Misr J. Ag. Eng., 20 (4): 919-936

Plows Performance under Egyptian Conditions Depicted by Artificial Neural Networks

Abdulwahed M. Aboukarima[1] **Mohamed N. El Awady[2]**
Abdulfadil G.El Kabany[3] **Mohamed H.A. Kabeel[4]**

Abstract

Multilayer feedforward neural network with *12* input and *4* output neurons was trained using a backpropagation learning algorithm. It was used to depict and predict plows performance during plowing process under Egyptian conditions. Data needed to train and test the artificial neural network (ANN) model was obtained from previous similar field experiments found in literatures. The obtained data set were *430* data points where *320* and *110* of them were used for training and testing ANN model respectively. The input parameters were soil texture index, chisel plow, moldboard plow, disc plow, rotary plow, plowing depth, rated width of plow, forward speed, initial soil moisture content, initial soil bulk density, rated tractor power, and number of plow passes over the soil. The results showed that the variation between observed and predicted plows performance parameters was small and the coefficients of determination (R^2) were *0.86*, *0.74*, *0.80* and *0.79* for effective field capacity (*fed/h*), fuel consumption (*lit/h* and *lit/fed*), and plowing energy (*kW.h/fed*) respectively. Verification of the ANN model in prediction was conducted using field data for chisel plow operating at three forward speeds and one plowing depth. The results indicated that the ANN model was able to predict plows performance parameters and the trends of the predicted results of fuel consumption and plowing energy with forward speed were the same as published in local previous studies for chisel plow.

Introduction

Computer programs like simulation are being used to assist farm manager in decision making about how to manage their machines or production operations and how to select their machinery requirements effectively.

1. **Ass. Res., Ag. Eng. Res. Inst., Dokki, Gizza.**
2. **Prof. Emt. Ag. Eng., Col. Ag., Ain Shams Univ.**
3. **Ass. Prof. Ag. Eng., Col. Ag., Ain Shams Univ.**
4. **S. Res. Ag. Eng. Res. Inst., Dokki, Gizza.**

Tillage is one of the most fundamental and essential operations in agricultural production and is one of the fully mechanized operations in Egypt (El Awady, *1986*). The availability of plows performance data is an important factor not only in analysing farm mechanization systems but also knowing plows performance data may help for planning cost estimation. However, plows performance data include fuel consumption, effective field capacity, and plowing energy.

On the other hand, farms managers employ plows performance data to estimate not only the proper tractors size but also they can minimize ownership and operating costs of both tractors and tillage implements. Therefore, predicting plows performance during plowing process is important for farm machinery management. However, Michel et al. (*1985*) showed that energy requirements for plowing vary greatly with soil type, soil moisture, soil density, previous treatment, ground cover, and operation speed and depth.

El Awady (*1978*) investigated importance of fuel consumption as it is important for cost estimation and economy of operation and it is a good indication of tractor condition and age. Imara (*1996*) got high coefficients of determination (R^2>0.9) of equations to predict effective field capacity (*fed/h*), fuel consumption (*lit/fed*), and plowing energy (*kW.h/fed*) for different plows using multiple linear regression where the affecting variables were forward speed, soil moisture content and plowing depth.

Artificial neural networks are essentially parallel computational models comprised of densely interconnected adaptive processing units with simulation of knowledge acquisition and organizational skills of the human brain. A very important characteristics of neural networks includes that it can learn from the experience (experimental data) and is capable of generalization according to the knowledge that has been gained (Kushwaha and Zhang, *1997*).

Artificial neural network (ANN) has the capability of correlating large and complex data sets without any prior knowledge of the relationship between them (Sablani et al. *1997*). They have become powerful tools for modeling a system that had incomplete or a little understanding regarding its governing law (Kushwaha and Zhang, *1997*).

In recent years, there has been an increasing use of ANN models in the field of agricultural engineering due to (1) ability in solving a variety of the formidable problems, including pattern classification and prediction (Shaalan et al. *1999*) and (2) performed well even with noisy, incomplete or inconsistent data (Sablani et al. *1997*).

Hassan and Tohmaz (*1995*) used the neural networks to evaluate the tractive performance of a rubber-tire skidder operating on soft organic soil. They used three tire sizes inflated at each of three inflation pressures (*69*, *103*, and *172 kPa*). Their results indicated that the ANN (*4-5-3-1*) simulation of the pull-load relationship was in close agreement with the statistical model of the actual pull-load data.

Kushwaha and Zhang (*1997*) studied the soil-tool interacting system using neural networks to recognize soil-tool response and evaluate the system performance. The model input included soil types, five tool types, and operating speed. The output was tool horizontal force (draft). The results showed that the neural networks gave a good prediction of tool response to the system inputs.

Al-Janobi et al. (*2001*) developed ANN model to predict specific draft for different plows working with different forward speeds in sandy loam soil. Their results indicated that the ANN model (*8-24 -12-1*) gave a good correlation ($R^2 = 0.97$) between measured and predicted values of the specific draft of plows.

El Awady et al. (*2002*) developed ANN model to predict the energy consumed during plowing process with chisel, moldboard and disc plows working at different forward speeds and levels of soil moisture content in clay loam soil. Their ANN model (*5-24 -2*) was comparable to statistical model and good correlation ($R^2 = 0.98$) was obtained between measured and predicted energy values using ANN model.

Korthals et al. (*1994*) reported that the number of nodes and layers in ANNsystem is selected by the user to reach an appropriate model to the problem being addressed. Zhang and Trimble (*1996*) mentioned that there is no universally applicable formula to be used for deciding the size of hidden layers in ANN applications. Also, a network with more hidden neurons requires more computing power and more training time.

The objective of this research is seeking the optimal structure of an ANN to depict and predict plows performance parameters including fuel consumption, effective field capacity, and plowing energy during plowing process under Egyptian conditions.

Materials and Methods

There are many different neural network algorithms to solve practical problems. For prediction-related problems, the feedforward network structure is suitable for handling nonlinear relationships between input and output variables (Park et al. *1994*). However, multilayer feedforward networks have proven to be suitable for agricultural engineering applications (Stone and Kranzler,*1999*) and Shuhui et al. (*2001*) showed that multilayer network has been applied successfully to solve many difficult and diverse problems by training them in a supervised manner. As with linear regression methods, neural network models must be constructed with consideration of two important effects: under-prediction and over-prediction therefore, the neural network models have to be optimized (Park et al. *1994*).

A feedforward ANN consists of nodes grouped in layers connected from one layer to another in one direction by weighting factors. It has input, output, and usually one or more hidden layers. The input layer just passes the input signals on to the nodes of the next layers. At each node of the network (except from the nodes in the input layer) the signals from the previous layer are weighted with their respective weights and summed. Then the summed signals are fed to the so called activation function and the outputs of these functions are passed on to the next layer, which may be another hidden layer or the output layer. The activation functions may be linear or nonlinear. If the network has to perform a nonlinear input-output mapping, at least some of the nodes need to contain a nonlinear activation function (Pasterkamp and Pacejka, *1998*). Common choices for nonlinear activation functions are sigmoid and the hyperbolic tangent functions.

The number of nodes and layers is selected by the user to reach at a model appropriate to the problem being addressed. Weights of connections are learned by the network model. The neural network training procedure for a neural network involves the following steps:

1. Present network with experimentally derived inputs and outputs (target outputs).
2. Compute outputs for present inputs.
3. Compute error as difference between target output and model output.
4. Adjust weights of connections to reduce error.
5. Repeat until error has been reduced to acceptable level.

The learning rule that is most frequently used for feedforward networks is the backpropagation technique (Hecht-Nielsen, *1990*) where it is a gradient search technique, which minimizes the root mean square error between desired and actual network outputs. During the training phase, the vectors from the training set were presented to the input nodes.

If the output of a vector did not match the output of the model, the connection weights in the network were adjusted in proportion to the difference between the observed and desired output using the generalized delta rule (Park et al. *1994*). The weights were modified by an iterative procedure by propagated the error back from the output layer to the lower layers.

A commercially available software, Vesta Services (Vesta Services, *2000*), implementation of the backpropagation network was used to develop a model to predict plows performance parameters during plowing process under Egyptian conditions.

The ANN model input parameters are four famous seedbed preparation implements in Egypt namely: chisel, moldboard, disc and rotary plows. These plows are working under different conditions including plowing depth, rated plow width, forward speed, soil texture index, initial soil moisture content, initial soil bulk density, rated tractor power (according to tractor operator's manual), and number of plow passes over the soil.

The output parameters are fuel consumption, effective field capacity, and plowing energy. So, data related to these parameters are needed to construct, train, and test the ANN model. As the type of plow is not in numerical form, the plows were assigned with numerical values using the binary coding, each plow had only two distinct values: *0* and *1* in the training and testing data.

By browsing in literatures (El Sheikha, *1989*; El Nakib, *1990*; Obaia, *1991*; Morad, *1992*; Morad and El Shazly, *1994*; El Ansary et al.*1995*; Imara, *1996*;Taieb, *1998*; El Sayed, 2000 and Helmy et al. *2001*) the data needed to show the different plows used in different Egyptian sites and variable working conditions were found. Collected data sets were *430* data points. Table (1) shows inputs and corresponding outputs of some collected data used in training and testing the ANN model.

Table (1): Inputs and corresponding outputs of some collected data used in training and testing the developed ANN model.

Data points	Inputs											
	C	D	M	R	RTP	RPW	NSP	PD	FS	STI	ISMC	ISBD
					hp	m	---	cm	km/h	---	%, d.b	g/cm^3
1	1	0	0	0	76	1.75	2	20	2.30	0.50	15.40	1.45
2	0	0	0	1	65	1.40	1	10	1.50	0.56	21.00	1.30
3	1	0	0	0	140	3.10	1	20	3.15	0.62	20.65	1.47
4	0	0	1	0	45	1.05	1	20	3.23	0.54	18.20	1.58
5	0	0	0	1	60	1.75	2	10	5.30	0.69	18.30	1.62
6	1	0	0	0	67	1.75	2	20	3.11	0.03	28.26	1.46
7	0	0	1	0	75	1.05	1	10	4.50	0.65	23.06	1.73
8	0	0	1	0	80	1.05	1	20	3.37	0.52	49.60	1.84
9	0	1	0	0	80	0.85	1	10	3.70	0.52	49.20	1.83
10	0	1	0	0	80	0.85	1	15	3.67	0.52	50.20	1.86
11	0	0	1	0	65	1.05	1	25	3.80	0.77	17.30	1.29
12	1	0	0	0	65	1.75	1	13	4.50	0.61	18.90	1.38
C.V. (%)					34	34.7	–	37.7	31.8	20.1	30.3	11.6

Data points	Outputs			
	Effective field capacity	Fuel consumption		Plowing energy
	fed/h	lit/fed	lit/h	kW.h/fed
1	0.27	8.30	2.24	26.47
2	0.39	5.42	2.12	17.30
3	1.30	13.85	18.00	44.17
4	0.60	21.00	12.60	66.99
5	1.72	2.35	4.00	7.41
6	1.00	7.10	7.10	22.65
7	0.70	14.31	9.98	45.65
8	0.67	12.91	8.60	41.20
9	0.59	15.14	8.95	48.29
10	0.59	17.21	10.10	54.91
11	0.81	14.59	11.80	46.40
12	1.46	6.95	10.15	22.11

C = chisel plow
D = disc plow
M = moldboard plow
R = rotary plow
PD = plowing depth
FS = forward speed
C.V. = Coefficient of variation

RTP = rated tractor power
RPW = rated plow width
NSP = No. of plow passes over the soil
STI = soil texture index
ISBD = initial soil bulk density
ISMC = initial soil moisture content

Soil texture, presented in this study, was soil texture index developed by Zein Eldin (*1995*) as follows:

$$STI = \frac{log\,(S_i^{\,C} + S_a)}{100} \qquad (1)$$

Where:

STI = soil texture index (*dimensionless*)

S_i = silt content in soil (%)

S_a = sand content in soil (%)

C = clay content in soil (%)

However, Zein Eldin (*1995*) mentioned that soil texture index (*STI*) is the best to describe soil texture compared to clay ratio mentioned by Witney (*1988*).

In this study, in order to find the optimum structure of the ANN model to predict plows performance parameters, *1* to *3* hidden layers with a range of *4* to *30* neurons in each hidden layer and *1000* to *120000* learning runs were tested (results not included). The optimum structure was based on minimizing the difference between the model output and the desired output using training data set (*320* 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 ANN model was tested with testing data set (*110* data points). The computed errors converged to a minimum value at two hidden layers with *12* neurons in the first hidden layer and *24* neurons in the second hidden layer and *20000* learning runs. The hidden layers and the output layer have a hyperbolic tangent activation function. The learning rate was *0.003* and momentum parameter was *0.8*. Fig. (1) depicts the architecture of the developed ANN model.

Root mean square error ($RMSE$) of predicted and observed plows performance parameters is used to determine adequacy of the ANN output response for a given input data set as follows:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{i=n}(Y_i - F_i)^2}{n}} \qquad (2)$$

Where:

n = number of data points during testing process

Y_i = predicted plows performance parameters

F_i = observed plows performance parameters

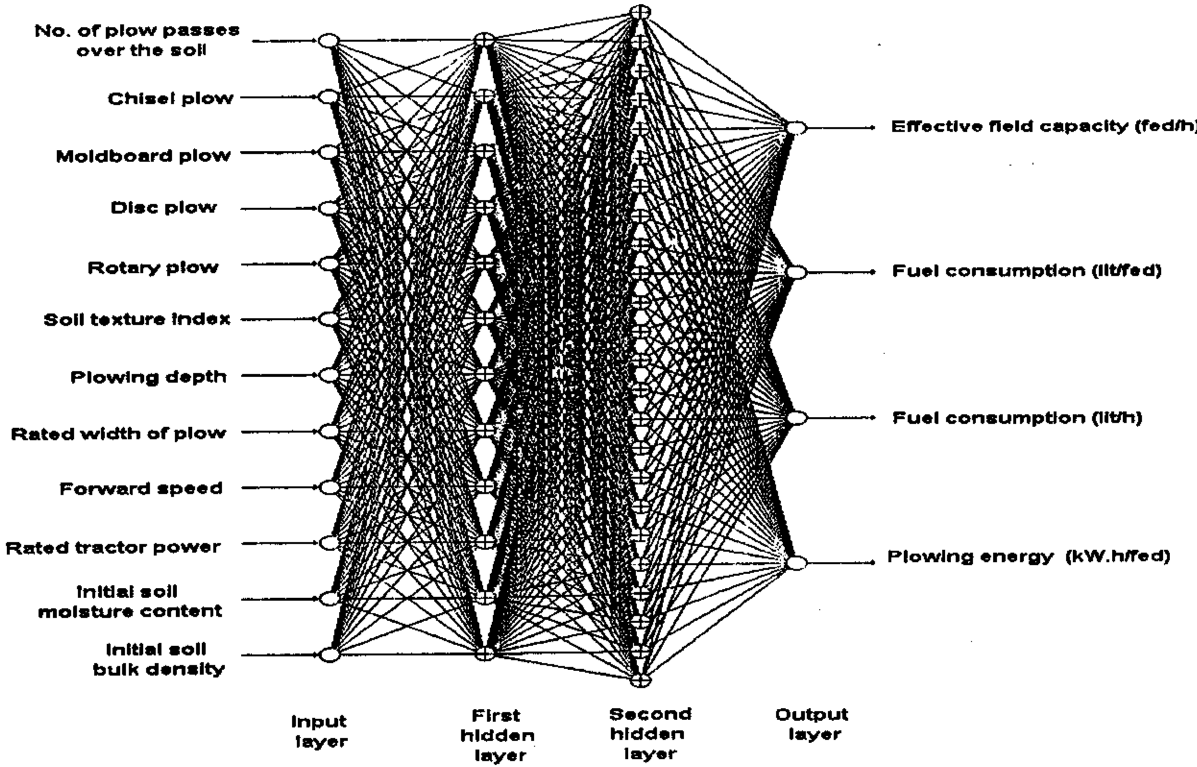

Fig. (1): Architecture of the developed ANN model.

RMSE emphasizes the deviation between observed and predicted values. Also, the coefficient of determination *(R^2)* was used as a parameter to indicate the correlation of relationship between observed and predicted plows performance parameters.

To examine the validity of the developed ANN model in prediction, three field experiments were conducted and repeated three times at Farm of Rice Mechanization Center, Meet El Deeba, Kafer El Sheikh Governorate. The characteristics of experiment site are listed in Table (2). The soil was without crop residues. Measurements of soil moisture content and soil bulk density were carried out as the procedures described in Imara (*1996*).

Table (2): The characteristics of experiment site.

S_a	S_i	*C*	*STI*	ISBD [+]	ISMC [+]
%	%	%	——	g/cm^3	%, *d.b*
28.53	*17.73*	*53.74*	*0.671*	*1.35*	*17.42*

[+] at depth of *7-20* cm

A rear mounted chisel plow was used in the field experiments. This implement is representative of the standard primary tillage implement most commonly used for seedbed preparation in Egypt. The specifications of the chisel plow is as follows: Type RAU "Behera Co." with *7* shanks arranged in *3* tool bars as ?, *2* and *3* from front to rear at *75* cm spacing between each two shanks on the same row. Rated width and weight of the chisel plow are *1.75* m and *330* kg respectively. Three forward speeds (*2.4, 3.5* and *4.8 km/h*) were obtained by changing tractor gears settings. These forward speeds and one plowing depth (*10 cm*) were applied during performing plowing (one pass).

A block of approximately (*25 m* long by *5 m* width) was used as a plot area during performing plowing. The plowing depth was preset before experiments. The chisel plow was hitched to Ford *TW15* tractor, which had rated power of *110 hp* at *2575 rpm*. The arrangements of leveling the chisel plow were done. The apparatus which shown by El Sayed (2000) was used to measure the consumed fuel by the tractor for each forward speed. Both the time for plowing plot area and the time required to consume a constant volume of diesel fuel were recorded using digital stopwatch.

Excel spreadsheet was used to get averages and to make calculations of the chisel plow performance parameters. However, the following equations were utilized to get the chisel plow performance parameters.

$$FC = \frac{V}{T_f} \times 3.6 \tag{3}$$

$$EFC = \frac{A}{T_p} \times 0.86 \tag{4}$$

$$FCA = \frac{FC}{EFC} \tag{5}$$

$$PE = \frac{FC \times \rho \times Hg \times \zeta_{bt}}{3600} \tag{6}$$

$$EE = \frac{PE}{EFC} \tag{7}$$

Where:

- FC = fuel consumption per unit time (*lit/h*)
- V = constant volume of diesel fuel consumed during plowing plot area (cm^3)
- T_f = the time required to consume a constant volume (V) of diesel fuel by the tractor (*sec*)
- T_p = the time required for plowing plot area (*sec*)
- EFC = effective field capacity (*fed/h*)
- A = plot area (m^2) ($1\ fed = 4200\ m^2$)
- FCA = fuel consumption per unit area (*lit/fed*)
- PE = tractor engine brake power (*kW*) according to Srivastava et al. (*1993*)
- ρ = density of diesel fuel (assumed to be *0.85 kg/lit*, according to Srivastava et al. *1993*)
- ζ_{bt} = brake thermal efficiency of the tractor engine (assumed to be *32%* for diesel engine)
- Hg = gross heating value of diesel fuel (assumed to be *45500 kJ/kg* for diesel fuel, according to Srivastava et al. *1993*)
- EE = plowing energy (*kW.h/fed*)
- 3.6 = units conversion factor
- 0.86 = units conversion factor
- 3600 = units conversion factor

Results and Discussion

The prediction performance of the ANN model is depicted in Fig. (2) as plots of ANN predicted values vs. observed values (actual values), for all plows performance parameters. The predicted values were not evenly and tightly distributed around regression line.

As seen in Fig. (2), the prediction accuracy were not high (R^2 <0.9) compared to previous studies in this field. The low level of prediction of the plows performance parameters in the present study, could be due to the high variation in collected data or due to the sudden and sharp changes in input data in the data set used to train the developed ANN model. In other words, the data had much noise; however, coefficient of variation was more than *20%* for some input parameters, Table (1), making it difficult for the ANN model to predict the exact number. The associated errors with the ANN outputs are compared in Table (3). The observed high R^2 value (*0.86*) indicated excellent correlation of ANN predicted with the observed values of effective field capacity.

Relatively, slightly lower correlation was observed while predicting both plowing energy and fuel consumption per unit time and per unit area. To examine the validity of the developed ANN model in prediction, chisel plow (one pass) was used to perform plowing with three forward speeds at one plowing depth in the field to collect performance data.

Table (3): Error indicators of plow performance parameters.

Error indicators	Effective field capacity	Fuel consumption		Plowing energy
	fed/h	*lit/h*	*lit/fed*	*kW.h/fed*
RMSE	*0.166*	*3.01*	*3.89*	*12.29*
R^2	*0.86*	*0.74*	*0.80*	*0.79*

Fig. (3) depicts the relationship between forward speed and both experimental and predicted effective field capacity, fuel consumption and plowing energy for chisel plow. From the results shown in Table (3), it easy to see that the ANN is a powerful technique that can predict plows performance parameters. These predictions lead us to conclude that artificial neural networks could have immense potential prediction in the plowing field specially, where the data requirements may be limited or need to get expensive measurement instruments to collect technical data. From Fig. (3), it is seen over-predicted the effective field capacity (*fed/h*) and fuel consumption per unit time but in the case of fuel consumption per unit area prediction, the model has a tendency to predicted under-predicted data. However, the general shape of the predicted curves is similar to that developed from the experimental results. From Fig. (3), there is a strong positive correlation between forward speed and both predicted and experimental fuel consumption (*lit/h*) where R^2 equals *0.98* and *0.96* respectively. While a negative correlation is seen between forward speed and both predicted and experimental plowing energy (*kW.h/fed*) where R^2 equals *0.96* and *0.98* respectively. Also, the results showed that the trends of predicted fuel consumption per unit time and per unit area and plowing energy (*kW.h/fed*) with forward speed are the same as published in the local previous studies for chisel plow.

Conclusion

In this study, ANN model was developed to predict and depict plows performance parameters under Egyptian conditions. The model inputs were soil texture index, chisel plow, moldboard plow, disc plow, rotary plow, plowing depth, rated width of plow, forward speed, initial soil moisture content, initial soil bulk density, rated tractor power and number of plow passes over the soil. The architecture of optimal ANN model consisted of two hidden layers with *12* and *24* processing elements in the first and the second hidden layers respectively. In spite of low level of prediction of the plows performance parameters in the present study compared to other studies in this field, artificial neural networks could have immense potential in predicting plows performance data specially where the data requirements may be limited or expensive measurement sets are needed. Verification of the ANN model in prediction was done using field experiments data with chisel plow. The results indicated that the ANN model was able to predict chisel plow performance parameters. The trends of the predicted results of fuel consumption and plowing energy with forward speed were the same as published in local previous studies for chisel plow.

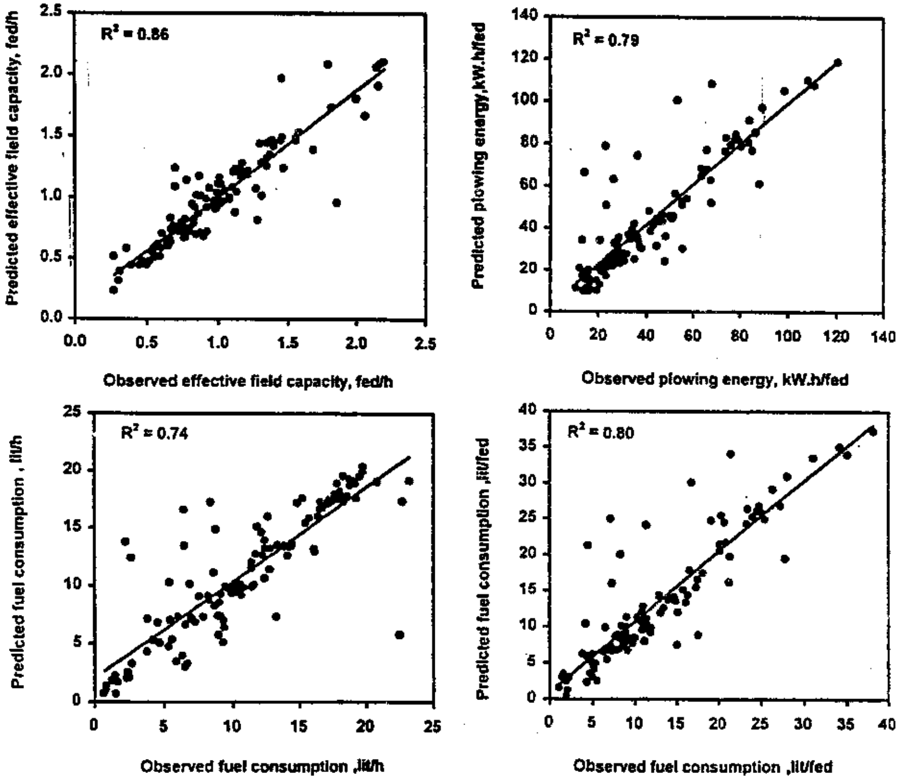

Fig. (2): Observed plows performance parameters compared to predicted using the developed ANN model.

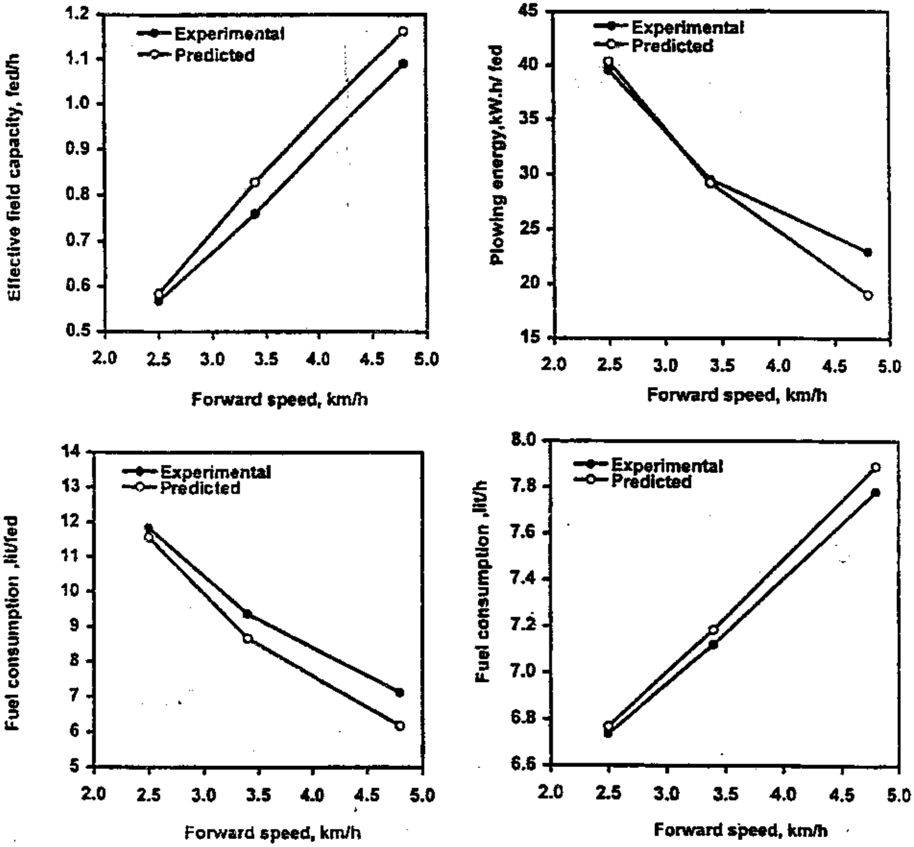

Fig. (3): Relationship between forward speed and both experimental and predicted effective field capacity, fuel consumption, and plowing energy for chisel plow.

References

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.

El Ansary, M.Y.; Z.A. El Haddad and M.T.M. Tohamy (1995). Minimizing tillage power and cost required to achieve a proper seedbed preparation. Misr J. Ag. Eng., 12 (1): 3-14.

El Awady, M. N. (1986). Factors considered in future mechanization planning for Egypt. Proc. Strategy for Approp. Tech. Trans. in Mech. for Egyptian Agric., 27-30 April 1986: 94-109.

El Awady, M.N. (1978). Tractor and farm machinery. Textbook, Col. of Agric., Ain Shams Univ.: 164-167.

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 Tenth Conf. of Misr Society of Ag. Eng., 16-17 October 2002, Agric. Eng. Dept., Fac. of Agric., Al-Azhar Univ., Cairo: 115-126 (In Arabic).

El Nakib, A.A. (1990). Relation between fuel consumption and draft force with different tillage treatments in clay-loam soil. Misr J. Ag. Eng., 7 (3): 224-237.

El Sayed, R.A. (2000). Effects of a combined active and passive tillage tools on soil compaction and the required energy. M.Sc Th., Dept of Agric. Eng., Fac. of Agric., Ain Shams Univ.: 56-61.

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

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.

Hecht-Nielsen, R. (1990). Neurocomputing. Addison-Wesly Pub. Company, Inc.: 21-41, 110-162.

Helmy, M.A. ; S.M. Gomaa; H.M. Sorour and H.A. El Khateeb (2001). Effect of some different seedbed preparation systems on irrigation water consumption and corn yield. Misr J. Ag. Eng.,18 (1):169-181.

Imara, Z.M.I.(1996). Development a combined machine for primary and secondary tillage under local conditions. Ph.D Th., Agric. Mech. Dept., Fac. of Agric., Tanta Univ., Kafer El Sheikh: 210-227.

Korthals, R.L.; G.L. Hahn and J.A. Nienaber (1994). Evaluation of neural networks as a tool for management of swine environments. Trans. ASAE, 37 (4): 1295-1299.

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

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

Morad, M.M. (1992). Effect of some operating parameters on disc plow performance. Misr J. Ag. Eng., 9 (1): 108-115.

Morad, M.M. and M.A. El Shazly (1994). Effect of some operating parameters on rotary plow performance. Misr J. Ag. Eng., 11 (4): 1009-1020.

Obaia, A. R. A. (1991). Agricultural machinery selection based on tillage power requirements. M.Sc. Th., Agric. Mech. Dept., Fac. of Agric., Mansoura Univ.: 139-143.

Park, B.; Y.R. Chen; A.D. Whittaker; R.K. Miller and D.S. Hale (1994). Neural network modeling for beef sensory evaluation. Trans. ASAE, 37 (5): 1547-1553.

Pasterkamp, W.R. and H. B. Pacejka (1998). Optimal design of neural networks for estimation of tyre/road friction. Vehicle System Dynamics Supplement, 28:312-321.

Sablani, S.S.; H.S. Ramaswamy; S. Sreekanth and S. O. Prasher (1997). Neural network modeling of heat transfer to liquid particle mixtures in cans subjected to end-over-end processing. Food Res. Int., 30 (2): 105-116.

Shaalan, K.; M. Riad; A. Amer and H. Baraka (1999). Speculative work in neural network forecasting: an application to Egyptian cotton production. The Egyptian Computer Journal, ISSR, Cairo Univ., 27 (1):58-79.

Shuhui, L.; D. C. Wunsch; E. O'Hair and M. G. Giesselmann (2001).Comparative analysis of regression and artificial neural network models for wind turbine power curve estimation. J. of Solar Energy Eng., 123:327-332.

Srivastava, A.K.; C.E. Goering and R.P. Rohrbach (1993). Engineering principles of agricultural machines. ASAE Textbook No. (6) Published by ASAE: 10-23.

Stone, M.L. and G.A. Kranzler (1999). Artificial neural networks in agricultural machinery applications. http//: WW.agen.okstate.edu/Home/mstone/nnet.htm.

Taieb, A. (1998). Effect of different tillage methods on some physical properties of soil and sunflower yield. Misr J. Ag. Eng., 15 (1): 159-173.

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

Witney, B. (1988). Choosing and using farm machines. Longman Scientific & Technical, Longman Group UK Limited, Longman House, Burnt Mill, Harlow, Essex CM20 2JE, England: 251-255.

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

Zhang, E. and P. Trimble (1996). Predicting effects of climate fluctuations for water management by applying neural networks. World Resource Review, 8 (3): 1-15.

الملخص العربي

وصف أداء المحاريث تحت الظروف المصرية بالشبكات العصبية الاصطناعية

م./ عبد الواحد محمد أبوكريمة[1] أ. د./ محمد نبيل العوضي[2]
د./ عبد الفضيل جابر القباني[3] د./ محمد حسن أحمد قابيل[4]

في هذه الدراسة استخدمت الشبكات العصبية الاصطناعية (ش ع إ) للتنبؤ بالمتغيرات التي تصف أداء المحاريث تحت الظروف المصرية. شملت المتغيرات السعة الحقلية الفعلية ومعدل استهلاك الوقود وطاقة الحرث. تم استخدام بيانات من الأبحاث السابقة (٤٣٠ مشاهدة) لأربعة أنواع من المحاريث الشائعة الاستخدام لتمهيد مرقد البذرة في مصر وهي (حفار وقلاب مطرحي وقلاب قرصي ودوراني) تحت ظروف تشغيل مختلفة (عمق الحرث،عرض المحراث، قدرة الجرار المستخدم، عدد مرات مرور المحراث على التربة، السرعة الأمامية، دليل قوام التربة، المحتوى الرطوبي الابتدائي والكثافة الظاهرية الابتدائيـة للتربـة) لإنشاء نموذج (ش ع إ). استخدمت الشبكة متعددة الطبقات ذات التغذية الأماميـة وطريقـة التعليم الخلفية و ٣٢٠ مشاهدة لبناء وتدريب واختبار (ش ع إ). وللوصول إلى التركيب الأمثل تم تغيير ثلاثة متغيرات أساسية، شملت عدد الطبقات المختفية، عـدد العنـاصر فـي الطبقـات المختفية، وعدد مرات التدريب. وتكونت (ش ع إ) المثالية من أربعة طبقات: واحدة للمدخلات (١٢ عنصر)، واثنتين مختفيتين شملت الأولى والثانية ١٢ و٢٤ عنصـرًا علـى الترتيب، وأخيرًا واحدة للمخرجات شملت ٤ عناصر، وذلك عند معدل تدريب قدره ٠,٠٠٣ باسـتخدام ٢٠٠٠٠ مكررة. وللتأكد من كفاءة (ش ع إ) التي تم تدريبها، فقد تم التنبـؤ بمتغـيرات أداء المحاريث لعدد ١١٠ مشاهدة لم يسبق للشبكة التعرض لها من قبل. وقد تم الحصـول علـى نتائج تتوافق جيدًا مع القيم المشاهدة، وكانت معاملات التحديد (R^2) تسـاوي ٠,٨٦، ٠,٧٤، ٠,٨٠ و٠,٧٩ للسعة الحقلية الفعلية (فدان/س)، واستهلاك الوقود (لتر/س ولتر/فدان) وطاقـة الحرث (كيلووات.س/فدان) على الترتيب، مما يوضح إمكان التنبؤ بـهذه القيـم للمحـاريث المذكورة تحت ظروف تشغيلية مختلفة باستخدام (ش ع إ) بدقة مقبولـة. ولتحقيـق النمـوذج المقترح تم إجراء تجارب حقلية باستخدام المحراث الحفار عند ثلاثة سرعات أمامية وعمـق حرث واحد (١٠ سم) وتمت مقارنة أداء المحـراث بمخرجـات نمـوذج (ش ع إ) لنفس متغيرات الأداء، وأظهرت النتائج وجود علاقة قوية بين كل من السـرعة الأماميـة ومعـدل استهلاك الوقود (لتر/فدان) وطاقة الحرث(كيلووات.س/فدان) وأخذت المنحنيات نفس الاتجـاه بما هو منشور في الدراسات المحلية.

١. باحث مساعد، معهد بحوث الهندسة الزراعية، الدقي، الجيزة .
٢. أستاذ الهندسة الزراعية المتفرغ، ك. الزراعة، ج.عين شمس.
٣. أستاذ مساعد الهندسة الزراعية، ك. الزراعة، ج.عين شمس.
٤. باحث أول، معهد بحوث الهندسة الزراعية، الدقي، الجيزة .