J. Agric. Sci. Mansoura Univ., 30 (9): 5365 - 5379, 2005

A NEURO-FUZZY FRAMEWORK FOR ASSESSMENT SOIL COMPACTION DUE TO TRAFFIC OF AGRICULTURAL IMPLEMENTS ON DIFFERENT SOILS

Elbanna, E. B.[1]; A. M. Aboukarima[2] and R. I. A. Mourad[3]
[1]Agric. Eng. Dept., Faculty of Agric., Mansoura Univ.
[2]Agric. Eng. Res. Inst., Agric. Res. Center, Ministry of Agric. and Land Reclamation
[3]Agric. Eng. Dept., Faculty of Agric., Fayoum Univ.

ABSTRACT

In this research work Adaptive Neuro-Fuzzy Inference System (ANFIS) in the frame of Matlab was applied to develop a tool for soil compaction assessment that may help planning of mechanized operations in order to increase the sustainability of agricultural activity. The parameters of the triangular membership functions and the zero-order Sugeno fuzzy model were computed by means of hybrid learning. The model considers soil moisture content, clay ratio (represents soil type), wheel index and the number of wheel passes over the field as input variables. The model has been built based on field experimental data. The predicted index of soil compaction was compared with measured values. The results demonstrate that neuro-fuzzy model derived by the proposed framework delivered satisfactory outcome in spite of the significant complexity of the considered problem.

INTRODUCTION

Soil compaction has been concerned because it affects soil conditions that influence in general the crop yield. Soil compaction is a national problem of significant consequence that cannot be economically assessed accurately (Sadaka, 1988). To understand the impact of traffic of agricultural implements effect on the changes in soil properties and on yield reduction, field experiments have to executing to assess the index of soil compaction. However, there are different variables affecting the index of soil compaction. These variables have four different categories including soil, implements, weather conditions and type of field operations.

Ahmed *et al.* (1988) and Abou-Habaga (1989) reported that soil compaction is affected by different variables such as soil type, moisture content, weight of machines and number of passes over the field. Elbanna (1990b) showed that the variables affecting soil compaction are clay ratio, number of wheel passes over the field, soil moisture content, wheel inflation pressure and wheel section width. Morad and Arnaout (1993) stated that the number of tractor passes, tractor forward speed, moisture content and wheel inflation pressure are considered variables affecting the soil compaction.

Gysi *et al.* (2000) showed that heavy agricultural machinery cause structural degradation in agricultural subsoil and this has negatively affects on plant growth. Voorhees (2000) reported that the most variables affecting soil compaction are axle load, soil water regime and soil texture and their interactions. Canillas and Salokhe (2001) used wheel variables (section width, diameter, inflation pressure), soil variables (moisture content, initial cone index), and external variables (travel speed, axle load, number of passes) to build a model to predict soil compaction as related to bulk density and cone index. Their results showed that axle load and number of wheel passes were the most prominent variables that greatly influence soil compaction. Furthermore, soil moisture content, aspect ratio, and wheel inflation pressure also revealed significant effects. Since soil changes induced by machine traffic compaction can lead to soil degradation, superficial water pollution and an increasing demand for no-renewable natural resources, it is fundamental to develop useful tools to evaluate the effects of a machine on soil and predict final soil conditions after traffic, in order to avoid serious soil compaction problems (Canillas and Salokhe, 2002). There are different equations predicting index of soil compaction due to traffic of agricultural implements. These equations have different forms and derived based on statistical analysis (Elbanna,1990a, Elbanna,1990b and Helmy *et al.*,1999).

Soil compaction by machine traffic is a complex process with many interacting variables. For this reason, mathematical models have been developed to help to understand this phenomenon (Defossez and Richard,2002). Much scientific knowledge has been accumulated on this subject, but not in a useful way for farm management decisions. Defining exactly what constitutes compacted soil is a difficult task due to the many uncertainties involved in the process. These uncertainties include a large diversity in plant and environmental response to soil compaction, spatial variability of soil attributes and measurement errors (De Araùjo and Saraiva,2003). Like other soil processes, compaction cannot be adequately represented with discrete categories (crisp classification) since soil changes are continuous. In general, a specific soil condition cannot be clearly described as compacted or not compacted.

Fuzzy logic provides a formal mathematical structure for analyzing complex processes where observations should be grouped in continuous classes (Zimmermann,1996). Fuzzy logic is a powerful concept for handling non-linear, time-varying, adaptive systems especially in applications to biological and agricultural systems (Center and Verma,1998). Fuzzy modeling has been applied in many scientific and engineering fields, and represents a useful framework to deal with 1) the complexity of soil compaction processes, 2) the uncertainty due to measurement errors and imprecise boundaries and, 3) qualitative knowledge generally associated with site-specific soil compaction evaluation. Soil science presents many possibilities for fuzzy logic application according to McBratney and Odeh (1997).

Fuzzy logic could provide a prospective tool during predicting crop water stress index for tall fescue (Al-Faraj *et al.*, 2001), predicting of paddy soil normal adhesion to steel surface (Jun-Zheng and Zhi-Xiong, 1998), successfully to determine filed trafficability (Thangavadivelu and Colvin, 1991) and improving efficiency of Egyptian rice milling process (Aboukarima, 2003). Gassoumi (2000) mentioned that the combination of the artificial neural networks and fuzzy logic creates what is known as neuro-fuzzy system. However, neuro-fuzzy has emerged as a new and very powerful technique which allows for learning from data; incorporating both initial set of knowledge and data into a simple decision making framework; extracting knowledge from data for the sake of explanation and understanding; adaptive tuning of existing knowledge according to new data. Neuro-fuzzy nowadays is a comprehensive and robust methodology for knowledge engineering and problem solving (Bellei *et al.*,2001; Dixon *et al.*,2001; Lee *et al.*,2003 and Odhiambo *et al.*,2004).

The objective of this research work is to develop a neuro-fuzzy model to predict index of soil compaction due to agricultural implements traffic on different soil types. The model considers soil moisture content, clay ratio (represents soil type), wheel index and the number of wheel passes over the field as input variables.

MATERIALS AND METHODS

Field measurements were made on soil moisture content and degrees of soil compaction under different vehicle wheel paths with varying wheel inflation pressures and loads in four soil types. A 25-m wheel track distance and divided it into 5 m sub-distance; five replications of soil moisture and bulk density were averaged to represent sub-distance field measurements. All measurements were taken after wheel passes on the soil. All measurements readings were taken at a 10 cm depth from the soil surface. Two samples from each field were analyzed and averaged to represent the soil type. Seven tractors and one combine (rubber crawler) were used on four soil types. These combinations gave different axle loads, wheel dimensions and inflation pressures. Table (1) shows soil fractions, tractors power, combine characteristics, axle loads, wheel dimensions and inflation pressures used in field experiments.

Table (1):Soil fractions, tractor powers, combine characteristics, axle loads, wheel dimensions and inflation pressures used in field experiments.

Different items		Soil type						
		Sandy loam		Clay loam		Clay		
Soil fractions	Sand (%)	60.78	60.78	41.60	41.60	21.50	14.43	14.43
	Silt (%)	20.50	20.50	21.53	21.53	36.83	31.31	31.31
	Clay (%)	18.72	18.72	36.87	36.87	41.67	54.26	54.26
Clay ratio (----)		0.230	0.230	0.584	0.584	0.714	1.186	1.186
Tractor power (kW)		33.58	93.28	29.85	49.97	55.97	55.97	59.7
Axle load (kN)	Front	7.40	18.61	11.38	12.71	11.57	11.73	14.69
	Rear	12.77	54.94	17.06	27.01	21.97	21.81	27.29
Wheel dimensions (in)	Front	5.5-16	11.0-16	8.0-16	6.5-20	6.5-20	6.5-20	7.5-20
	Rear	13.6-28	18.4-38	13.6-28	14.0-38	14.0-38	14.0-38	16.9-38
Inflation pressure (kPa)	Front	103.43	275.80	137.90	220.64	206.85	227.54	206.85
	Rear	68.95	131.90	137.90	184.74	137.90	137.90	137.90

Table (1) continued.

Combine characteristics (Kubota RX 2750-D)			**Soil fractions (clay soil)**			**Clay ratio**
			Sand	**Silt**	**Clay**	
Power	Track area	Total load	%	%	%	-----
22.39 (kW)	0.4608 (m^2)	18.29 (kN)	21.50	36.83	41.67	0.714

Soil structure, moisture content and bulk density were measured according to standard methods. Raw data, calculations, instruments and experiments procedures are in Elbanna (1990a). In this research work, the index of soil compaction (DSC,%) and the clay ratio were calculated as follows:

$$DSC = \left[\frac{\rho_2 - \rho_1}{\rho_1}\right] \times 100$$ Cited from Elbanna (1990a) (1)

$$Clay\ ratio = \frac{Clay\ \%}{Sand\ \% + Silt\ \%}$$ Cited from Elbanna (1990a) (2)

where ρ_1 *and* ρ_2 are the initial and final soil bulk densities (g/cm^3) respectively.

The general principle that applies to pneumatic wheels is that the pressure exerted by the wheel on the soil surface is approximately equa. to the wheel inflation pressure (Kemp,1990). In some cases, this principle can not be obtained during field operation (i.e. the wheel has less or high inflation pressure compared to the ground pressure of the wheel), so to make the developed model (neuro-fuzzy) more generalization, wheel index was derived based on ground and inflation pressures for tractor front and rear wheels.

To develop the wheel index, the contact area of the tractor wheels (front and rear) must be obtained. There are different models in literatures to calculate contact area of the tractor wheels (*A*). In this research work, the contact area of the tractor wheels is obtained based on rigid surface according to the following procedures:

$$L = C \times \sqrt{d \times \delta - \delta^2}$$ (Lyasko,1994) (3)

$$C = \frac{23}{\left|\frac{d}{b} - 3.5\right| + 11.9}$$ (Lyasko,1994) (4)

$$T = 2 \times \sqrt{\frac{b+h}{2.5} \times \delta - \delta^2}$$ (Lyasko,1994) (5)

$$\delta = 0.67h \times \left(\frac{P \times d \times b}{W}\right)^{-0.8} \qquad h = b$$ (Godbole *et al.*,1993) (6)

$$d = dr + 2h$$ (Lyasko,1994) (7)

$$A = \frac{\pi}{4} \cdot L \cdot T \qquad T < u$$ (Lyasko,1994) (8)

where in Eqs. (5 and 7) h = 0.87b according to Srivastava *et al.* (1993), *L* is the length of contact area on ground for tractor wheels as shown in Fig. (1), d is overall tractor wheels diameter, *b* is the wheel section width, δ is the wheels deflection as shown in Fig. (1), *T* is the width of contact area on ground for tractor wheels, *C* is constant coefficient, *W* is the vertical load on each wheel, *P* is the inflation pressure of the wheel, *dr* is wheel fitted diameter, *h* is wheel section height and *u* is tread width. This procedure gave nearly equal contact area of the tractor wheels compared to values measured by Elbanna (1990a), Fig. (2).

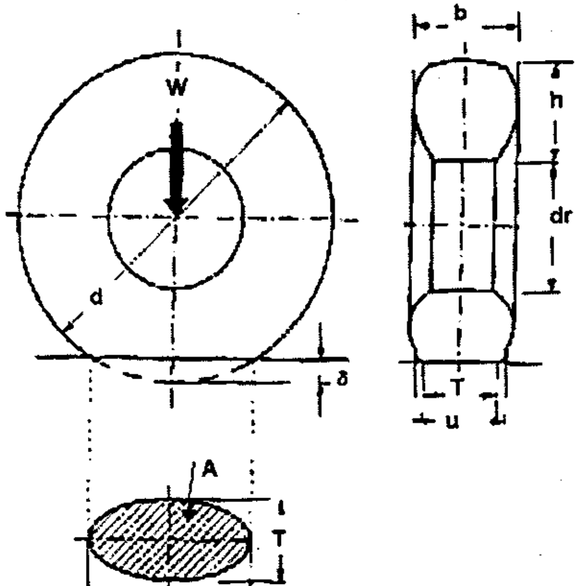

Fig. (1):Diagram of a wheel deformation under a vertical load (cited from Lyasko,1994).

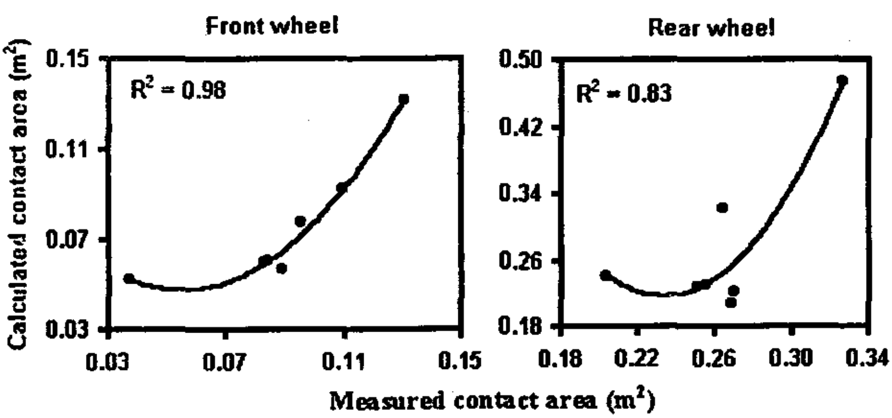

Fig. (2):The relationship between measured and calculated contact area of the tractor wheels.

The ground pressure under tractor wheels (P_S) and the wheel index (*WTI*) for any of front or rear wheels could be calculated as follows:

$$P_S = \frac{W}{A} \tag{9}$$

$$WTI = \frac{P_S}{P} \tag{10}$$

then the final wheel index (*WTI*) that used in the neuro-fuzzy model is the summation of wheel index of front and rear wheels. For rubber crawler combines, assume the inflation pressure is to be 100 kPa, so the *WTI* is calculated as follows:

$$WTI = \frac{P_{SC}}{100} \tag{11}$$

where P_{SC} is the ground pressure (kPa) for rubber crawler combines and calculates as follows:

$$P_{SC} = \frac{CTL}{TA} \tag{12}$$

where *CTL* is the total load of the rubber crawler combine (kN) and *TA* is the track area (m^2).

Adaptive Neuro-Fuzzy Inference System (ANFIS):

The model was structured and formulated using Matlab version 6.1 and the fuzzy logic toolbox, as a Sugeno fuzzy model (Mathworks, 2001). The first step in designing the fuzzy logic model was to identify the fuzzy input and output variables. Four variables were selected as fuzzy inputs namely: soil moisture content (*MC*), clay ratio (*CR*), wheel index (*WTI*) and the number of wheel passes over the field (*NWP*). The index of soil compaction (*DSC*) was considered as one fuzzy output variable.

In ANFIS the data clusters are partitioned optimally, and a set of fuzzy IF-THEN rules is generated. These rules provide a basis for prediction. However, in this research work the best results were obtained when the consequents are simply constants not first-order polynomials in the input variables. These kinds of ANFIS are called zero-order Sugeno-type and are very convenient for fitting procedures (Jang and Sun,1995). The rules are of the form:

R_i: *IF* (x_1 *is* A_{i1} *and* x_2 *is* A_{i2} *and*…x_p *is* A_{ip}) *THEN* ($y_i = q_i$) $i = 1,2,\ldots k$

So, the output *y* is computed by taking the weighted average of the individual rules' contributions as follows:

$$y = \frac{\sum_{i=1}^{k} \beta_i(x) q_i}{\sum_{i=1}^{k} \beta_i(x)} \tag{13}$$

With the degree of fulfillment:

$$\beta_i(x) = \min(\mu A_{i1}(x_1),..., \mu A_{ip}(x_p)) \quad or$$
$$\beta_i(x) = \mu A_{i1}(x_1) \cdot \mu A_{i2}(x_2) \cdots \mu A_{ip}(x_p) \tag{14}$$

where R_i is the *ith* rule determining the total number of rules; $x_1, x_2,....x_p$ *and* y_i are, respectively, the input and output system variables; A_{ip} are the antecedent linguistic terms (or fuzzy sets) in rule (*i*) with being the number of antecedent variables; q_i are the rule consequents and they are simply constants; $\beta_i(x)$ is the degree of fulfillment of the *ith* rule and $\mu A_{ip}(x_p)$ is the membership grades of the fuzzy set belongs to input variables. In many fuzzy applications, the membership functions are arbitrarily selected as either trapezoid, triangular, or gausian depending upon the ranges selected. The triangular membership function was selected because of its simplicity. The soil moisture content, clay ratio, wheel index and the number of wheel passes over the field were partitioned into two fuzzy sets, Fig. (3). All data (200 observations) were randomized by authors then partitioned into two sets. The first set was 175 pairs for training process and the second set was 25 pairs for testing process. After 60 epochs of hybrid learning using the ANFIS function of the Matlab fuzzy logic toolbox (Mathworks,2001), the training error (root mean square error) was 3.264 %. The total number of rules was 16 ($2 \times 2 \times 2 \times 2$). Examples of the obtained rules after training process are as follows:

R_1: IF (MC is Dry and CR is Low and WTI is Low and NWP is Little)
THEN DSC = 26.78%

R_4: IF (MC is Dry and CR is Low and WTI is High and NWP is More)
THEN DSC = 16.93%

R_7: IF (MC is Dry and CR is High and WTI is High and NWP is Little)
THEN DSC = 28.43%

R_{16}: IF (MC is Wet and CR is High and WTI is High and NWP is More)
THEN DSC = 33.28%

Model Performance Criteria:

To evaluate the model performance, three criteria are used. The root mean square error (*RMSE*) is selected as the common performance measure as it shows the global goodness of the fit. *RMSE* equals to zero for a perfect prediction. *RMSE* can be computed as follows:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(Y_{ai} - Y_{pi}\right)^2}{n}} \tag{15}$$

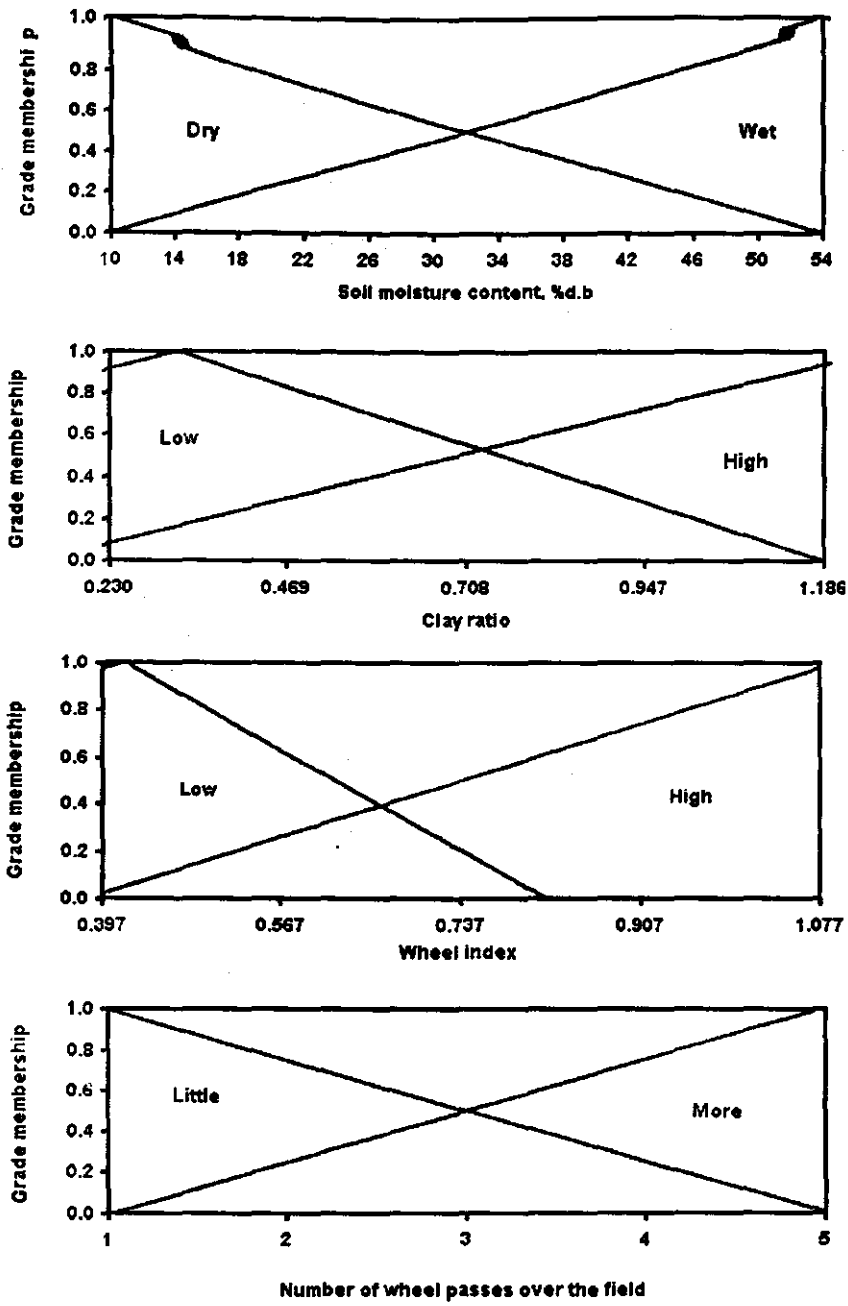

Fig. (3): The fuzzy membership functions for 4 inputs (range of soil moisture content is 10.1-54.0 %, d.b; rang of clay ratio is 0.230-1.186; rang of wheel index is 0.397-1.077 and range of the number of wheel passes over the field is 1-5).

The prediction error is selected as another performance measure and can be computed as follows:

$$APE = \frac{\dfrac{\sum_{i=1}^{n} \left| Y_{ai} - Y_{pi} \right|}{Y_{ai}}}{n} \qquad (16)$$

where *APE* is prediction error according to Hsieh and Weng (2005), *RMSE* is root mean square error according to Makridakis *et al.* (1998), Y_{ai} and Y_{pi} are measured and predicted index of soil compaction respectively and *n* is the number of observations (*n* =175 for training process and 25 for testing process). The correlation coefficient is selected to measure the linear correlation between the measured and the predicted index of soil compaction according to Makridakis *et al.* (1998). The optimal correlation coefficient value is unity and a value smaller than 0.7 is assumed to be problematic (Coulibaly *et al.*,2000). The developed neuro-fuzzy model was validated by conducting field experiments by authors and by using data from other works in this field. The characteristics of validation data are shown in Table (2).

Table (2): The characteristics data that used in validation of the developed neuro-fuzzy model.

Different items		Jorajuria and Draghi (1997)		Helmy *et al.* (1999)	Abdel-Mageed *et al.* (1991)*		Field experiments by authors+
Axle load (kN)	Front	6.87	13.73	8.29	-----		23.99
	Rear	22.56	26.49	13.83	81.42		39.03
Wheel dimensions (in)	Front	6-16	7.5-16	6.5-20	----		14.9-26
	Rear	12.4-36	18.4-34	14-30	23.1-26		18.4-38
Inflation pressure (kPa)	Front	180	210	147.1	----		205
	Rear	114	128	88.26	100	150	125
Soil fractions	Sand (%)	18		20.72	29.81		28.33
	Silt (%)	61		34.16	17.88		47.25
	Clay (%)	21		45.12	52.31		24.45
Forward speed (m/s)		1.6	1.5	----	1.1		1.2
Depth from the soil surface (cm)		0-15		0-10	0-10		0-10

*** Data for combine.** **+ Data not included in training and testing sets.**

RESULTS AND DISCUSSION

Figure (4) shows the graphical depiction of the sixteen rules generated to map the input data (antecedent) with the output (consequent). In the figure each rule is represented in an individual row, while variables are represented in individual columns. The first four columns depict the membership functions for the four input variables (*MC*, *CR*, *WTI*, and *NWP*), referenced by the antecedent or the "if-part" of each rule. The fifth column consisting of sixteen plots shows the membership functions used by the consequent or the "then-part" of each rule. The vertical lines in the first four columns indicate the current data inputs for *MC* (soil moisture content) to be 32 %, d.b; the second variable, *CR* (clay ratio) shows 0.706. The input for the third variable, *WTI* (wheel index), is 0.737, meanwhile, the fourth input, *NWP*, (number of wheel passes over the field) is 3. The bottom plot in the right column is the aggregate of each consequent. The defuzzified output value is represented by a thick line passing through the aggregate fuzzy set. For system inputs: *MC* of 32, *CR* of 0.706,*WTI* of 0.737, and *NWP* of 3, the defuzzified output is shown to be indicating it to be 11.7.

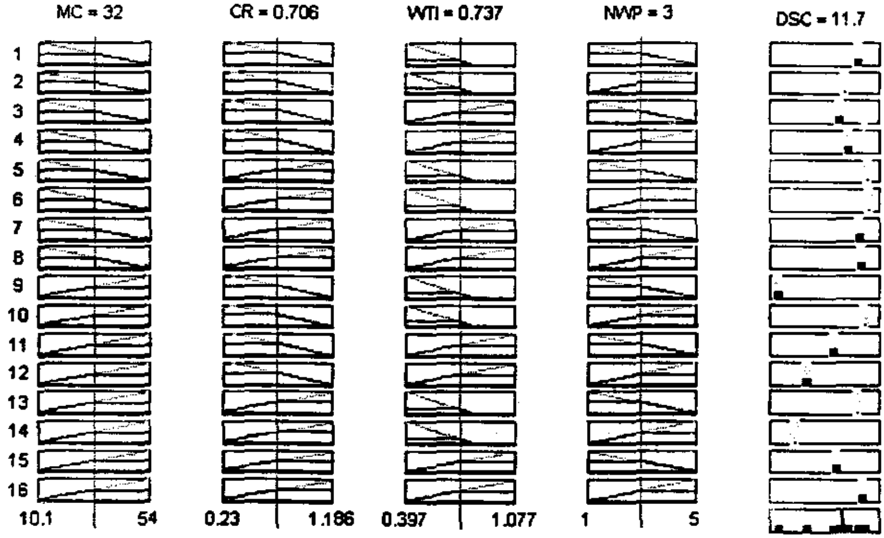

Fig. (4): Rule generation and defuzzified output in the ANFIS.

The criteria of accuracy for neuro-fuzzy model to predict index of soil compaction during testing processes are shown in Table (3). Examination of Table (3) indicates that, neuro-fuzzy provides the accurate prediction.

Table (3): The criteria of accuracy for neuro-fuzzy model to predict index of soil compaction during testing process.

Criteria of accuracy	Units	Value
The root mean square error (*RMSE*)	%	3.332
The prediction error (A*PE*)	----	0.169
Correlation coefficient (r)	-----	0.852

In general, a correlation coefficient value greater than 0.8 indicates a very satisfactory model performance and this fact is verified in Fig. (5). This suggests that the proposed neuro-fuzzy model is acceptable for predicting index of soil compaction as statistical model proposed by Elbanna (1990a), but the neuro-fuzzy model is more fairly as it could be used as a tool for a decision support system for compaction assessment in agricultural soils. It is clear from Fig. (5) that the data from neuro-fuzzy model are less scattering around regression line. So, by using the developed neuro-fuzzy model, it is easy to study the effect of different input variables on index of soil compaction. The neuro-fuzzy approach seems promising and could provide a prospective tool to assess agricultural implements traffic effects on soil.

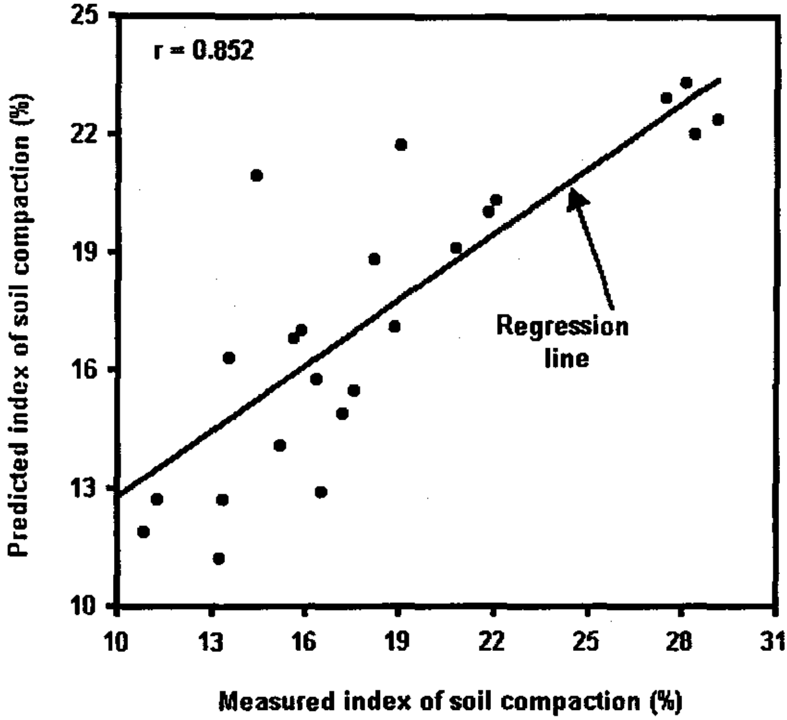

Fig. (5): The measured against predicted index of soil compaction using neuro-fuzzy model during testing process.

The developed neuro-fuzzy model was validated. Values of input variables corresponding to measured and predicted index of soil compaction by neuro-fuzzy model are shown in Table (4). The relative high values of error may be due to the validation data run with different forward speeds, however, the forward speed affects the index of soil compaction (Canillas and Salokhe,2001) and the compaction experiments run on soil has different degree of pulverization or without pulverization.

CONCLUSION

Four inputs were considered to develop the neuro-fuzzy model to predict the index of soil compaction. Clay ratio, soil moisture content, number of wheel passes over the field and wheel index were selected as the most important for the compaction process, based on a bibliographic review on this matter. The model performance was evaluated by the correlation coefficient and by the root mean square error between the predicted and measured results. The neuro-fuzzy model was trained with 175 data pairs and has 16 rules with training error of 3.264 %. The neuro-fuzzy model performance was good compared to measured values. The fuzzy approach seems promising and could provide a prospective tool to assess agricultural implements traffic effects on soil.

Table (4): Values of input variables corresponding to measured and predicted index of soil compaction by neuro-fuzzy model.

Source of data	Input variables				Index of soil compaction		Error *
	MC	CR	WTI	NWP	Measured	Predicted	
	%,d.b	----	----	-----	%	%	%
Jorajuria and Draghi (1997)	27.00	0.220	0.706	1	4.96	3.98	0.98
	27.00	0.220	0.781	5	4.26	5.82	-1.56
	27.00	0.220	0.706	5	10.35	10.10	0.25
Helmy *et al.* (1999)	33.10	0.822	0.817	1	7.44	11.90	-4.46
	30.00	0.822	0.817	2	13.11	14.20	-1.09
	30.20	0.822	0.817	3	11.24	15.40	-4.16
	32.40	0.822	0.817	4	12.44	15.90	-3.46
Abdel-Mageed *et al.* (1991)	49.90	1.097	0.687	1	9.37	12.80	-3.43
	49.90	1.097	0.687	2	11.57	11.00	0.57
	49.90	1.097	0.687	3	13.46	9.13	4.33
	49.90	1.097	0.521	2	12.28	10.20	2.08
	42.60	1.097	0.521	3	8.83	8.58	0.25
Field experiments by authors	18.21	0.324	0.621	1	11.24	13.10	-1.86
	18.21	0.324	0.621	2	11.74	13.90	-2.16
	18.21	0.324	0.621	3	13.11	14.80	-1.69
	18.21	0.324	0.621	4	16.74	15.60	1.14
	18.21	0.324	0.621	5	18.57	16.40	2.17

***Error = Measured – Predicted**

REFERENCES

Abdel-Mageed, H.N.; M.A. El Sheikha and M.M. El Eraqi (1991). Soil compaction due to combine harvester traffic devices. Misr J. Ag. Eng., 8(4): 348-360.

Abou-Habaga, M. (1989). Effect of seed preparation systems on soil natural compaction and crop yield. Egyptian-German Conf. Ag. Mech. 4-6 October, Mansoura Univ., Egypt:71-80.

Aboukarima, A. M. (2003). Fuzzy logic for improvement efficiency of Egyptian rice milling process. The 11th Conf. of Misr Soc. Ag. Eng., 15-16 October, Rice Mech. Center, Meet El Deeba, Kafer El Sheikh Governorate: 262-272.

Ahmed, S.F.; S.M. Ismail and S.S. Sadaka (1988). Compaction by different tractor types in silt-loam and sandy-clay soils. Misr J. Ag. Eng., 5(2): 129-138.

Al-Faraj, A.; G.E. Meyer and G.L. Horst (2001). A crop water stress index for tall fescue (Festuca arundinacea Schreb.) irrigation decision-making - a fuzzy logic method. Computers and Electronics in Agric., 32:69-84.

Bellei E.; D. Guidotti; R. Petacchi ; L.Reyneri and I. Rizzi (2001). Applications of neuro-fuzzy classification, evaluation and forecasting techniques in agriculture. ESANN'2001 Proceedings - European Symposium on Artificial Neural Networks Bruges (Belgium), 25-27 April, D-F Acto Public.: 403-408.

Canillas, E. C. and V. M. Salokhe (2001). Regression analysis of some factors influencing soil compaction. Soil & Tillage Res., 61:167-178 .

Canillas, E. C. and V. M. Salokhe (2002). A decision support system for compaction assessment in agricultural soils. Soil & Tillage Res.,65: 221-230.

Center, B. and B. P. Verma (1998). Fuzzy logic for biological and agricultural systems. Artificial Intelligence Review, 12 (1-3): 213 - 225.

Coulibaly,P.; F. Anctil and B. Bobe´e (2000).Daily reservoir inflow forecasting using artificial neural networks with stopped training approach. Journal of Hydrology, 230: 244–257.

De Araùjo, A. G. and A. M. Saraiva (2003). Fuzzy modeling of soil compaction due to agricultural machine traffic. EFITA 2003 Conference 5-9, July, Debrecen, Hungary: 79-102.

Defossez, P. and G. Richard (2002). Models of soil compaction due to traffic and their evaluation. Soil & Tillage Res., 67:41-64.

Dixon , B.; H. D. Scott; J. V. Brahana; A. Mauromoustakos and J. C. Dixon (2001). Application of neuro-fuzzy techniques to predict ground water vulnerability in northwest Arkansas. Publication No. PUB-183, Arkansas Water Resources Center, University of Arkansas, Fayetteville, Arkansas, USA: 65p.

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

Elbanna, E.B. (1990b). Effect of trafficability on soil compaction. Misr J. Ag. Eng., 7 (2): 160-172.

Gassoumi, H. (2000). A soft computing approach for classification of insects in agricultural ecosystems. Ph D. Dissertation, New Mexico Sate University, Las Cruces, New Mexico: 250p.

Godbole, R.; R. Alcock and D. Hettiaratchi (1993). The prediction of tractive performance on soil surfaces. Journal of Terramechanics, 30(6): 443-459.

Gysi, M. ; G. Klubertanz; A. Ott and L. Vulliet (2000). Soil compaction due to heavy wheel traffic- a comparison of field data to a model approach. 4th Int. Conf. on Soil Dynamic (ICSD-IV), 26-30 March, Adelaide, Australia.

Helmy, M.A.; E.B. Elbanna and H.M. Sorour (1999). Effect of traffic of some agricultural equipment on soil compaction. Misr J. Ag. Eng., 16 (3): 160-172.

Hsieh, C.L. and S.-F. Weng (2005). Prediction of physical properties of orchid seedlings *'Phalaenopsis Sogo Vivien F819'* in a flask by digital imaging. Canadian Biosystems Engineering, 47: 3.23-3.32.

Jang, J. R. and C. Sun (1995). Neuro-fuzzy modeling and control. Proc. IEEE, 83:378-406.

Jorajuria, D. and L . Draghi (1997). The distribution of soil compaction with depth and the response of a perennial forage crop. J . agric . Engng Res., 66: 261 – 265

Jun-Zheng, P. and L. Zhi-Xiong (1998). Prediction of paddy soil normal adhesion to steel surface by fuzzy logic. Journal of Terramechanics, 35:103-107.

Kemp, H. R. (1990). Climbing ability of four-wheel-drive vehicles. Journal of Terramechanics, 27(1): 7-23.

Lee, K.; N. Zhang and S. Das (2003). Comparing adaptive neuro-fuzzy inference system (anfis) to partial least-squares (pls) method for simultaneous prediction of multiple soil properties. ASAE Paper No. 03-3144, ASAE, St. Joseph, Michigan, USA.

Lyasko, M. I. (1994). The determination of deflection and contact characteristics of a pneumatic wheel on a rigid surface. Journal of Terramechanics, 31(4): 239-242.

Makridakis,S.; S.C. Wheelwright and R.J. Hyndman (1998). Forecasting: methods and applications. Third Edition, John Wiley & Sons, Inc., New York: 642 p.

Mathworks, T. (2001). Fuzzy logic toolbox for use with Matlab. User's guide, version 2. Natick, MA: The Mathworks, Inc. MA: MIT Press.

McBratney, A.B. and I.O.A. Odeh (1997). Application of fuzzy sets in soil science: fuzzy logic, fuzzy measurements and fuzzy decisions. Geoderma, 77:85-113.

Morad, M.M. and M.A. Arnaout (1993). Effect of tractors traffic on soil compaction. Misr J. Ag. Eng., 10 (1): 103-110.

Odhiambo, L. O.; R. S. Freeland; R. E. Yoder and J. W. Hines (2004). Investigation of a fuzzy-neural network application in classification of soils using ground-penetrating radar imagery. Applied Engineering in Agriculture, 20(1): 109-117.

Sadaka, S.S. (1988). Compaction of some Egyptian agricultural soils and its effects on crop yield and physical properties of soil. M Sc. Thesis, Agric. Eng. Dept. Faculty of Agric., Alexandria Univ.
Srivastava, A.K.; C.E. Goering and R.P. Rohrbach (1993). Engineering principles of agricultural machines. ASAE Textbook No.6, Published by ASAE, St. Joseph, Michigan, USA.
Thangavadivelu, S. and T.S. Colvin (1991). Trafficability determination using fuzzy set theory. Trans. ASAE, 34 (5): 2272-2278.
Voorhees, W.B. (2000). Interaction of axle load, soil water regime and soil texture on long – term subsoil compaction and crop yield in North America. 4th Int. Conf. on Soil Dynamic (ICSD-IV), 26-30 March, Adelaide, Australia.
Zimmermann, H.-J. (1996). Fuzzy set theory-and its applications. Boston, Kluwer Academic Publishers.

إطار مشوش-عصبي لتقييم إنضغاطية التربة بسبب مرور المعدات الزراعية على أراضي مختلفة

الشحات بركات البنا[1]، عبد الواحد محمد أبو كريمة[2] ، رجب إسماعيل أحمد مراد[3]
[1]قسم الهندسة الزراعية، كلية الزراعة، جامعة المنصورة
[2]معهد بحوث الهندسة الزراعية، مركز البحوث الزراعية، وزارة الزراعة واستصلاح الأراضي
[3]قسم الهندسة الزراعية، كلية الزراعة، جامعة الفيوم

يهدف هذا البحث إلى استخدام نموذج بإطار مشوش-عصبي كآلية مناسبة لوصف وتقييم عملية إنضغاطية التربة نتيجة مرور الآلات الزراعية فوقها. هذه الآلية تساعد على تخطيط عمليات الميكنة الزراعية لكي تزيد استمرارية النشاط الزراعي. واعتبر النموذج المتغيرات التالية:المحتوى الرطوبي للتربة، نسبة الطين (تمثل قوام التربة)، دليل العجلة*، وعدد مرات مرور العجلة فوق الحقل كمدخلات. بُنى النموذج مستنذا على البيانات التجريبية الحقلية باستخدام توليفة مختلفة من الجرارات الزراعية وآلة حصاد (كومباين). قورن دليل إنضغاطية التربة المتوقع بتلك المقاس في الحقل وتم التحقق من دقة النموذج. وبينت النتائج أن النموذج الذي تم إنشائه وتدريبه واختباره بالإطار المقترح أعطى نتيجة مقنعة بالرغم من التعقيد للمشكلة تحت الدراسة، ويمكن اتخاذه كوسيلة لاتخاذ القرار لتفادي إنضغاطية التربة المرتفعة نتيجة مرور الآلات الزراعية فوقها.

---

*دليل العجلة = (ضغط تلامس العجل الأمامي مع التربة) / (ضغط الهواء للعجل الأمامي) + (ضغط تلامس العجل الخلفي مع التربة) / (ضغط الهواء للعجل الخلفي)

حيث:

ضغط تلامس العجل الأمامي مع التربة = (الوزن على عجلة أمامية واحدة) / (مساحة تلامس عجلة أمامية واحدة مع التربة)

ضغط تلامس العجل الخلفي مع التربة = (الوزن على عجلة خلفية واحدة) / (مساحة تلامس عجلة خلفية واحدة مع التربة)

* دليل العجلة (حالة الكتينة) = (ضغط تلامس الكتينة مع التربة (كيلوبسكال)) / (١٠٠ (كيلوبسكال))

حيث:

ضغط تلامس الكتينة مع التربة = (الوزن الكلي للمعدة الزراعية ذات الكتينة (كيلونيوتن)) / (مساحة تلامس الكتينة مع التربة (متر مربع))