EVALUATION OF USING A COMBINATION OF SIMULATED AND EXPERIMENTAL DATA TO PREDICT DRAFT FORCE OF A MOLDBOARDPLOW

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ABSTRACT

Information is required on draft force for tillage implements as it plays an important role in design and development of such implements. Due to the complexity of draft force prediction models of the moldboard plow, there is a need to develop a simple draft prediction model of the moldboard plow, as affected by soil properties and working conditions. In this research, two models were implemented. The first one was by artificial neural network (ANN) and the second was by a multiple linear regression (MLR). The required draft data were obtained by the available Excel spreadsheet. The soil parameters required in the spreadsheet were obtained from experimental work at different sites in Saudi Arabia. For generating draft data, the plowing depths and the plowing speeds were assumed. All combinations were addressed and the total data were 2268 rows. However, 2172 rows were used to build the ANN and MLR models for predicting draft of a moldboard plow. Meanwhile, 96 data points were used to test the models. The mean relative error (MRE) between simulated and predicted values, using regression draft equation and ANN model were 1.86% and -8.966%, respectively during testing phase. The performance of the two models was validated by a field experiment data and points from literature. MRE values between measured and predicted values of validation data using field data were 5.19% and 12.32% when using ANN and MLR models, respectively. The encouraging results can push to utilize the developed models to be a tool for evaluation in farm machinery management process.

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INTRODUCTION

Soil tillage by moldboard plow is one of the fundamental phases of agricultural production (**Formato et al., 2005**) since it has been encountered with two problems; the possibility of plow pan formation which could have negative effects on vertical water movement into the soil and low penetration rate (**Abas et al., 2008**). On the other hand, information is required on draft force for such plow (**Kheiralla et al., 2004**) as it plays an important role in design and development of it (**KarimiInchebron et al., 2012**). Moreover, the draft force required to pull a tillage implement is of great importance since it determines fuel consumption and the tractor power required (**Arvidsson and Hillerstrom, 2010**).

It is known that the draft force of a moldboard plow depends on the geometry of the plow body as well as soil properties as its hardness, density, friction and adhesion (**Godwin et al., 2007**). In addition, the draft is dependent on operating factors such as depth of plowing, plow speed and the number of bodies in use. So, different studies were conducted to assess such affecting factors on the draft force of a moldboard plow. Besides, different draft models for moldboard plow were developed to calculate such force by the help of soil mechanic theory as the study conducted by (**Godwin et al., 2007**), or by regression analysis (**Gee-Clough et al., 1978**; **Oskoui and Witney, 1982; Oskoui et al., 1982; Elbanna, 1989; El Khadrawy, 1990; Elbanna, 1992; Kheiralla et al. 2004**) or by artificial neural networks as the study conducted by **Aboukarima (2004)**. However, several authors found ANN predictions for draft, pull and energy requirements of tillage implements to be an effective tool, as shown in studies by **Hassan and Tohmaz (1995), Tohmaz and Hassan (1995), Kushwaha and Zhang (1997), Zhang and Kushawaha (1999), Al-Janobi et al. (2001), Aboukarima et al. (2003), El Awady et al. (2003), Aboukarima (2007), Aboukarima and Saad (2006), El Awady et al. (2004), Roul et al. (2009)** and **Al-Janobi et al. (2010)**. Also, the analytical and the finite element methods have been used to investigate soil cutting process (**Mouazen and Neményi, 1998**). Such models are essential for improving the design and selection of moldboard plows (**Aluko and**

Seig, 2000). Adding, traditional plow design and manufacture have been based on empirical methods and experiments (**Shrestha et al., 2001**), depending on the type of soil in the different areas.

There are different research works to study the impact of soil properties such as soil bulk density, soil moisture content, etc. on the draft of tillage implements. These influencing factors were the main axis of interest of previous research, which adapted field experiments to understand how these factors affect this draft (**Mouazen and Ramon, 2002**). Addition result showed that soil moisture content is an important variable to draft of a tillage implement, however, a dry soil requires an excessive power and also accelerates wear of the cutting edges (**Gill and Vanden Berg, 1968**), where, they indicated that in soil bin tests, an observed increase of moisture content from 9.1 to 11.7% (db) reduced the specific draft in a fine sandy loam by 15 to 35%. Meanwhile, they reported a 15 to 35% increase in draft when the bulk density of a fine sandy loam was changed from 1680 kg/m^3 to 1830 kg/m^3. In the same findings, **Mouazen et al. (2003)** reported that draft for a tillage implement decreased with increasing moisture content.

Arvidsson et al. (2004) presented a study to measure the specific draft (force per cross-sectional area of worked soil) for a moldboard plow. The plow was set to working depth of 13 cm. Plowing was carried out at three different water contents (‘‘Wet’’, ‘‘Moist’’ and ‘‘Dry’’) on two sites. The results showed that draft increased with decreasing soil water content.

Tong and Moayad (2006) found that from field experiments with a chisel plow the draft increased with increasing soil bulk density. **KarimiInchebron et al. (2012)** measured draft for moldboard plow in different depths (10, 15 and 20 cm) and soil moisture contents (16-18%), (19-22%) and (23-25 %db). The results indicated that plowing depth and soil moisture content had significant effect ($P<0.01$) on the draft. It was also found that draft decreased significantly with increase in the soil moisture content.

Summers et al. (1986) studied the effects of plowing speed and depth on moldboard plow draft in clay loam soil and silt loam soil. Their measured drafts in clay loam soil and silt loam soil were 7 and 13%, respectively, lower than the ASAE Standard (**ASAE Standards, 1984**).

Khadr (2008) reported that by increasing the plowing speed from 0.89 to 1.62 m/s for moldboard plow, the draft increased from 18.82 kN to 21.66 kN in clay soil.

Abas et al. (2008) evaluated the effects of five plow share types (deep-suck share (control), trapezium-shaped share with/without share point, and serrated share with/without share point) under two soil moisture contents (0.85 and 0.55 plastic limit (PL)), and two plowing depths (15 and 20 cm) on draft of the moldboard plow in a silty clay loam soil. The results showed that when soil moisture content was reduced from optimum value for plowing (0.85PL) to dry condition (0.55 PL); the draft of plow with deep-suck share equipped with share point significantly increased (by 28%). Also, increasing the plowing depth by 33%, draft significantly increased by 33%.

Godwin et al. (1981) showed that there are changes in the magnitude of the soil force with depth at two types of soil and the draft increases in an essentially linear matter with increasing forward speed.

Nadre and Datta (1991) mentioned that the draft increased with increasing in the depth of operation for moldboard plow. **Imara (1996)** developed equation to predict drawbar pull for moldboard plow using multiple linear regression and the affecting variables were forward speed, soil moisture content and plowing depth. The coefficients of soil moisture content in his equation was negative that mean increasing soil moisture content decreasing drawbar pull for specific case of forward speed and plowing depth. On the other hand, coefficients of forward speed and plowing depth in his equation were positive.

Gebresenbet et al. (1997) reported that there were differences in values of the draft force for a plow measured in fields of clay and sandy soil. **Summers et al. (1986)** showed the greater draft requirement for silt loam compared with other soils was due to the higher relative soil strength as judged by cone index values for moldboard plow.

Ward (1995) reported that there was no single model that adequately defines the impact of the various parameters on plow draft, as there was considerable variation from soil to soil. **Huijsmans et al. (1998)** mentioned that in general, a higher draft force was required on the clay soil than on sand soil for trailing-foot and shallow injection equipment. Higher soil moisture content led to a lower draft force requirement.

Al-Janobi and Al-Suhaibani (1998) applied field experiments to measure draft of a moldboard plow in sandy loam soil, and when they applied the proposed draft model by **Harrigan and Rotz (1995)** on their data, they found that the measured draft was close to the predicted draft and they attributed the difference between measured and predicted to the soil conditions.

Kheiralla et al. (2004) conducted a field experiment in sandy clay loam soil to measure draft of a moldboard and the effects of plowing speed and plowing depth upon the measured draft were investigated. A polynomial draft from orthogonal regression analyses was formulated based on linear and quadratic functions of plowing speed and plowing depth. The predicted moldboard plow draft was 4% lower than the draft computed with the ASAE Standard (**ASAE Standards, 1997**).

Rahman et al. (2011) developed a neural network model to predict energy requirement of a tillage tool from the laboratory data. The neural network model was trained and tested with soil moisture content, plowing depth and forward operating speed as input parameters. The measured energy requirement for a tillage tool in silty clay loam soil was used as output parameter. Their results showed that the variation of measured and predicted energy requirement was small.

Roul et al. (2009) applied a 5–9–1 artificial neural network (ANN) model with a back propagation learning algorithm to predict draft requirements of different tillage implements in a sandy clay loam soil. The input parameters were width of cut, depth of operation, speed of operation, soil moisture content and soil bulk density. The results indicated that the developed ANN model for draft prediction could be considered as an alternative and practical tool for predicting draft requirement of tillage implements under the selected experimental conditions in sandy clay loam soils.

There is a suggestion to conduct studies to measure draft and energy requirements of tillage implements under various soil conditions in the developed nations of the world (**Manuwa and Ogunlami, 2010**); this is due to the complexity of tillage implements draft force prediction. Thus, in the light of the aforementioned, it is clear that there is a need of a simple draft model for moldboard plow including soil properties and working condition. So, the aim of this research was to implement an

ANN model for draft force prediction of a moldboard plow using the combination of experimental and simulation data. For compression, a multiple linear regression technique was used to build the draft model. The two models will be validated by data from actual field experiment and data from literature.

MATERIALS AND METHODS

Field experiment site and soil properties data

Collecting soil samples were carried out from different sites in Saudi Arabia, during year of 2012. The purpose was to determine soil cohesion, soil moisture content, soil internal friction angle and soil bulk density. The latitude, longitude and altitude of each site are shown in Table (1). The samples were obtained in undisturbed condition using soil cylinder 0.16 m in height and 0.08 m in diameter. The soil samples were weighed using a balance and the weight of each sample was recorded. Then the samples were placed in an electric oven, maintained at 110°C for 48 h. The dried soil samples were reweighed and the weight was again recorded. The moisture contents were calculated on a dry weight basis and also soil bulk density values were addressed. In addition, soil from each site was classified by mechanical analysis. All laboratory tests were carried out according to the standard methods. Direct shear box method was used in determining soil cohesion and soil internal friction angle. Levels of soil moisture content similar to the soil moisture content in the field were tested, and for 2 replicates. If the results of 2 replicates for each sample were not close to each other, more tests were repeated to verify the real values of shearing force for that sample. During the shear experiments, soil wet density of the soil was maintained in the range related to soil bulk density. The loading rate during shear tests was constant rate of 0.12 mm/min. A soil sample was placed in a metal shear box and undergoes a horizontal force and the soil failed by shearing along a plane when the force was applied. Soil-metal friction angle (δ) was determined using the following formula (**Chung *et al.* 2008**),

$$\delta = \begin{bmatrix} (0.590 \times Sand\ \ fraction) + (0.735 \times Silt\ \ fraction) + \\ (0.375 \times Clay\ \ fraction) \end{bmatrix} \times \phi \quad \ldots. (1)$$

Where ϕ is the angle of soil–soil friction in deg. Table (1) illustrates soil properties in all the selected sites.

Table (1). Soil properties in the selected sites.

Soil Sample No.	Latitude (°N)	Longitude (°E)	Altitude (m)	Sand (%)	Silt (%)	Clay (%)	Soil moisture content (%)	Soil bulk density (g/cm^3)	Soil cohesion (kPa)	Angle of internal friction of soil (degree)	Soil–metal friction angle (degree)
1	26.21	43.89	644.11	72.8	15.2	12.0	2.75	1.63	15.7	42	24.90
2	26.41	43.82	642.36	88.8	7.2	4.0	5.62	1.98	24.5	41	27.42
3	26.44	43.69	699.53	88.9	8.1	3.0	8.98	1.69	11.8	34	21.36
4	26.43	43.71	689.59	84.8	10.2	5.0	8.85	1.96	18.6	44	28.39
5	28.40	36.87	802.34	80.6	9.4	10.0	11.20	1.60	3.9	34	19.02
6	28.40	36.87	802.67	75.7	12.3	12.0	7.30	1.40	12.8	32	18.72
7	28.40	36.80	799.19	68.5	17.5	14.0	10.60	1.70	33.4	37	24.34
8	28.40	36.78	797.59	63.6	16.4	20.0	7.50	1.70	73.6	43	33.18
9	28.43	36.62	770.92	63.8	15.2	21.0	15.10	1.90	19.6	31	17.41
10	24.32	47.13	465.06	82.2	9.9	7.9	1.30	1.55	7.8	38	22.02
11	24.18	47.22	446.84	86.4	8.8	4.8	10.65	1.66	4.9	35	20.57
12	24.26	47.26	444.74	75.3	16.7	8.0	5.30	1.58	6.9	35	20.75
13	24.21	47.57	400.00	71.8	17.2	11.0	4.10	1.74	41.2	43	30.30
14	24.20	47.56	401.61	85.7	7.3	7.0	5.36	1.95	27.5	39	25.50
15	24.20	47.24	442.60	77.3	16.7	6.0	8.00	1.69	21.6	40	26.13
16	20.42	44.74	702.18	74.8	17.2	8.0	7.08	1.90	19.6	39	25.27
17	20.43	44.73	702.93	80.3	15.7	4.0	7.50	1.47	4.9	32	19.44
18	20.42	44.71	710.37	79.7	16.3	4.0	7.20	1.64	14.7	32	20.65
19	20.44	44.74	698.69	84.4	12.6	3.0	10.00	1.67	13.7	32	20.55
20	29.99	40.12	611.06	88.8	7.2	4.0	5.77	1.80	23.5	42	27.94
21	30.00	40.12	607.94	80.7	8.3	11.0	10.60	1.60	13.7	33	19.43
22	29.89	38.58	609.09	83.6	11.4	5.0	5.00	1.60	11.8	42	26.09
23	29.89	38.57	614.94	85.2	10.8	4.0	9.30	1.40	4.9	32	19.21
24	27.79	41.73	871.74	74.1	15.9	10.0	8.87	1.40	7.8	34	19.84
25	27.80	41.75	870.11	77.3	13.7	9.0	9.82	1.46	22.6	32	20.52
26	27.80	41.75	869.90	71.7	15.3	13.0	9.67	1.72	54.0	39	29.07
27	27.82	41.73	862.34	65.9	20.1	14.0	9.92	1.73	55.9	41	30.45

Representing soil texture

A soil texture index was developed by combining all soil fractionssimilar to that developed by **Oskoui and Harvey (1992)**. However, due to the sand content is the major component in the selected sites, followed by silt then clay, another formula was developed, to calculate soil texture index (STI), as follows:

$$STI = \frac{log\ (Sa^{Si} + CCa\ )}{100} \qquad (2)$$

Where Sa is the percentage of sand content in the soil, S_i and $CC_a$are the percentages of silt and clay contents in the soil, respectively. **Oskoui and Harvey (1992)** showed that the STI reflects the effects of all three soil fractions. The STI produces unique numbers for every combination of sand, silt and clay contents.

Field experimental procedure for measuring draft force of a moldboard plow

Field experiments were conducted during April 2012 in the Agricultural Research and Experimental Farm in Dirab, Riyadh, Saudi Arabia. Longitude, latitude and altitude for the experiment site were 46.65°E, 24.41°N and 575.79 m, respectively. An experimental block about 50 m long by 3 m wide was utilized during experiments. A small block of approximately 10 m long by 3 m wide, in the beginning of each tested block, was used to enable the tractor and plow to reach a steady state condition of the required plowing speed and plowing depth. Plowing depth was measured as the vertical distance from the top of the undisturbed soil surface to the plow’s deepest penetration. In this work, the plowing depth was 15 cm. The horizontal force (draft) was measured using a load cell (model Omega with a capacity of 0-10000 lb) using the method described in (**PAES, 2001**). The moldboard plow was hitched to a Fendt tractor model 611LS. However, the auxiliary tractor was John Deer tractor model 6615.The draft was recorded within the distance of 40 m. The plowing speed was calculated by measuring of distance of five turns of the tractor rear wheel with time. On the same field, the plow was lifted out the ground and the rear tractor was pulled to record the idle draft force. The difference gave the draft of the plow. A moldboard of general purpose type with three bodies in the frame each of width 360 mm (Overum-S, Sweden), model 7073331) was used in this experiment. The plow specifications are depicted in Table (2). Three plowing speeds were obtained by changing tractor gear box gears. Soil properties of the field experiment are shown in Table (3).

Available moldboard draft requirement model

The moldboard plow geometric factors and the draft force components are shown in Figure (1) (**Godwin et al., 2007**). The total plow draft (**Godwin et al., 2007**) force H_t in kN is calculated from the following expression:

$$H_t = H_p + H_s + H_{mc} + H_e + H_{cs} + H_{ms} + H_{fs} \quad \text{.....................................(3)}$$

where H_p is the draft force due to the plow point in kN; H_s is the draft force due to the plow share in kN; H_{mc} is the draft force due to the moldboard soil momentum change and the draft force friction along the moldboard in kN; H_e is the draft force due to the increase in soil potential energy at the moldboard in kN; H_{cs}+H_{ms} are the draft force components arising from friction forces due to lateral forces at the share and moldboard, respectively, in kN; H_{fs} is the draft force arising from the lateral force at the moldboard due to soil lateral movement in kN.

Table (2). Specifications of the used moldboard plow.

Items	Value
Share sweep angle, β (°)	44
Moldboard angle,θ (°)	39
Point depth (cm)	6
Point width (cm)	7
Rake angle, α (°)	23
Share width (cm)	36
Moldboard length (cm)	87

Table (3). Soil properties and working condition during field experiment.

Soil Moisture content	Soil bulk Density	Plowing depth	Plowing speed	Sand	Silt	Clay
(% db)	(g/cm^3)	(cm)	(km/h)	(%)	(%)	(%)
7.5	1.67	15	2.5	84.6	12.4	3.0
7.5	1.67	15	3.4	84.6	12.4	3.0
7.5	1.67	15	5.3	84.6	12.4	3.0

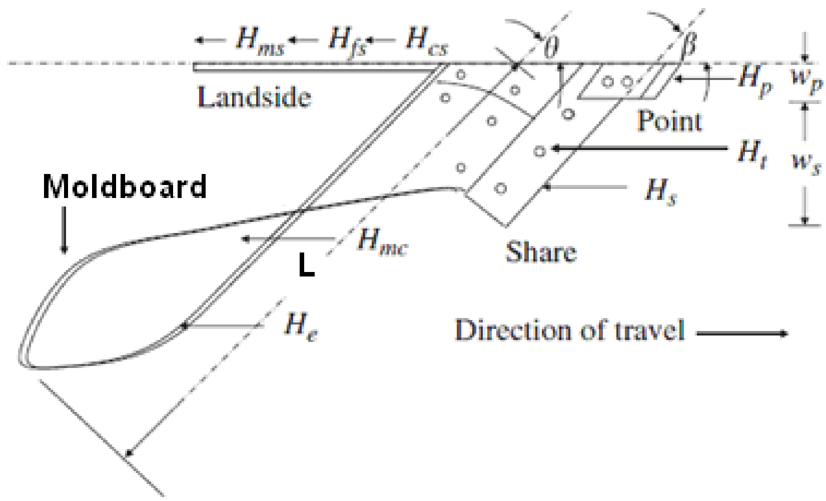

Figure (1). Diagram of the components of the draft force acting on moldboard plow.

The individual components of the draft force are given as follows:

$$H_p = \left[\begin{array}{c} \left(\gamma d_p{}^2 N_\gamma + C d_p N_{Ca}\right)\left(w_p + 0.55 d_p\left(m_s - \left(m_s - 1\right)/3\right)\right) \\ + \left(\dfrac{\gamma V^2 N_a d_p}{g}\right)\left(w_p + 0.33 d_p\right) \end{array} \right] \sin(\alpha_p + \delta) \quad (4)$$

$$H_s = \left(\gamma d_s{}^2 N_\gamma + C d_s N_{Ca} + \frac{\gamma V^2 N_a d_s}{g} \right) w_s \sin(\alpha_s + \delta) \sin\beta \quad (5)$$

$$H_{mc} = (\gamma / g)\left(w_p d_p + w_s d_s\right) V^2 \left(1 - (1 - \sin\theta \tan\delta)\cos\theta\right) \quad (6)$$

$$H_e = 2\gamma\left(w_p d_p + w_s d_s\right) d_s \quad (7)$$

$$H_{cs} = \left(\gamma d_s{}^2 N_\gamma + C d_s N_{Ca} + \frac{\gamma V^2 N_a d_s}{g} \right) w_s \sin(\alpha_s + \delta) \cos\beta \tan\delta \text{ ....(8)}$$

$$H_{ms} = (\gamma / g)(w_p d_p + w_s d_s) V^2 \sin\theta (1 - \sin\theta \tan\delta) \tan\delta \text{ ....(9)}$$

$$H_{fs} = L\gamma (w_p d_p + w_s d_s) \tan\phi_s \tan\delta \text{ ....(10)}$$

Where γ is soil bulk unit weight in kN/m^3; C is soil cohesion in kN/m^2; d_p is depth of plow point in m; w_p is width of plow point in m; m_s is soil-rupture distance ratio (the ratio between forward rupture distance and working depth); V is plow forward velocity in m/s; g is the acceleration due to gravity in m/s^2; α_p is point rake angle in deg; δ is angle of soil to metal friction in deg, N_γ, N_{ca} and N_a are dimensionless soil parameters, d_s is depth of plow share in soil in m; w_s is width of plow share in m; α_s is share rake angle in deg, β is angle of share edge to direction of plow motion in deg, θ is the mean angle of the moldboard to the direction of motion of the plow in deg and L is the effective length of the moldboard in m. **Godwin et al. (2007)** developed a spreadsheet (Figure 2) to enable calculations of moldboard draft force to be carried out without a detailed knowledge of all the underlying theory which can involve complex procedures using equations 3 through 10.

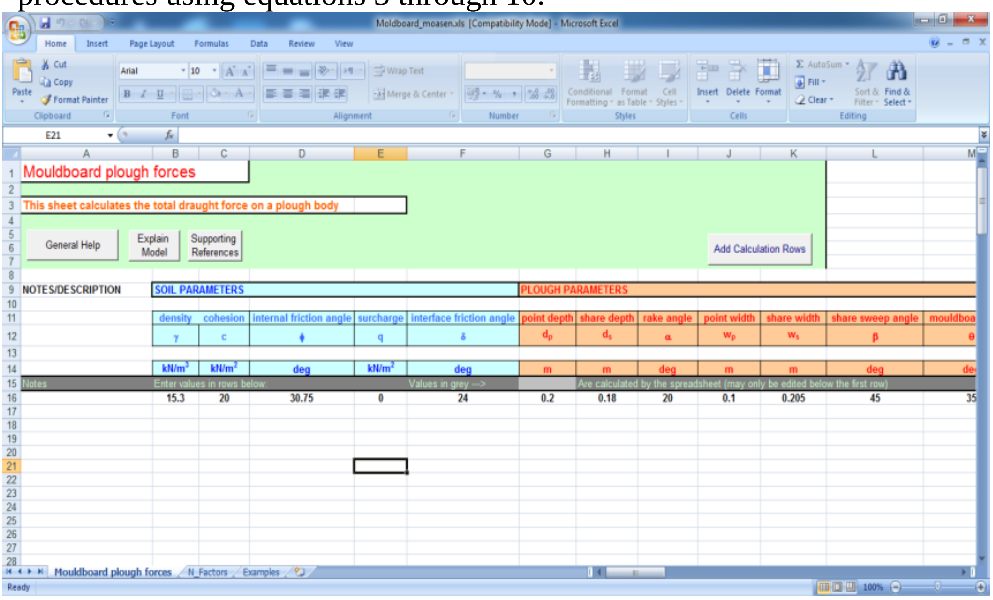

Figure (2). A screenshot of the spreadsheet to enable calculations of moldboard draft (**Godwin et al., 2007**).

In this research work, the soil parameters (soil cohesion, soil internal friction angle, soil metal friction angle and soil density) needed in the spreadsheet were obtained from experimental work in different sites. For generating draft data, the assumed plowing depths were 12,14,16,18,20,22 and 24 cm and the assumed plowing speeds were 2,2.5,3,3.5,4,4.5,5,5.5,6,6.5,7 and 7.5 km/h. The specifications of the moldboard plow are shown in Table (2). All combinations were addressed and the total data were 2268 rows. The simulated draft data were formulated using artificial neural network (ANN) model and regression equation to predict draft of a moldboard plow using less affecting parameters (soil moisture content, soil bulk density, plowing depth and speed and soil texture index).

Artificial neural network model

In order to design the ANN model, commercial neural network software of QNET 2000 for WINDOWS (**Vesta Services, 2000**) was used in this research. The ANN used in this study was a standard back-propagation neural network with three layers: an input layer, a hidden layer and an output layer. The neurons in the three layers are connected by weights. The weights connecting input neuron i to hidden neuron j are denoted by w_{ji}^{h} , while the weights connecting hidden neuron j to output neuron are denoted by w_{j}^{o} . The input of each neuron is the weighted sum of the network inputs, and the output of the neuron is a sigmoid function value based on its inputs. More specially, for the j th hidden neuron (**Zhang et al., 2005**).

$$\begin{cases} net_j^h = \sum_{i=1}^{n} w_{ji}^h x_{t-1} + b_j \quad , \\ \\ y_j = f\left(net_j^h\right) \end{cases} \qquad ....(11)$$

While for the output neuron

$$\begin{cases} net^o = \sum_{j=1}^{m} w_j^o y_j + c \quad , \\ \\ \tilde{x}_t = f\left(net^o\right) \end{cases} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (12)$$

Where b_j and c are thresholds (bias), this network has n neurons in the input layer and m neurons in the hidden layer, f is typically taken to be a sigmoid function, such as the logistic function

$$f(x) = \frac{1}{1+e^{-x}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (13)$$

The inputs to this network are soil moisture content, soil bulk density, plowing depth, soil texture index and plowing speed. The output has one $\tilde{x}_t$ that is draft of a moldboard plow (kN/body).

Before training, a certain pre-processing steps on the network inputs and targets to make more efficient neural network training was performed. The simulated draft data versus soil moisture content, soil bulk density, plowing depth, soil texture index and plowing speed were fed to an ANN model (a total of 2268) and 96 points of them were selected randomly to be used as testing data set. The training data set used in ANN model was also used to build the regression equation. Prior to their use in the model, the input and the output values were normalized between 0.15 and 0.85 according to the following equation:

$$T = \frac{(t - t_{\min})}{(t_{\max} - t_{\min})} \times (0.85 - 0.15) + 0.15 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (14)$$

Where t is the original values of input and output parameters,T is the normalized value; t_{max} and t_{min} are the maximum and minimum values of the input and the output parameters in training data set, respectively which are depicted in Table (4).

Table (4). The minimum and maximum of inputs and output data for building ANN model.

Parameters		Minimum	Maximum
Inputs	Soil moisture content (% db	1.3	15.1
	Soil bulk density (g/cm^3)	1.4	1.98
	Plowing depth (cm)	12	24
	Soil texture index (----)	0.1403	0.3656
	Plowing speed(km/h)	2	7.5
Output	Draft (kN/body)	0.64	13.2

Different number of neurons in the hidden layer, different values of the learning rate, different values of the momentum, and different transfer functions were investigated (data not shown). The performance of each model was evaluated using correlation coefficient and training error. The best ANN structure and optimum values of the network parameters were obtained on the basis of the lowest training error on training data set by trial and error. Results showed that among the various structures, the best training performance to predict draft belonged to the 5-8-1 structure. Figure (3) illustrates the developed ANN model. Meanwhile, training error during training process versus iterations is shown in Figure (4). The training error was 0.020006 after 200000 epochs and momentum factor was 0.8 and learning rate was 0.002784.

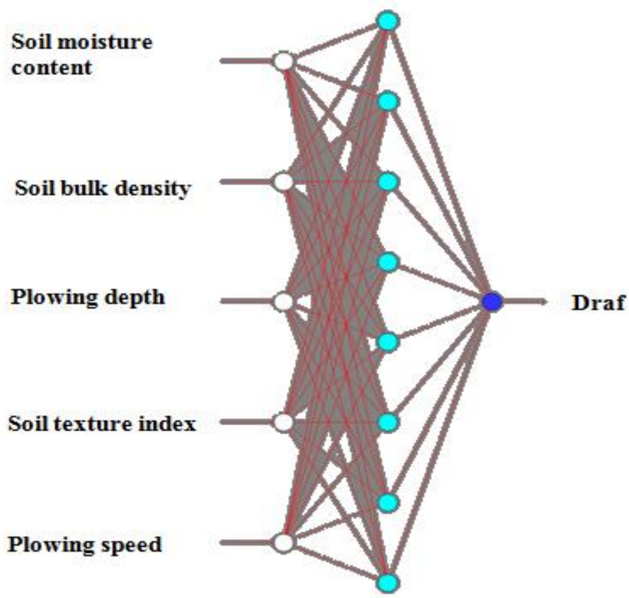

Figure (3). Structure of the ANN used in this study.

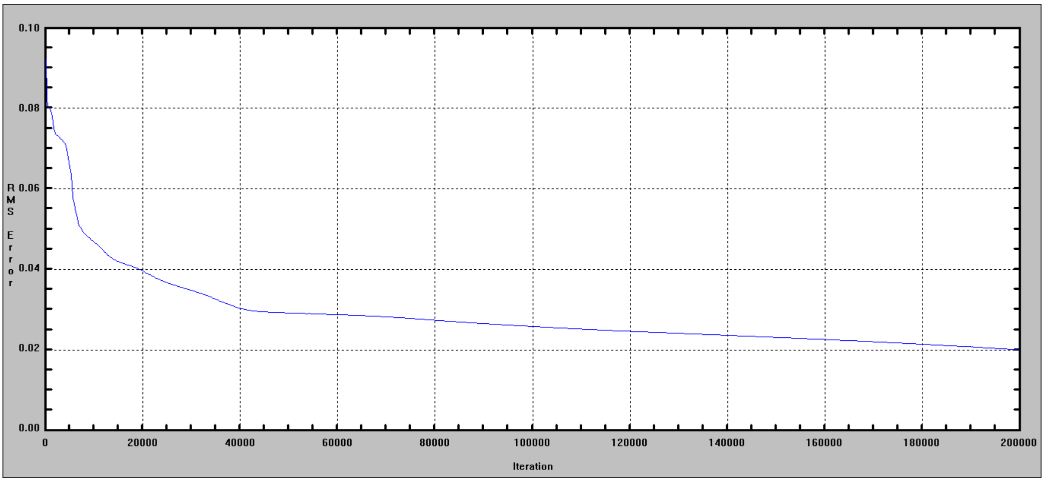

Figure (4). Training error versus iterations during training phase.

Multiple regression model (MLR)

The general purpose of a multiple regression is to learn more about the relationship between several independent or predictor variables and a dependent variable. The general form of the regression equation is as follows:

$$Y = b_0 + b_1 X_1 + ... + b_3 X_3 + ... + b_n X_n \qquad \text{.......................... (15)}$$

Where Y is the dependent variable representing draft, b_0 is a constant, where the regression line intercepts the y-axis, $b_1 ... b_n$ are regression coefficients, representing the amount of changes of the dependent variable Y, when the corresponding independent changes one unit and $X_1 - X_n$ are independent variables referring to the soil and working parameters in this study.

Using Excel spreadsheet, multiple regression analysis was carried out to correlate the simulated draft to three soil conditions including: soil moisture content, soil bulk density and soil texture index, besides two working parameters including plowing depth and speed were added to the soil parameters in the model. A multiple regression model to predict moldboard plow's draft is given as:

$$H\ (kN/body) = -12.584 - 0.0918 MC + 6.363 BD + 0.162 d + 0.121 V + 9.798 STI \qquad R^2 = 0.450 \qquad \text{.........(16)}$$

Where MC is soil moisture content (% db), BD is soil bulk density (g/cm^3), STI (dimensionless) is soil texture index as calculated by Eq. (2), d is plowing depth (cm) and V is plowing speed (km/h).

Models performance

For evaluating the performance of the ANN model and regression equation, difference between the predicted and simulated values of the draft was analysed. This difference can be evaluated through any of the following error values: root mean square error, mean absolute error and mean relative error as follows:

$$MAE = \frac{1}{N} \times \sum_{i=1}^{i=N} \left| E_{iobs} - E_{ipre} \right| \quad \ldots\ldots\ldots\ldots\ldots\ldots(17)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{i=N} \left(E_{i\,obs} - E_{i\,pre} \right)^2}{N}} \quad \ldots\ldots\ldots\ldots\ldots\ldots(18)$$

$$MRE = \frac{100}{N} \times \sum_{i=1}^{i=N} \left(\frac{E_{ipre} - E_{iobs}}{E_{iobs}} \right) \quad \ldots\ldots\ldots\ldots\ldots\ldots(19)$$

Where E_{iobs} and E_{ipre} are simulated or measured and predicted draft, N is number of observations, MAE is mean absolute error, RMSE is root mean square error and MRE is mean relative error. In addition, the coefficient of determination (R^2) was selected to measure the linear correlation between the calculated and the predicted values. The optimal R^2 value is unity.

RESULTS AND DISCUSSION

Performance of the models

In this paper, ANN and MLR models were applied. The ANN model with 5 neurons in the input layer, 8 neurons in the hidden layer and one neuron in the output layer for the prediction of draft was implemented. The inputs to the ANN model were plowing depth, plowing speed, soil texture index, soil moisture content and soil bulk density. However, statistical analysis was carried out using Excel 2007 software package to regress the draft of a moldboard plow as dependent variable on the soil and working parameters (as independent variables) including soil moisture content, soil bulk density, soil texture index, plowing depth and plowing speed. The multiple regression equation obtained is presented in Eq. (16) using the training data of the ANN model. Value of R^2 implies that changes in the independent variables explain 45.0% of the variation in the draft. The soil texture index has the highest regression coefficient compared to other coefficient of independent variables.

Table (5) illustrates mean absolute error, root mean square error, mean relative error and R^2 during building both models. It is clear that RMSE values were 0.359 and 1.442 kN/body when using ANN and MLR models in predicting draft, respectively. Meanwhile, MAE values were less when using ANN model to predict the draft compared to MLR. From Table (5), it is also clear that R^2 values during building the two models were 0.966 for ANN model and 0.450 for MLR model. These results demonstrated that ANN model could be considered as an alternative and practical tool for predicting draft requirement of moldboard plow under the selected experimental conditions. Moreover, the encouraged results can push to utilize the developed models to be a tool in evaluation or calculations in farm machinery management process.

To show the power of the two models, testing process was conducted using 96 points which are not used in the training data set. Figure (5) illustrates the relationship between simulated and predicted draft data during testing process. It is clear that testing patterns have low scattering around optimal agreement when using ANN model to predict the draft and reverse result was seen when using MLR in predicting the draft. This finding is proved by calculating error criteria for testing points as illustrated in Table (6). It is clear that R^2 values were 0.975 and 0.512 between simulated and predicted data using ANN and MLR models, respectively. Since the variations (MRE) were less than 15%, the developed models are acceptable for gathering agricultural machinery management data for selecting matching implements with tractors, estimating fuel consumption, simulating and comparing the performance of farming systems as reported by **Sahu and Raheman (2006)**.

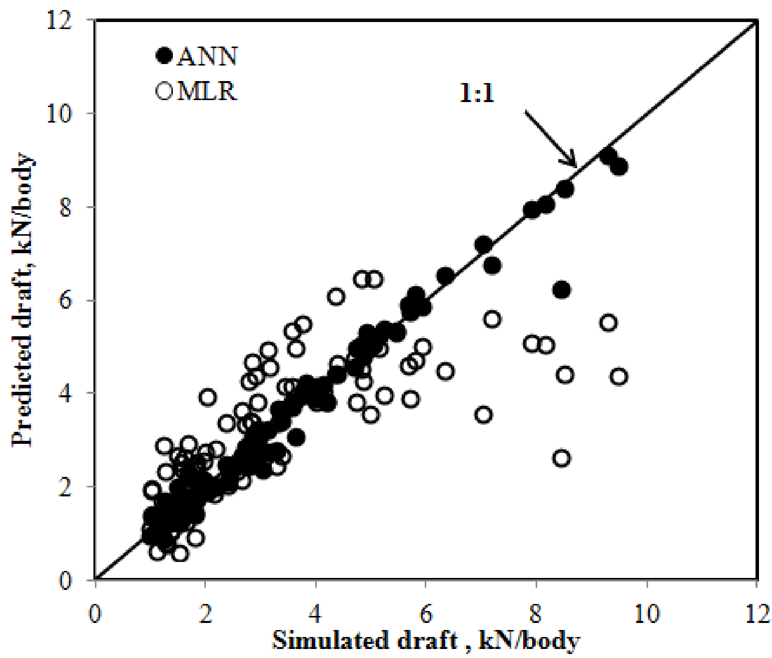

Figure (5). The relationship between simulated and predicted draft data during testing process.

Table (5). Error criteria during building ANN and MLR models.

Model	RMSE (kN/body)	MAE (kN/body)	MRE (%)	R^2
ANN	0.359	0.228	-0.474	0.966
MLR	1.442	0.993	-13.637	0.450

Table (6). Error criteria during testing ANN and MLR models.

Model	RMSE (kN/body)	MAE (kN/body)	MRE (%)	R^2
ANN	0.324	0.199	-1.002	0.975
MLR	1.425	0.972	-8.966	0.512

Validation of the models with experimental data and data from literature

To validate both models, draft data from actual field experiment and from literature were used. The field experiment was run using three plowing speed and one plowing depth. The soil and working parameters and measured and predicted draft of the field data are shown in Table (7). Meanwhile, the relationship between plowing speed and measured and predicted draft is shown in Figure (6). It is clear from Figure (6) that a good general agreement between the measured and the predicted draft was found. The mean absolute error between the measured and the predicted values of the draft were found to be 5.19% and 12.32% for ANN and MLR models, respectively. These variations are due to nature of each model, since ANN deals with nonlinear relationships between input and output variables (**Shirgure and Rajput, 2011**). The high values for R^2 indicate that the variables plowing depth, plowing speed, soil moisture content, soil bulk density and soil texture index can explain most of the variability in the experimental data. In Figure (6) also, the increase in draft is affected by the plowing speed since higher draft was obtained at higher speed.

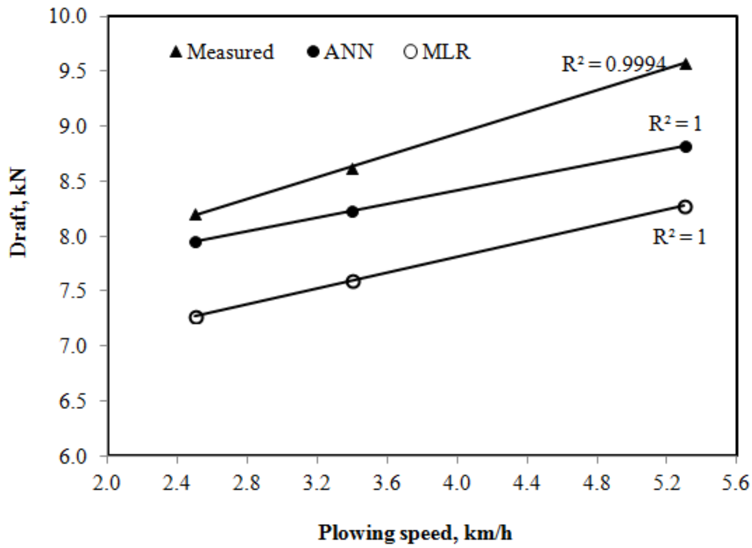

Figure (6). Relationship between plowing speed and measured and predicted draft data from actual field experiment.

Using draft data from **Al-Janobi and Al-Suhaibani (1998)**, both models were validated. In **Al-Janobi and Al-Suhaibani (1998)**, soil bulk density was not found, so, using the calculator on the web was used to get its value from soil fractions as shown in Figure (7). The soil and working parameters and the measured and the predicted draft data of **Al-Janobi and Al-Suhaibani (1998)** are shown in Table (8). The mean absolute errors between the measured and predicted values of the draft were found to be -13.19% and 17.68% for ANN and MLR models, respectively.

Sensitivity analysis of inputs in ANN model on draft prediction

The Qnet algorithm computed the contribution precent which indicates how the change in each input changes the output prediction. The contribution percentage of the five input variables to the output was calculated using the developed ANN model and the results are illustrated in Figure (8). It is clear that soil moisture content is the highest contributed variable (30.687%). However, impact of soil moisture content on the draft of tillage implements were addressed in several research papers (**Gill and Vanden Berg, 1968; Mouazen et al., 2003; Arvidsson et al., 2004**). Also, it is clear that all soil parameters together contributed by about 80% in draft predictions.

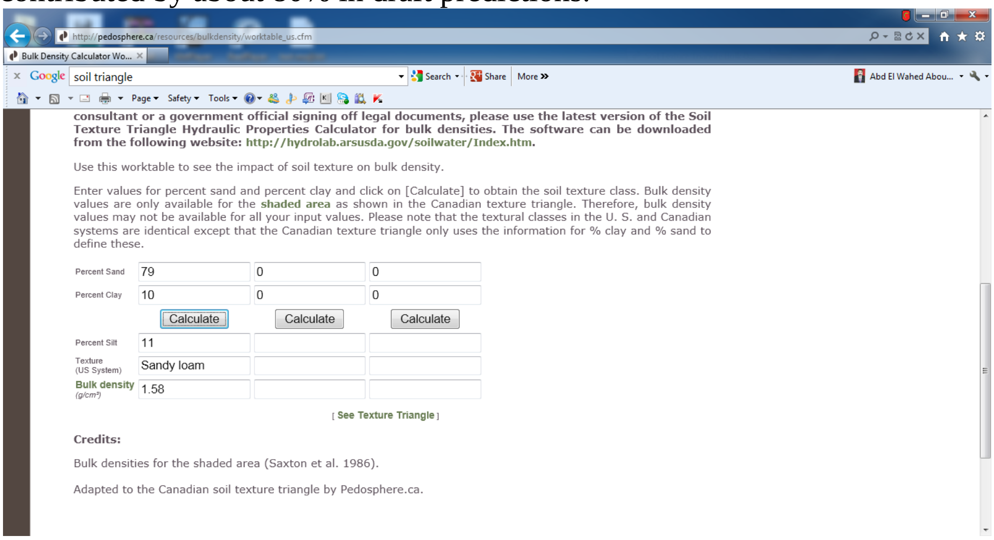

Figure (7). Soil bulk density calculator
(http://pedosphere.ca/resources/bulkdensity/worktable_us.cfm).

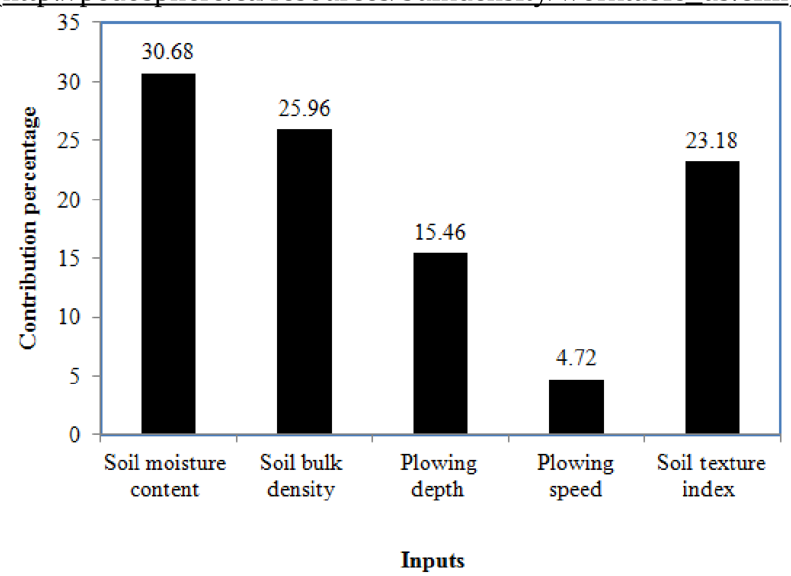

Figure (8). Contribution percentage of 5 independent variables used in the 5-8-1 ANN model for prediction of draft of a moldboard plow.

Table (7). Validation data from field experiment and measured and predicted draft of a moldboard plow.

Soil Moisture content	Soil bulk Density	Plowing depth	Plowing speed	Sand	Silt	Clay	STI	Draft (kN)			MRE (%)	
								Measured	Predicted			
(% db)	(g/cm^3)	(cm)	(km/h)	(%)	(%)	(%)	(---)		ANN	MLR	ANN	MLR
7.5	1.67	15	2.5	84.6	12.4	3.0	0.238994	8.21	7.95	7.27	3.11	11.46
7.5	1.67	15	3.4	84.6	12.4	3.0	0.238994	8.62	8.23	7.59	4.53	11.91
7.5	1.67	15	5.3	84.6	12.4	3.0	0.238994	9.58	8.82	8.28	7.94	13.59
Mean											5.19	12.32

Table (8). Validation data from **Al-Janobi and Al-Suhaibani (1998)** and measured and predicted draft of a moldboard plow.

Soil Moisture content	Soil bulk Density	Plowing depth	Plowing speed	Sand	Silt	Clay	STI	Draft (kN)			MRE (%)	
								Measured	Predicted			
(% db)	(g/cm^3)	(cm)	(km/h)	(%)	(%)	(%)	(---)		ANN	MLR	ANN	MLR
9.5	1.58	15	2.88	79	11	10	0.2087	5.29	6.69	4.25	-26.56	19.72
9.5	1.58	15	4.752	79	11	10	0.2087	5.99	7.35	4.92	-22.76	17.84
9.5	1.58	15	6.048	79	11	10	0.2087	6.69	7.82	5.39	-16.85	19.45
9.5	1.58	15	6.984	79	11	10	0.2087	7.29	8.16	5.73	-11.87	21.45
9.5	1.58	20	2.88	79	11	10	0.2087	8.03	8.67	6.67	-8.03	16.91
9.5	1.58	20	4.752	79	11	10	0.2087	8.56	9.35	7.35	-9.19	14.17
9.5	1.58	20	6.048	79	11	10	0.2087	9.01	9.81	7.81	-8.92	13.27
9.5	1.58	20	6.984	79	11	10	0.2087	10.02	10.15	8.15	-1.32	18.64
Mean											-13.19	17.68

CONCLUSION

An attempt was made to develop a simple model to predict draft of moldboard plow. Artificial neural networks (ANN) and multiple linear regression (MLR) models were used to get such simple model. An available excel spreadsheet (**Godwin et al., 2007**) was used to get the draft data. The soil parameters in this spreadsheet were obtained from actual field experiments. However, plowing speed and plowing depth were assumed. The specifications of the moldboard plow were fed into the spreadsheet. This plow was utilized in the field experiment to get data to validate the developed models. Data are also collected from literature to validate the models. The appropriate ANN model had one hidden layer with 8 neurons. Root mean square error values were 0.359 and 1.442 kN/body when using ANN and MLR models in predicting draft, respectively. A comparison of experimental draft data showed that the ANN model is able to predict draft force with good accuracy. The variations between measured and predicted draft were around 15%, so the developed ANN model or MLR model is acceptable for gathering agricultural machinery management data for selecting matching implements with tractors, estimating fuel consumption, simulating and comparing the performance of farming systems as reported by **Sahu and Raheman (2006)**.

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الملخص العربي

تقييم التفاعل ما بين بيانات تجريبية ومحاكاة للتنبؤ بقوة الشد لمحراث قلاب مطرحي

د./ عبد الواحد محمد أبوكريمة*

إن معرفة البيانات عن قوة الشد اللازمة لمعدات الحراثة عامل مهم عند اختيار تلك المعدات لأداء عمل مزرعي محدد. وحيث أن قياس قوة الشد للمحراث القلاب المطرحي حقليا يتطلب ترتيبات خاصة، لذا من المهم تطوير نماذج يمكن الاعتماد عليها في تقدير هذه القوى. في هذا البحث تم توظيف التفاعل ما بين بيانات تجريبية ومحاكاة للتنبؤ بقوة الشد لمحراث قلاب مطرحي، حيث تم تطوير نموذجين مبسطين يعتمدا على الشبكات العصبية الاصطناعية والارتداد الخطي المتعدد. تم استخدام ورقة عمل طورت بواسطة (**Godwin et al., 2007**) للحصول على قوة الشد لمحراث قلاب مطرحي. وتعتمد ورقة العمل في حسابات قوة الشد على ثلاثة أجزاء وهي بيانات عن خصائص المحراث وبيانات عن خصائص التربة وبيانات عن متغيرات التشغيل (عمق الحرث وسرعة الحرث). بيانات خصائص المحراث وبيانات خصائص التربة المطلوبة في ورقة العمل تم الحصول عليها تجريبيا في هذا البحث من خلال عينات تربة من عدة أماكن بالمملكة العربية السعودية، أما متغيرات التشغيل فتم فرضها. وهذه التفاعلات مابين خصائص التربة وبيانات متغيرات التشغيل أوجدت حوالي ٢٢٦٨ صف من بيانات قوة الشد. هذه البيانات تم استخدام ٢١٧٢ صف منها في بناء نموذج الشبكات العصبية الاصطناعية والارتداد الخطي المتعدد بمساعدة متغيرات دليل قوام التربة وعمق الحرث وسرعة الحرث والمحتوى الرطوبي للتربة والكثافة الظاهرية لها، وتم استخدام عدد ٩٦ زوج من البيانات لاختبار النموذجين، ومن النتائج في مرحلة اختبار النموذجين، وجد أن متوسط الخطأ النسبي بين قوة الشد التي تم التنبؤ بها من خلال نموذجي الشبكات العصبية والارتداد الخطي المتعدد والشد المحاكي كان ١,٨٦% و -٨,٩٦٦% على الترتيب. وللتحقق من أداء النموذجين المطورين تم إجراء تجربة حقلية فعلية باستخدام ذات المحراث القلاب المطرحي الذي استخدمت بياناته في ورقة العمل باستخدام ثلاث سرعات حرث عند عمق حرث واحد، وأوضحت النتائج أن هناك فرق بين قوة الشد المقاسة والمتنبأ بها من النموذجين المطورين، حيث وصل متوسط الخطأ النسبي إلى حوالي ٥,١٩% و ١٢,٣٢% عند استخدام نموذج الشبكة العصبية ونموذج الانحدار الخطي المتعدد على الترتيب. ومن خلال هذه النتائج يمكن استخدام نموذج الشبكة العصبية في استكشاف قيم الشد لمحراث قلاب مطرحي تحت ظروف تربة وتشغيل مختلفة، ويمكن استخدام أي من النموذجين كأداة تقييم في عمليات إدارة الميكنة الزراعية.

***باحث، معهد بحوث الهندسة الزراعية،مركز البحوث الزراعية. حاليا يعمل كأستاذ مساعد بجامعة شقراء بالمملكة العربية السعودية.**