Bulletin USAMV Agriculture, 67(2)/2010
Print ISSN 1843-5246; Electronic ISSN 1843-5386

An Excel Spreadsheet to Estimate Performance Parameters for Chisel Plow-Tractor Combination Based on Trained an Artificial Neural Network

Abdulrahman AL-JANOBI[1], Saad AL-HAMED[1], Abdulwahed M. ABOUKARIMA[2]

[1] Department of Agricultural Engineering, College of Food and Agricultural Sciences, P.O. Box 2460, Riyadh 11451, King Saud University, Saudi Arabia;
[2] Huraimla Community College, P.O. Box 300, Huraimla 11962, Shaqra University, Saudi Arabia;
dr_janobi@yahoo.com; alhamed@ksu.edu.sa; aboukarima@gmail.com

Abstract. An Excel spreadsheet to estimate performance parameters for chisel plow-tractor combination during tillage process based on trained an artificial neural network was developed. The performance parameters include field and fuel efficiencies, draft, and required energy. The spreadsheet may be used as extension method for agricultural engineers for solutions of farm mechanization management problems during tillage process. The loading factor of the tractor was selected to be an optimizing criterion for the operating parameters. The spreadsheet offers an educational help and clarification to most of the affecting parameters on performance parameters. It was validated by comparing predicted performance parameters with the results obtained during field experiments. It has proven to be very user-friendly and efficient to meet the requirement.

Keywords: fuel efficiency, draft, chisel plow, tractor, artificial neural network, field efficiency, Excel spreadsheet.

INTRODUCTION

The tillage operation is a basic practice in agriculture to produce a desired soil condition for crop establishment. The performance efficiency of tillage is measured in terms of draft or input energy (Gill and Vanden Berg, 1967). However, field machines contribute a major portion of the total cost of crop production. Proper selection and matching of farm machinery is essential in order to reduce the cost of crop production. Performance data for tractors and implements are, therefore, essential for farm machinery operators and manufacturers alike (Al-Suhaibani *et al.***,** 2010). On the other hand, the efficiency of tractors and machines applied in agriculture is usually estimated as an integrated value. Their performance should be evaluated by optimal parameters (Vilde and Pirs, 2008).

Many parameters affect draft of implements such as type and condition of soil and tractor-implements characteristics. Tillage depth, texture and moisture content of soil are important parameters that have effect on draft. Working width, geometry and stability arrangement of implements and forward speed are parameters that may have affect on draft (Kepner *et al.*, 1998).

Plowing is one of the most power consuming and expensive processes in agricultural production (Vilde *et al.*, 2009). Fuel and energy requirements of tillage operation depend upon soil moisture content. Energy requirement is an important consideration in selecting tillage system. Its requirement of any tillage operation depends up on type of operation (implement used, width, depth of operation), speed of operation and soil parameters. Energy required per ha could be calculated on the basis of fuel consumed and effective field capacity.

Using energy required per ha, the most efficient tillage practice could be identified (Swarnkar and Sharma, 2009). The soil properties that contribute to tillage energy are moisture content, bulk density, soil texture and strength (Olatunji and Davies, 2009). 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.

The performance parameter of an aggregated tractor and tillage machine is affected by a number of factors. Various models to predict these parameters such as draft, fuel consumption, energy, field efficiency, fuel efficiency, etc were developed by regression and dimensional analysis. These models developed based on field or soil bin experiments. In recent years, Artificial Neural Network (ANN) has been employed, quite frequently, as a promising tool for supporting the modeling of complicated systems, which incorporate multiple parameters or variables (Flood, 1994). ANN is generally the software systems that initiate the neural networks of the human brain (Saffari *et al.*, 2009). Neural networks are powerful tools that have ability to identify underlying highly complex relationships from input-output data only (Haykin, 1999).

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

Many authors found a high effectiveness of ANN estimation of draft of tillage implements with great success, as results of studies by Hassan and Tohmaz (1995), Zhang and Kushawaha (1999), Al-Janobi *et al.* (2001), Aboukarima and Saad (2006), Aboukarima (2007), and Roul *et al.* (2009). Based on the results of Roul *et al.* (2009), the ANN model, with a back propagation learning algorithm could be considered as an alternative and practical tool for predicting draft requirement of tillage implements. ANN may be useful for the integrated evaluation of tillage performance with multi-objectives and can be employed for simulation of a dynamic constitutes model and identification of soil conditions for agricultural soils (Kushawaha and Zhang, 1998).

Although the ANN model is applied successfully in agricultural engineering area and having capability in handling complex problems, which relate to many parameters. They are not being in applicable format to be used by any one. On the other hand, farm manager wants to know the performance parameters of tractor- plow combination at varying operating and soil conditions and varying types of tractors and plows for farm mechanization management solutions. In this case, numerous experiments with instrumentation systems are needed to get data and compare them to select the best combinations and the cost is very high. This is time consuming and generally is complex and expensive work. So, simulation technique by the help of available software like Excel spreadsheet to get performance data in this case is very useful, because the results obtained depend on data performing in the actual field.

With this objective in mind this particular investigation was undertaken. So, the objective of this research work is to develop an ANN model and the resulted weights after training were used to build an Excel spreadsheet in easy way to estimate performance parameters for chisel plow-tractor combination.

MATERIALS AND METHODS

Collecting required data

To develop the ANN model and Excel spreadsheet, available data for chisel plow in literatures, which directly relate to the subject, are collected. Whereas, these data are 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. Tab.1 shows some statistical parameters of collecting data for training process and testing process, respectively that describe affecting input variables used in ANN model for estimating performance parameters of tractor-chisel plow combination.

Development of estimation method

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 (X_i) are given weight coefficients (W_i), 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.

Tab.1

Statistical parameters of collecting data for training process

Statistical parameters	Inputs									Outputs	
	Tractor Power	Plow width	Plowing depth	Forward speed	Soil fractions			Initial soil moisture content	Initial soil bulk density	Effective field capacity	Fuel efficiency
					Sand	Silt	Clay				
	kW	m	cm	km/h	%	%	%	db%	g/cm^3	ha/h	lit/ha
Mean	68.04	1.95	16.64	3.99	36.07	25.64	38.24	20.30	1.36	0.60	28.10
Minimum	25.35	1.35	7.06	2.00	11.38	11.00	9.00	7.30	1.17	0.25	8.22
Maximum	104.40	3.40	30.00	6.92	80.00	55.20	53.20	50.20	1.86	1.68	74.88
Standard deviation	22.91	0.45	5.87	1.32	16.28	9.76	10.50	6.54	0.14	0.30	13.59
Skewness	-1.08	2.21	-0.51	0.10	0.82	0.97	1.06	10.67	2.73	3.51	1.27
Kurtosis	0.31	1.87	0.50	0.83	1.02	0.87	-1.14	2.23	1.36	1.86	1.17
Coefficient of variation (CV,%)	33.67	22.99	35.28	32.97	45.13	38.07	27.46	32.20	9.94	49.95	48.35
Count	133	133	133	133	133	133	133	133	133	133	133

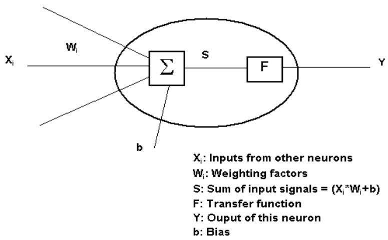


Fig. 1. Structure of a single neuron

In this study, single hidden-layer ANN model consisting of one hidden layer was developed. The task of identifying the number of neurons in the input and output layers is normally simple as it is dictated by the input and output variables considered in the model physical process. But, the number of neutrons in the hidden layer (s) can be determined through the use of trial and error procedure. The optimal architecture was determined by varying the number of hidden neurons (from 1- 40) and the best structure was selected. The training of the ANN model was stopped when the number of iterations reached 600000. The neural network with feed forward back propagation consist of input layer of nodes, output layers and one or more layers of nodes in between. The middle layers called hidden layers. The number of nodes in the input and output layers are determined by the nature of the problem consideration.

Fig. 2, shows the schematics of a three layer neural network with feed forwarded configuration. ANN was implemented by using Qnet2000 software package (Vesta Services, 2000). The artificial neural network used in the present study was characterized by the different parameters including: network layers are 3, input nods are 9, output nodes are 2, hidden nodes are 30, transfer function is sigmoid, learn rate is 0.010402, and momentum is 0.8. However, these configurations gave training error of 0.024104.

The input layer of the model consisted of the nodes corresponding to the following variables: tractor power (TP, kW), plowing depth, plow width (W, m), forward speed (S, km/h), sand percentage, silt percentage, clay percentage, initial soil moisture content, and initial soil bulk density. The output layer consisted of the two nodes related to effective field capacity (EFC, ha/h) and fuel efficiency (FE, lit/ha).

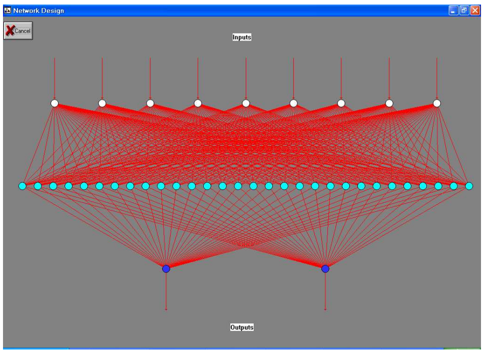


Fig. 2. The developed neural network with feed forwarded configuration implemented by using Qnet2000 software package (Vesta Services, 2000)

The whole data set (156 data points) was randomized. The number of 133 data points was used for training and the rest for testing. 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:

$$X_n = X(t) = \frac{(t - t_{\min})}{(t_{\max} - t_{\min})} \times (0.85 - 0.15) + 0.15 \tag{1}$$

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

The accuracy of ANN estimations was evaluated using the different error statistics as follows:

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

Where $RMSE$ is root mean square error and N is number of observations.

Estimation of the performance parameters

The effective field capacity and fuel efficiency could be estimated from the developed ANN model. However, fuel efficiency is the measure of amount of fuel required for a given tractor-implement system to cover 1 ha field. The reset of performance parameters could be found according as follows:

1- Fuel consumption (FC, lit/h) was calculated using relationship,

$$FC = FE \times EFC \qquad (3)$$

2- Energy requirement of a given tillage implement system (E, kWh/ha) was calculated from the fuel consumption in a specified time period and effective field capacity. Considering the calorific value of diesel fuel as 45460 kJ/kg, specific gravity of 0.85, and thermal efficiency of 0.25, the energy requirement was calculated using relation,

$$E = \frac{FC \times 45460 * 0.25 * 0.85}{EFC \times 3600} \qquad (4)$$

3- The theoretical field capacity (TFC, ha/h) was calculated using relation,

$$TFC = \frac{W \times S}{10} \qquad (5)$$

4- The field efficiency (F, %) was calculated using relation,

$$F = \frac{EFC}{TFC} \times 100 \qquad (6)$$

5- To obtain the required draft, the following procedures were achieved:

Assume value of the loading factor (X, decimal), however, X is fraction of equivalent PTO power available (ASABE, 2009), as follows:

$$X = \frac{P}{P_{rated}} \qquad (7)$$

Where P is equivalent PTO power required by current operation (kW) and P_{rated} is rated PTO power available (kW). ASABE (2009) reported that power at a given location in the driven train can be used to estimate power at another location. So, P_{rated} is calculated using relation (ASABE, 2009),

$$P_{rated} = TP \times 0.83 \qquad (8)$$

$$P = P_{rated} \times X \qquad (9)$$

Also, if drawbar power is desired, choose the tractor type and tractive condition to determine the ratio, in this study, the ration is averaged to be 0.68 to represent 2WD and MFWD tractors and firm, tilled and soft tractive condition (ASABE, 2009). So, calculate drawbar power to represent the required power for tillage process (DP, kW) using relation,

$$DP = P \times 0.68 \qquad (10)$$

$$DP = TP \times X \times 0.68 \times 0.83 \qquad (11)$$

Calculate specific fuel consumption for tillage process (SFCt, lit/kW.h) using relation,

$$SFCt = \frac{FC}{DP} \qquad (12)$$

Calculate specific fuel consumption (SFC, lit/kW.h) from ASAE equation (ASAE, 2000) using relation,

$$SFC = 2.64 \times X + 3.91 - 0.203\sqrt{738 \times X + 173} \qquad (13)$$

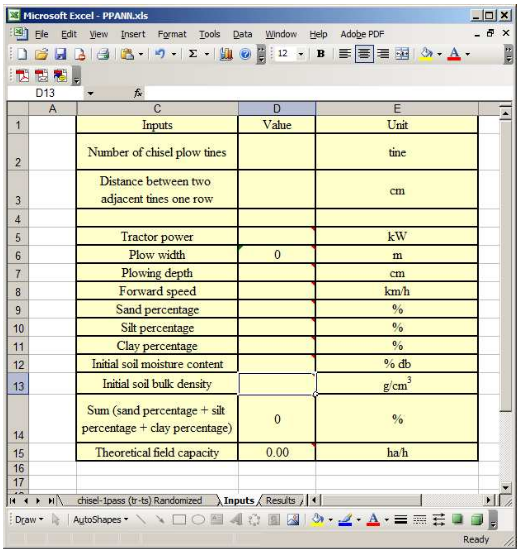
Load factor (X), in step 1, is changed manually until the calculated specific fuel consumption (Eq. 12) nearly equal to specific fuel consumption calculated from the equation of the ASAE (Eq. 13)

Obtain the new value of (DP, kW)

Calculate the required draft (D, kN) using relation,

$$D = \frac{\text{The new value of (DP, kW)} \times 3.6}{\text{S}} \qquad (14)$$

Excel spreadsheet development



Inputs	Value	Unit
Number of chisel plow tines		tine
Distance between two adjacent tines one row		cm
Tractor power		kW
Plow width	0	m
Plowing depth		cm
Forward speed		km/h
Sand percentage		%
Silt percentage		%
Clay percentage		%
Initial soil moisture content		% db
Initial soil bulk density		g/cm^3
Sum (sand percentage + silt percentage + clay percentage)	0	%
Theoretical field capacity	0.00	ha/h

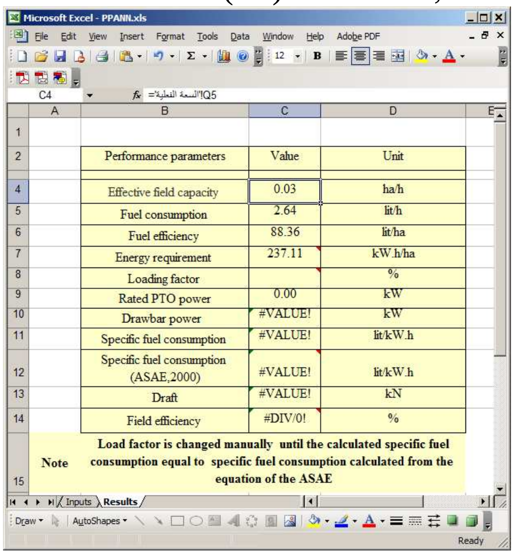
After obtaining the weights from training ANN model, a simple Excel spreadsheet that could use to estimate energy requirement of a chisel plow, field efficiency, specific fuel consumption for tillage process and the required draft was driven. On opening the spreadsheet, the user is presented with a blank table containing the inputs variables (Fig.2).

Fig. 2. Screen shot for inputs variables with their blanks in Excel environment to determine performance parameters of chisel plow-tractor combination based on trained ANN model.

The chisel plow width (W, m) could be entered as input value or could be calculated from,

$$W = \frac{Q \times L}{2 \times 100} \tag{15}$$

Where, Q is number of chisel plow tines and L is the distance between two adjacent tines in one row (cm). Be careful, the sum of soil fractions (sand + silt + clay) must be equal to 100 %. The user also has the opportunity to change soil type, initial bulk density, forward speed, plowing depth, plow width and water content at specific tractor to optimize performance parameters according to his opinion. The spreadsheet contains comments to ensure that the ranges of the data are not exceeded. Fig. 3 shows screen shot for outputs variables in Excel environment to determine performance parameters of chisel plow-tractor combination based on trained ANN model.



Performance parameters	Value	Unit
Effective field capacity	0.03	ha/h
Fuel consumption	2.64	lit/h
Fuel efficiency	88.36	lit/ha
Energy requirement	237.11	kW.h/ha
Loading factor		%
Rated PTO power	0.00	kW
Drawbar power	#VALUE!	kW
Specific fuel consumption	#VALUE!	lit/kW.h
Specific fuel consumption (ASAE,2000)	#VALUE!	lit/kW.h
Draft	#VALUE!	kN
Field efficiency	#DIV/0!	%
Note	Load factor is changed manually until the calculated specific fuel consumption equal to specific fuel consumption calculated from the equation of the ASAE	

Fig. 3. Screen shot for outputs variables in Excel environment to determine performance parameters of chisel plow-tractor combination based on trained ANN model.

RESULTS AND DISCUSSION

Fig. 4 and Fig. 5 show the relationship and coefficient of determination between observed and effective field capacity and fuel efficiency using ANN model, respectively. It shows that scattering points are around the regression line for effective field capacity and they are not close to regression line for fuel efficiency.

Tab. 2 shows error statistics for estimating effective field capacity and fuel efficiency of tractor-chisel plow combination using ANN. The results in Tab. 2 show that the ANN model estimated the effective field capacity and fuel efficiency of the chisel plow - tractor combination with acceptable accuracy.

Tab. 2

Error statistics for estimating effective field capacity and fuel efficiency of chisel plow -tractor combination using ANN

Error items	Effective field capacity (ha/h)		Fuel efficiency (lit/ha)	
	Training data set	Testing data set	Training data set	Testing data set
Root mean square error, RMSE	0.0137	0.0337	3.1804	3.7671
R^2	0.9979	0.9893	0.9448	0.6744

Al-Hamed and Aboukarima (2001) showed that the optimum performance of farm implements with tractor occurs at optimum load factor of 0.86 this give minimum specific fuel consumption. In this study, loading factor was used to judge the possibility of the selected operating variables to achieve tillage process in specific soil. The variables parameters like plow width, forwarded speed, plowing depth, soil moisture content, tractor power could be changed until field efficiency is in visible rage as reported by ASAE (2000).

After, simulations in Excel spreadsheet, the outputs are illustrated by the screen shot (Fig. 6). Changing loading factor from 0.2 to 0.9 at the specific inputs, the curves as illustrated in Fig.7 are obtained. However, this figure represents the relation between loading factor and specific fuel consumption calculated from the outputs (SFCt, Eq. 12) and from Eq. 13 (ASAE, 2000). The two curves are intersected at ideal point. It is at loading factor of 0.645. After that, the right drawbar power and draft are obtained. They are 27.34 kW and 21.08 KN, respectively.

To validate the developed spreadsheet for estimation of draft of a chisel-plow-tractor unit, the example data from Aboukarima (2007) are taken which are as follows:

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. 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 (1.366 g/cm^3). However, the draft from Aboukarima (2007) is 16.73 kN. After adjusting the loading factor to be 0.685 in the developed spreadsheet, the draft is 14.49 kN.

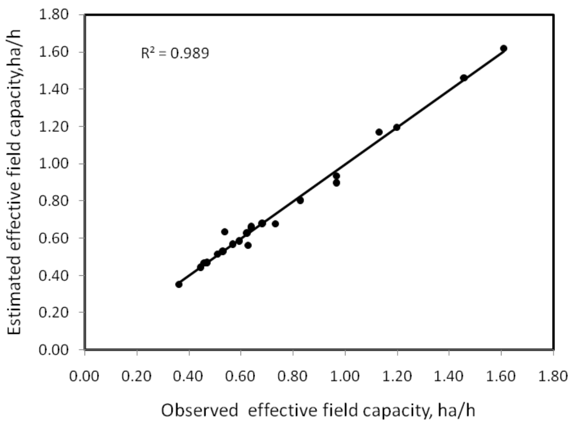


Fig. 4. The relationship between observed and estimated effective field capacity using ANN model during testing process

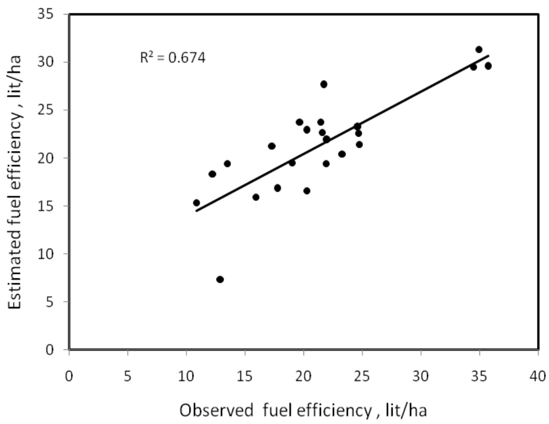
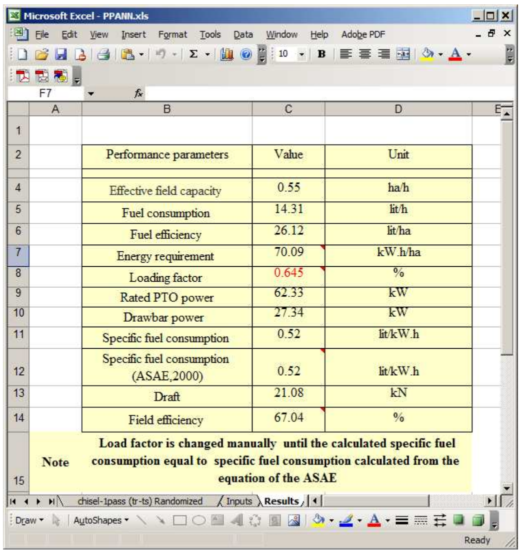


Fig. 5. The relationship between observed and estimated fuel efficiency using ANN model during testing process



Performance parameters	Value	Unit
Effective field capacity	0.55	ha/h
Fuel consumption	14.31	lit/h
Fuel efficiency	26.12	lit/ha
Energy requirement	70.09	kW.h/ha
Loading factor	0.645	%
Rated PTO power	62.33	kW
Drawbar power	27.34	kW
Specific fuel consumption	0.52	lit/kW.h
Specific fuel consumption (ASAE,2000)	0.52	lit/kW.h
Draft	21.08	kN
Field efficiency	67.04	%

Note: Load factor is changed manually until the calculated specific fuel consumption equal to specific fuel consumption calculated from the equation of the ASAE

Fig. 6.The outputs after the simulation using Excel spreadsheet

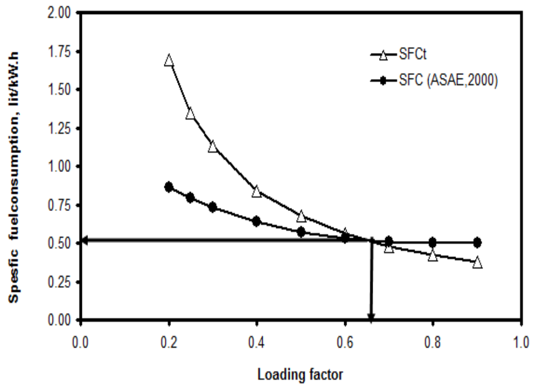


Fig. 7. Relation between loading factor and specific fuel consumption calculated from the outputs (SFCt, Eq. 12) and from Eq. 13 (ASAE, 2000)

CONCLUSIONS

An Excel spreadsheet was used to estimate performance parameters for chisel plow-tractor unit during tillage process. This spreadsheet was built using the weights obtained from the trained neural network model. The performance parameters estimated by ANN model were field and fuel efficiencies. The ANN result was also compared with the statistical based model based on their percentage accuracy. Whereas, the coefficients of determination (R^2) were 0.989 and 0.674 for estimation of effective field capacity and fuel efficiency during testing, respectively. Draft, field efficiency, and required energy based on fuel consumption were estimated by the help of spreadsheet. Loading factor of the tractor was selected to be a control statement between calculated specific fuel consumption from ANN model and calculated specific fuel consumption from ASAE (2000). If both loading factors are equal, the draft could be calculated. The spreadsheet offers an educational help. It has proven to be very user-friendly and efficient to meet the requirement.

REFERENCES

1. Aboukarima, A. M. (2007). Draft models of chisel plow based on simulation using artificial neural networks. Misr J. Ag. Eng. 24 (1):42-61.

2. 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.

3. 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. of Agricultural Engineering 18(2): 392-406. (In Arabic).

4. 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.

5. Al-Suhaibani, S. A., A. A. Al-Janobi and Y. N. Al-Majhadi. (2010). Development and evaluation of tractors and tillage implements instrumentation system. American J. of Engineering and Applied Sciences. 3 (2): 363-371.

6. Anantachar, M., P. G.V. Kumar and T. Guruswamy. (2010). Neural network prediction of performance parameters of an inclined plate seed metering device and its reverse mapping for the determination of optimum design and operational parameters. Computers and Electronics in Agriculture.

7. ASABE Standard. (2009). ASAE D497.6 Agricultural Machinery Management Data. ASAE. St. Joseph. MI: 49085. 1-8.

8. ASAE Standard. (2000). ASAE D497.4 Agricultural Machinery Management Data. ASAE. St. Joseph. MI: 49085, 350-357.

9. 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.

10. Flood, N. K. (1994). Neural networks in civil engineering-1: Principles and understanding. Journal of Computing in Civil Engineering. 8 (2):131– 148.

11. Gill, W. R. and G. E. Vanden Berg. (1967). Soil dynamic in tillage and traction. Agricultural Handbook No. 316. United States Department of Agriculture.

12. 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.

13. Haykin, S. (1999). Neural networks, a comprehensive foundation. 2^{nd} Edn. Prentice Hall. USA. ISBN: 13-9788120323735.

14. Kepner, R. A., R. Bainer and E. L. Barger. (1998). Principles of Farm Machinery. AVI Publication Company. Inc. Westport Conneticut.

15. Kushawaha, R. L. and Z. X. Zhang. (1998). Evaluation of factors and current approaches related to computerized design of tillage tools: a review. Journal of Terramechanics. 35:69-86.

16. Olatunji, O. M. and R. M. Davies. (2009). Effect of weight and draft on the performance of disc plough on sandy-loam soil. Research Journal of Applied Sciences. Engineering and Technology. 1 (1): 22-26.

17. Roul, A. K., H. Raheman, M. S. Pansare and R. Machavaram. (2009). Predicting the draft requirement of tillage implements in sandy clay loam soil using an artificial neural network. Biosystems engineering. 104: 476–485.

18. Saffari, M., J. Yasrebi, F. Sarikhani, R. Gazni, M. Moazallahi, H. Fathi and M. Emadi. (2009). Evaluation of artificial neural network models for prediction of spatial variability of some soil chemical properties. Research Journal of biological Sciences. 4(7):815-820.

19. Swarnkar, R. and A. K. Sharma. (2009). Soil moisture effects on energy requirement for different conservation tillage systems in sandy loam soil. IE (I) Journal–AG Volume 90. 39-42.

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

21. Vilde, A. and E. Pirs. (2008). Criteria for the estimation of the efficiency of agricultural tractors in field crop cultivation. 7th International Scientific Conference Engineering for Rural Development Proceedings May 29 – 30. 2008 Jelgava 2008 Latvia University of Agriculture Faculty of Engineering.

22. Vilde, A., A. Rucins and E. Pirs. (2009). Impact of soil humidity on draft resistance of plough body. Proceedings of 8^{th} International Scientific Conference Engineering for Rural Development. Jelgava. May 28 – 29. 2009:43-49.

23. 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.