upon the draft of a chisel plow were investigated by graphs and different draft models were obtained for each parameter by regression analyses.

RESULTS AND DISCUSSION

Fig. (3) shows the relationship and coefficient of determination between measured and predicted draft. It shows that scattering points are around the regression line with coefficient of determination (R^2) of 0.819. Whereas, Table (2) shows error statistics for predicting draft of chisel plow using artificial neural networks. Using the weights obtained from the trained neural network model, new formulations were presented in Annex (A) for the calculation of draft of chisel plow. These formulations could be employed with any programming language or spreadsheet program for the estimation of draft of chisel plow.

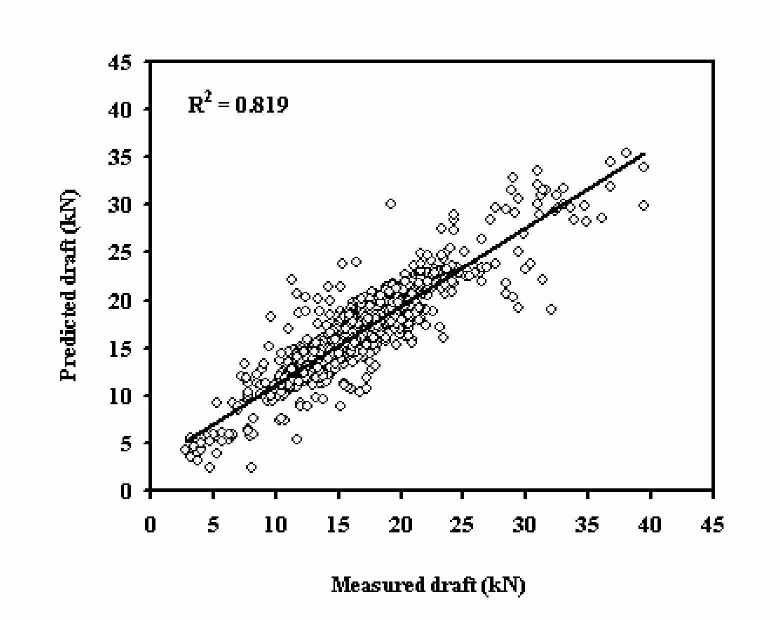

Fig. (3): The relationship between measured and predicted draft.

Table (2): Error statistics for predicting draft of chisel plow using artificial neural networks.

Error items	Value
Root mean square error, *RMSE*	2.14 kN
Mean absolute error, *MAE*	1.48 kN
Index of agreement, *D*	0.948

Using formulations in Annex (A), the effects of nominal tractor power, rated plow width, plowing depth, forward speed, soil texture index, initial soil moisture content and initial soil specific weight upon simulated draft of a chisel plow were depicted as shown in Figs. (4 through 10). Results showed that increasing forward speed, plowing depth, nominal tractor power, rated plow width, soil texture index and initial soil specific weight result in increasing simulated draft of chisel plow. Meanwhile, increasing initial soil moisture content results in decreasing simulated draft of chisel plow. These results are in agreement with the published data in literatures for the chisel plow. It is seen that increasing nominal tractor power from 45 to 70 kW i.e. by 56% results in increasing simulated draft by 21%, Fig. (4). Meanwhile, increasing rated plow width from 1.25 to 2.50 m i.e. by 80% results in increasing simulated draft by 68%, Fig. (5). Also, increasing plowing depth from 10 to 20 cm, i.e. by 100 % results in increasing simulated draft by120%, Fig. (6).

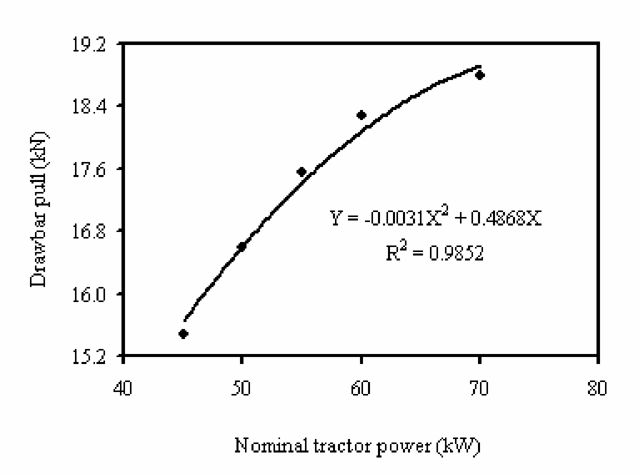

Fig. (4): Effect of nominal tractor power from 45 to 70 kW on simulated drawbar pull.
(Rated plow width =1.75 m, plowing depth =12 cm, forward speed = 4.5 km/h, soil texture index = 0.220, initial soil moisture content =16% d.b and initial soil specific weight = 12.16 kN/m^3)

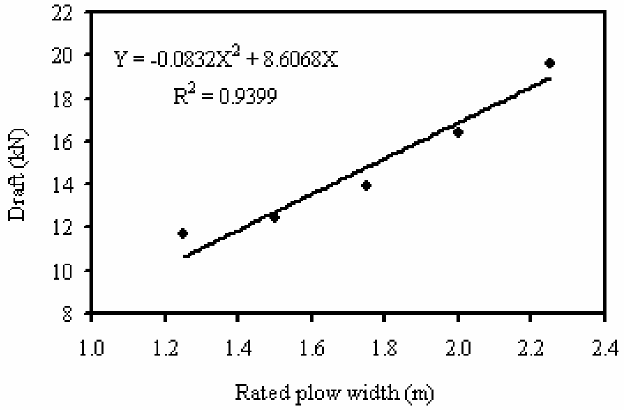

Fig. (5): Effect of chisel plow rated width from 1.25 to 2.25 m on simulated draft.
(Nominal tractor power = 80 kW, plowing depth =15 cm, forward speed = 3.5 km/h, soil texture index = 0.441, initial soil moisture content =25% d.b and initial soil specific weight = 13.34 kN/m^3)

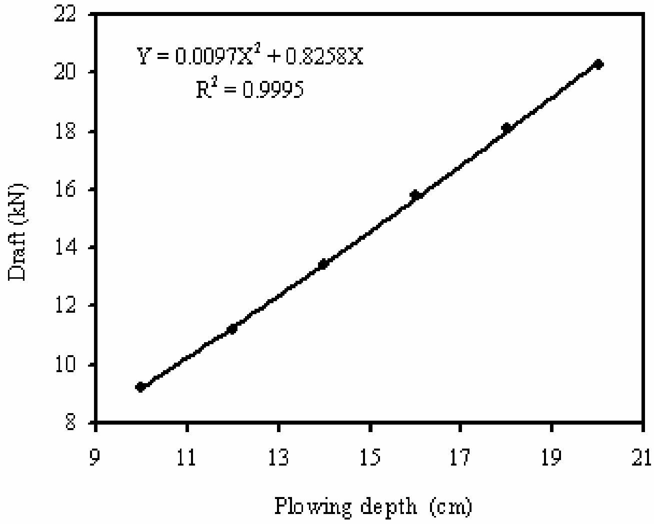

Fig. (6): Effect of plowing depth from 10 to 20 cm on simulated draft of a chisel plow.
(Nominal tractor power = 47 kW, rated plow width =1.75 m, forward speed = 4.5 km/h, soil texture index = 0.441, initial soil moisture content =22% d.b and initial soil specific weight = 13.34 kN/m^3)

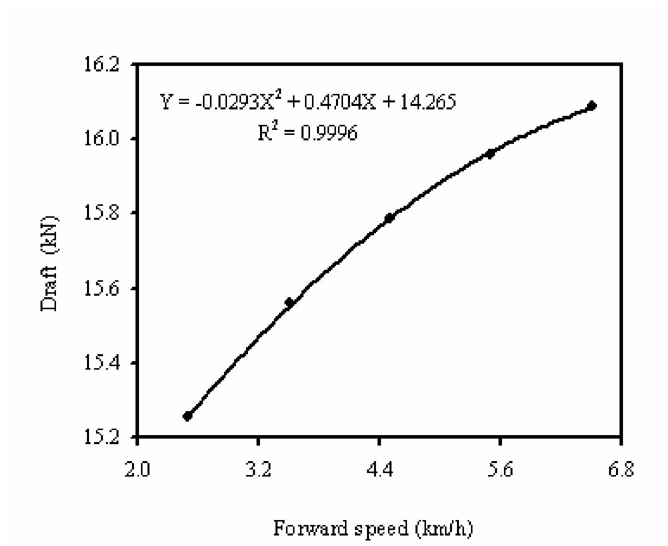

Fig. (7): Effect of forward speed from 2.5 to 6.5 km/h on simulated draft of a chisel plow.
(Nominal tractor power = 47 kW, rated plow width =1.75 m, plowing depth =16 cm, soil texture index = 0.441, initial soil moisture content =22% d.b and initial soil specific weight = 13.34 kN/m^3)

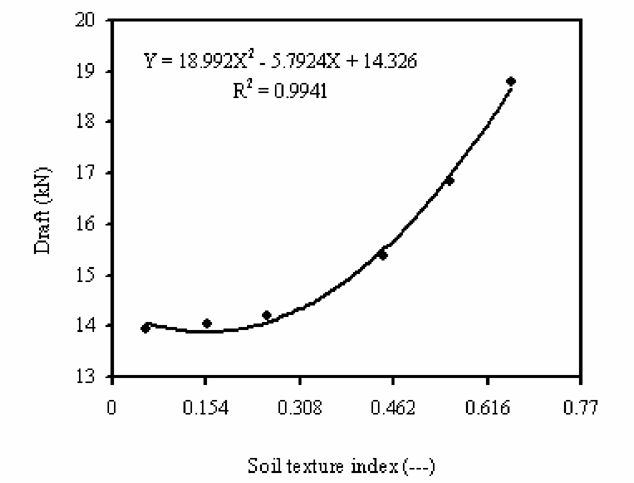

Fig. (8): Effect of soil texture index from 0.054 to 0.655 on simulated draft of a chisel plow.
(Nominal tractor power = 50 kW, rated plow width =1.75 m, plowing depth =15 cm, forward speed = 4.5 km/h, initial soil moisture content =25% d.b and initial soil specific weight = 12.15 kN/m^3)

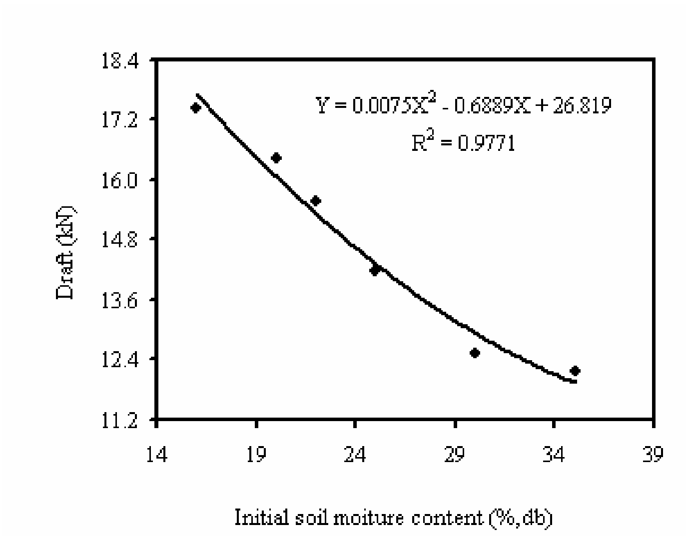

Fig. (9): Effect of initial soil moisture content from 16 to 35 % on simulated draft of a chisel plow.

(Nominal tractor power = 47 kW, rated plow width =1.75 m, plowing depth =16 cm, forward speed = 3.5 km/h, soil texture index = 0.441 and initial soil specific weight = 13.34 kN/m^3)

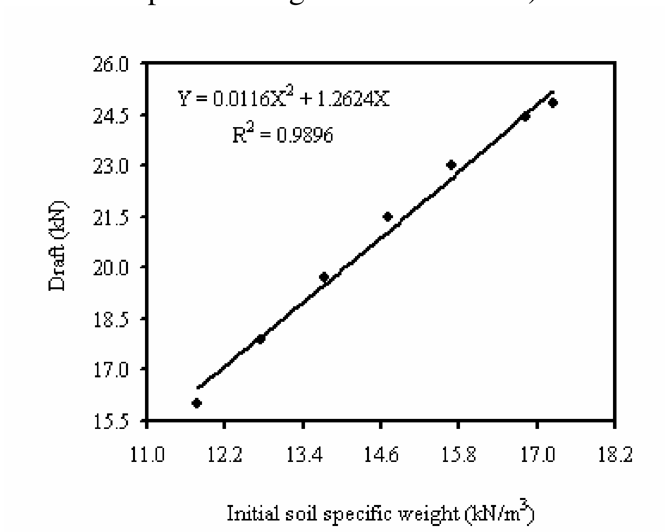

Fig. (10): Effect of initial soil specific weight from 11.77 to 17.24 16 kN/m^3 on simulated draft of a chisel plow.

(Nominal tractor power = 80 kW, rated plow width =1.75 m, plowing depth =20 cm, forward speed = 4.8 km/h, soil texture index = 0.255 and initial soil moisture content =18.5 % d.b)

From Fig. (7), increasing forward speed from 2.5 to 6.5 km/h, i.e. by 160 % results in increasing simulated draft by 5%. This indicates low contribution of forward speed in draft of chisel plow. Also, soil type had effect on draft of a chisel plow, where increasing soil texture index with over 100% (1113%) from 0.054 to 0.655 results in increasing simulated draft with 35%, Fig. (8). Meanwhile, increasing the initial soil moisture content by 119%, i.e. from 16 to 35% (d.b), result in decreasing simulated draft with 28%, Fig. (9). Also, increasing initial soil specific weight by 46% from 11.77 to 17.24 kN/m^3 simulated draft increases with 55%, Fig. (10). Coefficients of determination (R^2) of simulated draft models at different independent variables for chisel plow are higher than 93%. The obtained polynomial simulated draft models from regression analyses on each figure will be helpful to develop comprehensive information on draft of chisel plow for the formulation of Egyptian agricultural machinery management database. The high determination coefficients indicate that the draft of a chisel plow can be estimated as a function of nominal tractor power, rated plow width, plowing depth, forward speed, soil texture index represents soil type, initial soil moisture content and initial soil specific weight with a high degree of accuracy.

CONCLUSION

The effect of forward speed, plowing depth, nominal tractor power, rated plow width, soil texture index, initial soil specific weight and initial soil moisture content on simulated draft of chisel plow was investigated. Whereas, polynomial draft models from regression analyses were formulated based on simulated draft data obtained using artificial neural networks. The results showed that the trend between the simulated draft of chisel plow and the affecting variables was in agreement with the published data in literatures for the chisel plow. Whereas, the coefficients of determination (R^2) were higher than 93 %. Using the weights obtained from the trained neural network model, new formulations were presented for the calculation of draft of chisel plow. These formulations could be employed with any programming language or spreadsheet program for the estimation of draft of chisel plow. These obtained results will be helpful to develop comprehensive information on draft requirements of chisel plow for the formulation of Egyptian agricultural machinery management database.

REFERENCES

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

Abo-Elnor, M.; R. Hamilton and J.T. Boyle (2004). Simulation of soil–blade interaction for sandy soil using advanced 3-D finite element analysis. Soil & Tillage Res., 75: 61–73.

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

Aboukarima, A.M. and A. F. Saad (2006). Assessment of different indices depicting soil texture for predicting chisel plow draft using neural networks. Alexandria Sci. Exc. J., 27(2): 170-180.

Aboukarima, A.M.; A. M. Kishta and S. N. Abd El Halim (2006). Statistical models for estimating the field performance of a chisel plow as affected by some soil and working conditions. 1st Agric. Eng. Conf., Mansoura Univ., 17-18 July 2006: J. agric. Sci. Mansoura Univ.,31 (7):39-52.

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. Agr. Eng., 20 (4): 919-936.

Adamczyk, K.; K. Molenda; J. Szarek and G. Skrzyski (2005). Prediction of bulls' slaughter value from growth data using artificial neural network. J. Cent. Eur. Agric., 6(2): 133-142.

Al-Hamed, S.A. and A.M. Aboukarima (2001). Predicting the optimum performance of agricultural tractor and implement system based on minimum specific fuel consumption. Misr J. Agr. Eng., 18 (2): 392-406 (In Arabic).

Al-Janobi, A.; M. F. Wahby; A. M. Aboukarima and S.A. Al-Hamed (2002). Influence of chisel plow shank shape on horizontal and vertical force requirements. Ag. Science, Sultan Qaboos Univ, 7(1): 13-19.

Al-Janobi, A.; M. Kabeel and A. M. Aboukarima (2000). Evaluation of three mathematical models predicting horizontal and vertical forces of chisel tools. Misr J. Agr. Eng., 17(2): 412-431 (In Arabic).

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.

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

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.

Dahab, M.H. and M.D. Mutwalli (2002). Tractor tractive performance as affected by soil moisture content, tires inflation pressure and implement type. AMA, 33:29–34.

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: 395-407.

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., 15-16 October, Alexandria Univ.: 139-249.

El Awady, M.N.; A. G.El Kabany; M.H.A. Kabeel and A. M. Aboukarima (2002). Using neural networks and linear regression for predicting energy requirements in plowing. The 10th Conf. of Misr Soc. Ag. Eng: 115-126 (In Arabic).

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. (1992). Tillage tools draft: chisel and moldboard plows. Misr J. Ag. Eng., 9 (4): 491-510.

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

Godwin, J. and M.J. O'Dogherty (2007). Integrated soil tillage force prediction models. J. of Terramechanics, 44 (1):3-14.

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

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.

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.

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.

Kheiralla , A.F.; A. Yahya ; M. Zohadie ; W. Ishak (2004). Modeling of power and energy requirements for tillage implements operating in Serdang sandy clay loam, Malaysia. Soil & Tillage Res., 78:21–34.

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.

Mamman, E. and K.Oni (2005). Draft performance of a range of model chisel furrowers. Agricultural Engineering International: the CIGR E-Journal. Manuscript PM 05 003. Vol. VII. November, 2005.17 p.

Metwalli, S.M.; M.H. A. Kabeel; A. M. Aboukarima and S.E. Bader (2002). Effect of forward speed, plowing depth and inflation pressure on tractors performance during tillage I. In clay loam soil. Misr J. Agr. Eng., 19 (3): 597-610.

Mouazen, A. M.; R. Herman and De B. Josse (2003). Modeling compaction from on-line measurement of soil properties and sensor draft. Precision Agriculture, 4 (2): 203-212.

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. PhD 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.

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.

Sahu, R. K. and H. Raheman (2006). An approach for draft prediction of combination tillage implements in sandy clay loam soil. Soil & Tillage Res., 90 (1-2): 145-155.

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.

Shebi, J.G.; K.C. Oni and F. G. Braid (1988). Comparative tractive performance of three tractors. AMA, 19 (2): 25-29.

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

Tong, J. and B. Z. Moayad (2006). Effects of rake angle of chisel plow on soil cutting factors and power requirements: A computer simulation. Soil & Tillage Res., 88 (1-2): 55-64.

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

Willmott, C.J. (1981). Some comments on the evaluation of model performance. Bulletin American Meteorological Society, 63 (11): 1309-1313.

Yaya , A.M. (2004). Measurments and prediction of tillage draft and energy for chisel plow in silty clay loam. Misr J. Agr. Eng., 21 (1):201-212. (In Arabic).

Zadeh, S. R. A. (2006). Modeling of energy requirements by a narrow tillage tool. PhD Thesis, Dept. of Agric. and Bioresource Eng., Univ. of Saskatchewan, Saskatoon, Canada.

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

ANNEX (A)

The following equations were used to predict draft of chisel plow based on training artificial neural network model:

Step 1: Normalize the original input variables as follows:

$$X1 = \frac{(nominal\ tractor\ power,\ kW - 22.07)(0.85 - 0.15)}{(103.01 - 22.07)} + 0.15 \quad (1\text{-a})$$

$$X2 = \frac{(rated\ plow\ width,\ m - 1.00)(0.85 - 0.15)}{(3.10 - 1.00)} + 0.15 \quad (2\text{-a})$$

$$X3 = \frac{(plowing\ depth,\ cm - 8)(0.85 - 0.15}{(26 - 8)} + 0.15 \quad (3\text{-a})$$

$$X4 = \frac{(forward\ speed,\ km/h - 0.94)(0.85 - 0.15)}{(7.20 - 0.94)} + 0.15 \quad (4\text{-a})$$

$$X5 = \frac{(soil\ texture\ index,\ (\text{--}) - 0.022)(0.85 - 0.15)}{(0.781 - 0.022)} + 0.15 \quad (5\text{-a})$$

$$X6 = \frac{(initial\ soil\ moisture\ content,\ \%db - 4.60)(0.85 - 0.15)}{(41.73 - 4.60)} + 0.15 \quad (6\text{-a})$$

$$X7 = \frac{(initial\ soil\ specific\ weight,\ kN/m^3 - 8.79)(0.85 - 0.15)}{(17.95 - 8.79)} + 0.15 \quad (7\text{-a})$$

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

$$S1 = 5.458\times X1+5.088\times X2+2.080\times X3- 1.489\times X4-0.624\times X5 + 6.385\times X6 -2.703\times X7-8.838 \quad (8\text{-a})$$

$$S2 = -3.152\times X1+ 0.184\times X2 + 2.543\times X3 -1.516\times X4-1.718\times X5 -9.624\times X6 +1.463\times X7+2.463 \quad (9\text{-a})$$

$$S3 =3.501\times X1-0.588\times X2- 0.065\times X3 -1.240\times X4 +3.246\times X5 +0.034\times X6 -2.757\times X7-0.588 \quad (10\text{-a})$$

$$S4 =1.787\times X1+5.993\times X2+0.123\times X3 -0.480\times X4 +1.671\times X5 +5.394\times X6 -2.461\times X7-7.206 \quad (11\text{-a})$$

$$S5 = -5.519\times X1+2.621\times X2-3.011\times X3 +1.485\times X4-2.441\times X5 +6.113\times X6 +2.971\times X7-1.555 \quad (12\text{-a})$$

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

$$F1 = \frac{1}{1 + e^{-S1}} \quad (13\text{-a})$$

$$F2 = \frac{1}{1 + e^{-S2}} \quad (14\text{-a})$$

$$F3 = \frac{1}{1+e^{-S3}} \tag{15-a}$$

$$F4 = \frac{1}{1+e^{-S4}} \tag{16-a}$$

$$F5 = \frac{1}{1+e^{-S5}} \tag{17-a}$$

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

$$Y = -5.668\times F1 - 2.469\times F2 - 4.805\times F3 + 7.813\times F4 - 3.864\times F5 + 3.545 \tag{18-a}$$

Step 5: Compute the normalized output signal (draft) as follows:

$$X\ (draft\ \ normalized\ ) = \frac{1}{1+e^{-Y}} \tag{19-a}$$

Step 6: Denormalize the output signal (draft) as follows:

$$Draft\ (kN) = \frac{(X-0.15)(39.46-2.75)}{(0.85-0.15)} + 2.75 \tag{20-a}$$

Example: Predict draft (kN) of a chisel plow hitched by a tractor having nominal power of 50 kW and running at 4.8 km/h with depth of 15 cm in soil having 18.12% sand, 34.78% clay and 47.10% silt (soil texture index, $STI = \frac{log\ (34.78^{47.1}\ )}{100} = \frac{log\ (34.78^{47.1} + 18.12)}{100} = 0.726$). The rated plow width was 1.75 m, the initial soil moisture content was 15.40 % (d.b) and the initial soil specific weight was 13.44 kN/m^3.

The solution:

By applying equations (1-a through 19-a), the following results are obtained:

Equations (1-a through 7-a)	Equations (8-a through 12-a)	Equations (13-a through 17-a)	Equation (18-a)	Equation (19-a)
X1= 0.3916	*S1= -4.2614*	*F1= 0.0139*	*Y =-0.3373*	*X =0.4165*
X2= 0.4000	*S2= -2.5419*	*F2= 0.0730*		
X3= 0.4222	*S3= 1.0109*	*F3= 0.7332*		
X4= 0.5816	*S4= -2.3381*	*F4= 0.0880*		
X5= 0.7992	*S5= -1.3619*	*F5= 0.2039*		
X6= 0.3536				
X7= 0.5057				

Then by applying equation (20-a), the draft value is obtained and equals to 16.73 kN.

<u>الملخص العربي</u>

نماذج قوة الشد للمحراث الحفار على أساس المحاكاة مستخدما الشبكات العصبية الاصطناعية

د./عبد الواحد محمد أبو كريمة*

في هذا البحث تم الحصول على بيانات قوة الشد للمحراث الحفار والذي يعمل تحت ظروف مختلفة للتربة واتساع المحراث ومتغيرات التشغيل بمساعدة نتائج المحاكاة مستخدما الشبكات العصبية الاصطناعية، حيث تعطي المحاكاة منها نتائج دقيقة لأنها في مرحلة تدريبها تعتمد على قياسات حقلية فعلية للمدخلات والمخرجات المقابلة لها وليس معادلات مستنبطة. وتم الحصول من هذه النتائج باستخدام الانحدار متعدد الحدود على نماذج لقوة الشد، حيث كانت اتجاهات تأثيرات عوامل الدراسة على قوة الشد المحراث الحفار متفقة مع ما هو منشور في الدراسات السابقة، حيث تراوح معامل الارتباط لأكثر من ٩٣%. وتعتبر هذه الدراسة وسيلة سهلة ومبسطة لاتخاذ القرار عند تحديد وحدة الميكنة المناسبة (جرار + محراث حفار) للعمل تحت ظروف تشغيل محددة للمحراث وقدرة الجرار ونوع التربة. ومن قيم الأوزان المتحصل عليها من تدريب الشبكة العصبية الاصطناعية أمكن تطوير مجموعة من المعادلات يمكن برمجتها بأي لغة برمجة أو داخل ورقة عمل، ومن خلال ذلك يمكن إيجاد قيم قوة الشد للمحراث الحفار تحت ظروف التشغيل المختلفة دون الحاجة للشبكات العصبية الاصطناعية.

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* باحث، معهد بحوث الهندسة الزراعية، مركز البحوث الزراعية.