Application of adaptive neuro-fuzzy inference system to predict draft and energy requirements of a disk plow

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Abstract: The energy and draft requirements of a disk plow have been recognized as essential factors when attempting to correctly match it with tractor power. This study examines the possible of using an adaptive neuro-fuzzy inference system (ANFIS) approach and its performance compared to a multiple linear regression (MLR) model to determine the energy and draft requirements of a disk plow. A total of 133 data patterns were obtained by conducting experiments in the field and from the literature. Of these 133 data points, 121 were arbitrarily selected and used for training, and the remaining 12 were used for testing the models. The input variables were plowing depth, plowing speed, soil texture index, initial soil moisture content, initial soil bulk density, disk diameter, disk angle, and disk tilt angle, and output variable was draft of the disk plow. Four membership functions were used with ANFIS: a triangular membership function, generalized bell-shaped membership function, trapezoidal membership function, and Gaussian curve membership function. An evaluation of the outcomes of the ANFIS and MLR modeling shows that the triangular membership function performed better than the other functions. When the ANFIS model draft predictions were compared to the measured values, the average relative error was –1.97%. A comparison of the ANFIS model with other approaches showed that the energy and draft requirements of the disk plow could be estimated with satisfactory accuracy.

Keywords: ANFIS, MLR, disk plow, draft, tillage

DOI: 10.25165/j.ijabe.20201302.4077

Citation: Al-Dosary N M N, Al-Hamed S A, Aboukarima A M. Application of adaptive neuro-fuzzy inference system to predict draft and energy requirements of a disk plow. Int J Agric & Biol Eng, 2020; 13(2): 198–207.

1 Introduction

Tillage plays a significant role in agricultural crop production. It produces changes in the soil structure with the goal of improving the tilth[1] and can be performed using primary and secondary tillage implements. One of the primary tillage implements is a disk plow which is used to plow, cut, pulverize, and invert hard soil[2]. For additional penetration, disk plows have inclined disks to the rear and the disk angle is the attachment angle of the disk relative to the direction of travel[3]. The backward slant of the disk from the vertical is commonly referred to as tilt[4]. As shown in Figure 1, the disk angle has a range of 35°-55° and the tilt angle has a range of 15°-25°[5]. The disk diameter is commonly 60-70 cm.

The draft, energy, and fuel requirements for a disk plow have been recognized as essential factors when attempting to correctly match it with tractor power[6]. Moreover, for choosing appropriate tillage implements for a particular operation, the accessibility of data on the draft of tillage tools is a vital issue[7]. However, factors affecting the forces on a disk plow include the soil type, plowing speed, disk and tilt angles, the cut width, soil bulk density, plowing depth, and others[4,8-18]. Unfortunately, the measurement of this draft under field conditions is time consuming and requires expensive devices. Accordingly, predicting the draft under field conditions is of great value for both tillage implement designers and managers[19]. Hence, to estimate the power and draft force of a disk plow, researchers have utilized different techniques such as the method of finite element[15], the creation of a model based on the laws of classical mechanics[9,20], regression analysis[14,21], dimensional analysis[22], and artificial neural network techniques[7,23,24].

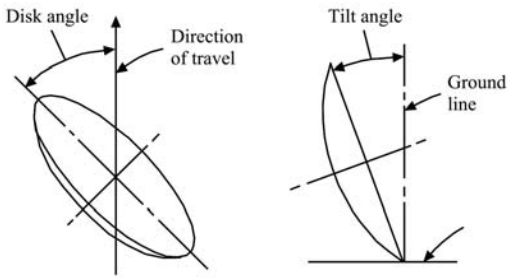

Figure 1 Disk and tilt angles[25]

Currently, fuzzy inference systems are employed as alternate statistical tools for developing predictive models to estimate the needed parameters. One such system is the adaptive neuro-fuzzy inference system (ANFIS), which is a combination of an artificial

Received date: 2018-01-29 **Accepted date:** 2019-09-26

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neural network and a fuzzy inference system. It is being widely used in agricultural applications[26-29].

In modeling field of the draft for tillage tools, fuzzy logic, as modeling techniques employed by different researchers for some of the primary tillage tools[19,30-32], except for the disk plow. Marakoglu and Carman[19] developed a model for a fuzzy knowledge-based system, based on the Mamdani approach to fuzzy modeling principles, to predict the draft efficiency in tillage. The mean relative error of the actual and estimated values was 2.68%. Mohammadi et al.[30] developed a fuzzy inference system (FIS) model in order to determine the draft requirements of two-winged share tillage tools used in a soil had loam texture under varying working conditions. The input variables of the FIS were the plowing depth, plowing speed, and cut width. The FIS output was the draft of the used tillage tool. The findings of the investigated FIS were compared with the actual data and the coefficient of determination of (R^2) was found to be 0.92. Such results specify that the studied FIS model could be an alternative method in the domain of the draft prediction of tillage tools. Abbaspour-Gilandeh and Sedghi[31] developed a knowledge-based fuzzy logic system using experimental data and used it to predict the energy and draft force requirement of a tillage operation. When compared with traditional methods, the fuzzy logic model was more effective at creating a relationship between multiple inputs to achieve an output signal in a nonlinear range. The prediction results showed a close relationship between the actual and predicted values, with mean relative errors for the measured and predicted values of 3.1% for the draft resistant force and 2.94% for the energy required for a subsoiling operation. Shafaei et al.[32] utilized the ANFIS technique for the draft force modeling of a chisel plow. The plowing speed and depth were selected as input variables, and the draft force was selected to be the target. An assessment was also completed between the findings of the best ANFIS model and those of the empirical model suggested by ASABE (American Society of Agricultural and Biological Engineers). The required draft force for a chisel plow was appraised. The results verified that the best ANFIS model with an acceptable R^2 value of 0.994 was more precise than the ASABE model as well as recommended the practical use of the ANFIS model for the suitable selection of the tractor size to operate with a chisel plow in the most well-organized mode. Therefore, this study was directed to examine the effectiveness of the ANFIS model in rising a technique for predicting the energy and draft requirements of a disk plow.

2 Materials and methods

2.1 Soil texture index calculation

The soil texture index (STI) was determined using the method used by Oskoui and Harvey[33] because it yields single numbers for sand, silt, and clay contents combination. This STI represents the soil components and can be calculated by:

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

where, S_i and CC_a are the silt and clay contents in the soil samples, respectively. The sand fraction is denoted indirectly because the sum of the sand, silt, and clay fractions is continually constant. Oskoui and Harvey[33] showed that the STI reflects the effects of all three of the soil fractions.

2.2 Energy requirement calculation

The energy (kW·h/hm^2) requirement for a disk plow was calculated according to Smith[34] by the following equation:

$$Energy = \frac{F \cdot V \times 1000}{3600 \times AFC} \tag{2}$$

where, F is the draft force, kN; V is the plowing speed, km/h; and AFC is the actual field capacity, hm^2/h. The AFC could be determined by:

$$AFC = \frac{W \cdot V \times 1000}{10000} \cdot \eta \tag{3}$$

where, η is the field efficiency; and W is the total plowing width (m) which could be determined by:

$$W = N \times w \tag{4}$$

where, N is the number of disks, and w is the actual width of the cut of a disk. It could be determined as follows[35]:

$$w = \frac{2\cos\beta}{\cos\alpha}\sqrt{d\left(D \cdot \cos\ \alpha - d\right)} \tag{5}$$

where, β is the disk angle, (°); α is the tilt angle, (°); D is the disk diameter, cm; and d is the plowing depth, cm.

2.3 Data required for modeling energy and draft requirements of disk plow

The available draft data set for disk plows that are directly linked to the theme was collected from numerous studies in the literature[3,4,15,21,22,36-38]. In these studies, laboratory or field trials were performed using different disk plows in soils having different bulk densities, moisture contents. Moreover, in these studies, the soil textures were differed under different irregular operating conditions. Table 1 illustrates the statistical criteria for the collected inputs and outputs used in training and testing the ANFIS model.

Table 1 Statistics for collected inputs and outputs used in training and testing ANFIS model

Items	Mean	Kurtosis	Skewness	Range	Coefficient of Variation/%
Plowing depth/cm	16.21	–0.822	–0.402	16.7	25
Plowing speed/km·h^{-1}	4.22	1.661	1.343	8.8	47
Soil moisture content/%db	16.34	–0.541	0.370	23.1	41
Disk angle/(°)	45.44	7.041	2.621	15	6
Tilt angle/(°)	19.53	–0.974	0.069	10	12
STI	0.24	–0.382	1.160	0.710	108
Disk diameter/cm	62.77	0.106	–1.253	13	8
Soil bulk density/g·cm^{-3}	1.44	–1.332	0.284	0.45	10
Draft per disk/N	3784	–1.04	0.555	7080	54

2.4 Characteristics of field experiment sites

The experiments were carried out at three sites (i.e., soil 1, soil 2, and soil 3) on special farms located in the Al-Kharj region (Riyadh, Saudi Arabia). The field experiments were aimed to acquire data on the draft force of a disk plow to rising and testing the ANFIS model. The soils at the sites had different sand, silt, and clay percentages. The mean characteristics of the soils are listed in Table 2. The soil cohesion and internal friction angle of the soil (ϕ) were measured using a direct shear box. Meanwhile, the soil-metal angle (δ) was obtained using the following formula[39]:

$$\delta = [(0.590 \times sand\ fraction) + (0.735 \times silt\ fraction) + (0.375 \times clay\ fraction)] \cdot \phi \tag{6}$$

2.5 Draft measurement of disk plow

In the field experiments at the three sites, a disk plow consisting of three disks with diameters of 66 cm was used. The disk and tilt angles were 45° and 16°, respectively. The disk plow was also attached to a New Holland tractor and Fendt tractor (as an auxiliary tractor) and both were employed simultaneously. In soil 1, three plowing speeds (1.85 km/h, 2.43 km/h, and 3.04 km/h) were used by changing the gears of the tractor, one speed of 3.02 km/h used for soil 2 and 3.15 km/h for soil 3. The tillage depth was unfixed in all the tests and was randomly acquired with the help of a steel ruler at five selected places starting from the bottom of the furrow to the surface level of the soil. Table 3 lists the plow specifications during the field tests.

Table 2 Mean characteristics of soil at sites for experiments

Items	Unit	Soil 1	Soil 2	Soil 3
Sand	%	82.2	86.4	80.1
Silt	%	9.9	8.8	12
Clay	%	7.9	4.8	7.9
Initial soil bulk density at depth (0-25 cm)	$g\cdot cm^{-3}$	1.45	1.57	1.62
Initial soil moisture content (0-25 cm)	% db	6.47	9.21	10.27
Soil cohesion	kPa	7.85	10.79	7.47
Internal friction angle of soil	(°)	35.25	39.02	38.5
Soil-metal angle	(°)	20.70	23.12	22.73
STI		0.088865	0.05995	0.10772

Table 3 Plow specifications during field tests

Items	Soil 1	Soil 2	Soil 3
Calculated plow width/cm	134.8	132.0	133.5
Disk angle/(°)	45	45	45
Rake angle/(°)	16	16	16
Number of disks	3	3	3
Plowing speed/$km\cdot h^{-1}$	1.85	3.02	3.15
	2.43	---	----
	3.04	---	----
Working depth/cm	22.3	20.4	21.4
Radius of the disk/cm	33	33	33
Mass of the disk/kg	130	130	130

A block with 60 m long by 3 m wide at the experimental field was employed to run the experiments. At the beginning of each test, a small block with 10 m long by 3 m wide was employed to be a preparation zone to permit the mechanization unit to achieve the required plowing speed and depth. The required horizontal force was picked up by a calibrated load cell with a capacity of 0-10 000 lb (model Omega) having two hitching points. The load cell was horizontal and parallel to the direction of travel to measure draft force. The measurements were made using a previously described method[40]. As well as, in this study, the used disk plow was joined to a New Holland tractor model 100-90 (power = 74.57 kW) and also a Fendt tractor model 312LSA was utilized as an auxiliary tractor. The two tractors were used together to single run trials when measuring horizontal force that they were tied to each other using a two hitching points strain gage load cell which was installed between the two tractors as described by PAES[40] standard. The draft was recorded within a distance of 60 m. The plowing speed was considered by determining the five turns distance of the tractor's rear wheel over time. In the same soil surface, the plow was raised of the ground, and the behind tractor was pulled to acquire the idle draft force. The difference was the draft requirement of the plow.

2.6 Adaptive neuro-fuzzy inference system (ANFIS)

ANFIS utilizes neural network algorithms and the fuzzy logic reasoning to generate an output[41]. Figure 2 shows the basic design of a first-order Sugeno fuzzy model of ANFIS with two inputs (a and b), four rules, and one output (c). The first-order model of the Sugeno fuzzy type[42] has four fuzzy rules (if-then), which are given by:

Rule 1: if a is X_1 and b is Y_1 then $f_{11}=m_{11}a+n_{11}b+q_1$ (7)

Rule 2: if a is X_1 and b is Y_2 then $f_{12}=m_{12}a+n_{12}b+q_{12}$ (8)

Rule 3: if a is X_2 and b is Y_1 then $f_{21}=m_{21}a+n_{21}b+q_{21}$ (9)

Rule 4: if a is X_2 and b is Y_2 then $f_{22}=m_{22}a+n_{22}b+q_{22}$ (10)

where, X_1, X_2, Y_1, and Y_2 are fuzzy sets of inputs a and b; f_{ij} (i, j = 1,2) are the outputs in the fuzzy stated region by the fuzzy rule, for inputs a and b; and m_{ij}, n_{ij}, and q_{ij} (i, j = 1,2) are the design factors that were evaluated during the learning process.

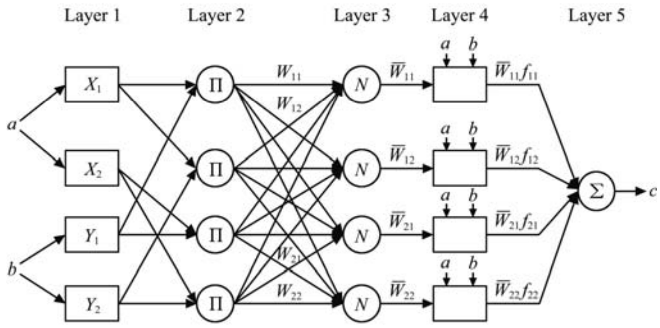

Figure 2 Five-layer ANFIS diagram[41]

Figure 2 contains five layers, where each layer executes a different function as follows:

Layer 1: Every node is an adaptive node and produces a membership grade input, where the outputs given by this layer are given by:

$$O^1_{X_i} = \mu_{X_i}(a) \quad i=1,2 \tag{11}$$

$$O^1_{Y_i} = \mu_{Y_i}(b) \quad j=1,2 \tag{12}$$

where, a and b are crisp inputs to node i (i = 1, 2 for a and j = 1, 2 for b), and X_i and Y_j are fuzzy sets.

Layer 2: All the nodes are static nodes considered Π. The function is a simple multiplier, and the output is specified as given below and represents the firing strength of each rule:

$$O^2_{ij} = W_{ij} = \mu_{X_i}(a)\,\mu_{Y_i}(b) \quad i,j=1,2 \tag{13}$$

Layer 3: Every node is again a fixed node, labeled as N, and shows a normalization part in the network. The output is given as expressed below and represents a normalized firing strength:

$$O^3_{ij} = \overline{W}_{ij} = \frac{W_{ij}}{W_{11}+W_{12}+W_{21}+W_{22}} \quad i,j=1,2 \tag{14}$$

Layer 4: Every node is an adaptive node, and the output is the product of the normalized firing strength and first-order polynomial and is set by the equation below. The variables in this layer are said to be consequent variables.

$$O^4_{ij} = \overline{W}_{ij} f_{ij} = \overline{W}(m_{ij}a + n_{ij}b + q_{ij}) \quad i,j.....=1,2 \tag{15}$$

Layer 5: The only node in this layer is a fixed node and labeled as ∑ (Sigma). The overall output is the sum of all the incoming signals and given by:

$$\begin{aligned} O^5_1 &= \sum_1^2 \sum_1^2 \overline{W}_{ij} f_{ij} = \sum_1^2 \sum_1^2 \overline{W}_{ij}(m_{ij}a + n_{ij}b + q_{ij}) \\ &= \sum_1^2 \sum_1^2 \left[(W_{ij}a)\, m_{ij} + (W_{ij}b)\, n_{ij} + (W_{ij})\, q_{ij}\right] \end{aligned} \tag{16}$$

ANFIS contains two adaptive layers: layer 1 with parameters $\{X_i, Y_i\}$ and layer 4 with parameters $\{m_{ij}, n_{ij}, q_{ij}\}$. Adjusting the ANFIS algorithm tunes all the amendable parameters so that the

ANFIS output ties the training. Adjusting these amendable parameters is a two-step process called a hybrid training algorithm. The premise parameters are kept constant in the hybrid raining algorithm during the forward pass, the node output goes forward until layer 4, and the subsequent parameter is accredited by the least square manner. The consequent parameter is kept fixed during the backward pass. The error signal is transmitted backward, and the premise variables are modernized by the gradient descent method. The details of the hybrid learning algorithm can be found in Jang[43].

2.7 ANFIS model for draft and energy requirement prediction of disk plow

In the current study, ANFIS was used to model the association between the inputs and a target, and executed the model using MATLAB-based fuzzy logic with the Sugeno-type approach, as shown in Figure 3[42]. There are no static measures for creating an ANFIS model[44,45]. Numerical ranges were used for the plowing depth (6.7-23.4 cm), plowing speed (1.2-10 km/h), initial soil moisture content (4.9-28%db), STI (0.030989–0.741153), initial soil bulk density (1.22-1.67 g/cm^3), disk diameter (53-66 cm), disk angle (40°-55°), disk tilt angle (15°-25°), and draft (920-8000 N/disk).

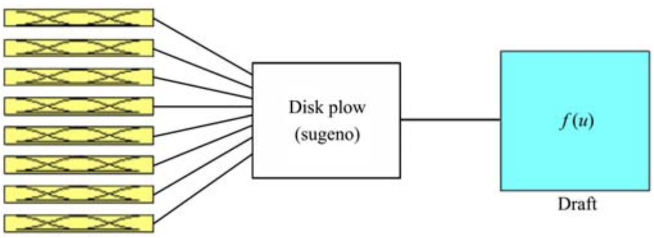

Figure 3 Sugeno ANFIS model with eight inputs

A hybrid training algorithm was utilized to train the ANFIS model. In the ANFIS training phase, the forward pass and backward pass were each composed of an epoch. In the forward pass, a learning set of input patterns (an input vector) was offered to the ANFIS, a neuron output was deliberate on a layer-by layer basis, and rule resultant parameters were recognized. As soon as the rule resultant variables were known, a true network output vector was firm, and the error vector was computed, as well as this process finished at the desired epochs[43].

In this study, two linguistic terms {L: low and H: high} were utilized, and our reasoning for using two linguistic terms for each input was to decrease the number of rules. A total of 133 data sets obtained from tests in the field and the literature. Of these 133 data sets, 121 patterns were arbitrarily selected and were used those for learning phase, and the residual 12 patterns were used for validating the models. The purpose of the learning process for the ANFIS model was to reduce the error between the actual output and ANFIS output. In the performance analysis, a new data set (validation data that did not exist in the learning set) was presented to the learned system for appraisal. If the test error was sufficiently small, it showed that the system had a respectable general capability. The fuzzy logic toolbox of MATLAB 7.11.0.584 (R2010b) was used for modeling the ANFIS.

To create fuzzy IF-THEN rules, the first-order Takagi-Sugeno system was engaged with five inputs, and employed the hybrid training algorithm to define the variables of the Sugeno-type fuzzy inference systems. For all the membership functions tested, the number of epochs was not altered but was fixed at five epochs, and the matching training error was obtained. The training error was the difference between the learning data output value and the output of the ANFIS matching to the same training data input values.

Also, different membership functions were tested. These functions included a triangular membership function (trimf, ANFIS1), generalized bell-shaped membership function (gbellmf, ANFIS2), trapezoidal membership function (trapmf, ANFIS3), and Gaussian curve membership function (gaussmf, ANFIS4). The results showed that ANFIS1 was the most accurate membership function, with a training error of 208.0271. Meanwhile, the training error values for ANFIS2, ANFIS3, and ANFIS4 were 236.2131, 248.3241, and 240.2472, respectively. Figure 4 shows the structure of the ANFIS model, Figure 5 shows the training process, and Figure 6 shows the final triangular membership functions of the test variables. The characteristics of the established ANFIS model were 555 nodes, 2304 linear parameters, 48 nonlinear parameters (making a total of 2352 parameters), and 256 fuzzy rules. The variation pattern for the actual and predicted drafts of a disk plow for the learning data set (number of test data points on X-axis) is shown in Figure 7 using triangular membership function. The plot of draft values of the disk plow shows the consistency of the data distribution.

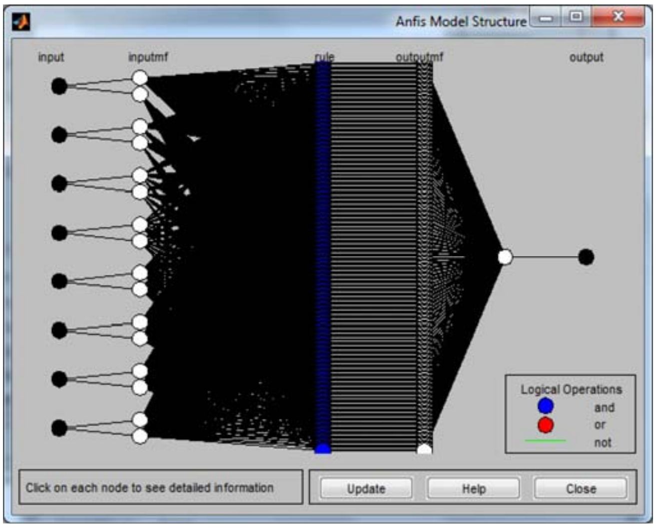

Figure 4 Structure of ANFIS draft of disk plow model using triangular membership function

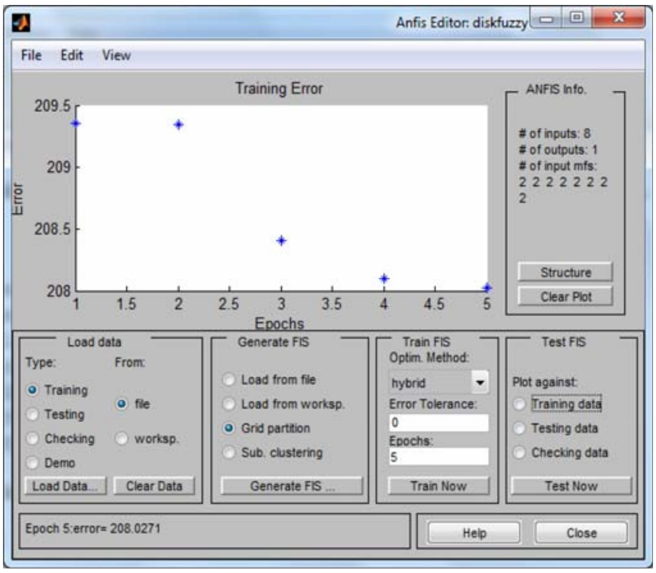

Figure 5 Training process using triangular membership function

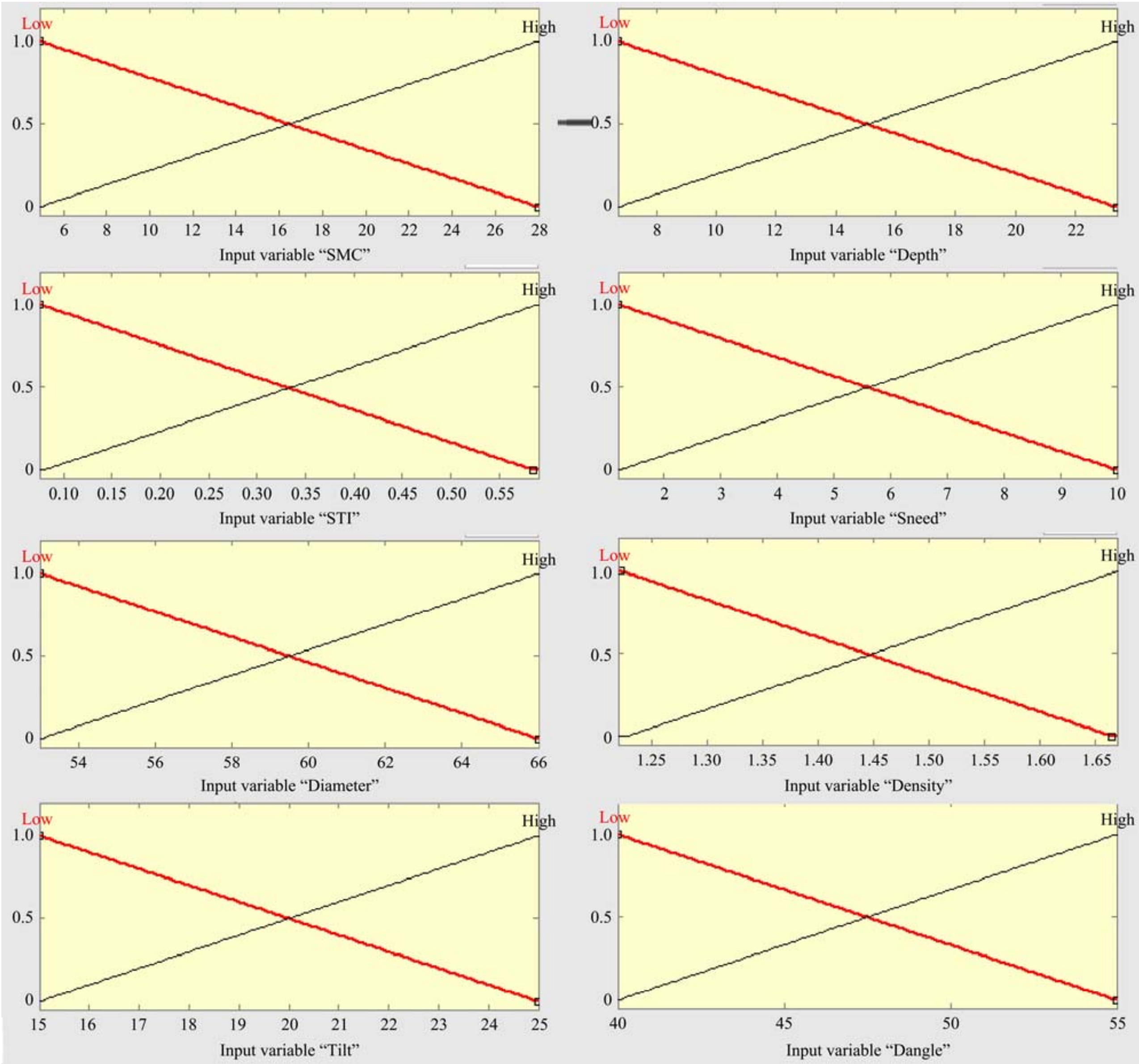

Figure 6 Final triangular membership functions of test variables

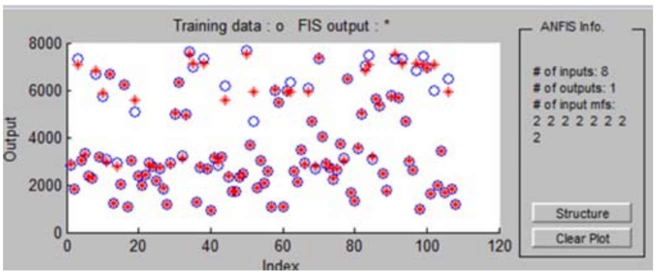

Figure 7 Online distribution of predicted and actual draft values of disk plow in training data (index on X-axis means data points) using triangular membership function

2.8 Comparison between linear regression and ANFIS model

The performance of the ANFIS model was compared using different error statistics, as given by:

$$MAE = \frac{1}{N_t}\sum_{i=1}^{i=N_t}\left|E_{iobs} - E_{ipre}\right| \tag{17}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{i=N_t}(E_{iobs} - E_{ipre})^2}{N_t}} \tag{18}$$

where, E_{iobs} and E_{ipre} are the actual and predicted draft values; N_t is the number of data patterns; *MAE* is the mean absolute error, and *RMSE* is the root mean square error. Moreover, the determination coefficient (R^2) was designated to measure the linear association between the actual and predicted values. The optimal coefficient of determination value was unity.

2.9 Multiple linear regression models

To verify the ANFIS model, the ANFIS model outputs have been compared regarding the draft of a disk plow with the corresponding results of a multiple linear regression (MLR) model developed with the data employed in the learning phase. The derived MLR model was expressed by:

$$\begin{aligned} \text{Draft (N/disk)} &= -11257.884 + 53.364X11 + 100.609X22 \\ &+209.859X33 + 82.404X44 - 181.103X55 - 249.289X66 \\ &+52.830X77 + 4778.826X88 \qquad R^2 = 0.832 \end{aligned} \tag{19}$$

where, $X11$ is the tillage depth, cm; $X22$ is the tillage speed, km/h; $X33$ is the initial moisture content of soil, % db; $X44$ is the disk angle; $X55$ is the tilt angle, (°); $X66$ is texture index of the soil; $X77$ is the diameter of the disk, cm; and $X88$ is the initial soil bulk density, g/cm^3. Also, a comparison of the output of the MLR model and the observed draft values of a disk plow in soil 1, soil 2, and soil 3 was passed.

3 Results and Discussion

3.1 Data analysis of collected inputs and outputs used in training and testing the ANFIS model

Table 1 lists the variation coefficient, which is a scale-adjusted measure of the spread of the data. It is calculated by dividing the standard deviation over the mean. The values of the variation coefficient for the data of the tillage depth, tillage speed, moisture content of the soil, disk angle and tilt angles, STI, disk diameter, bulk density of the soil, and draft are 25%, 47%, 41%, 6%, 12%, 108%, 8%, 10%, and 54%, respectively, as illustrated in Table 1. The higher difference in the data may be ascribed to the data being collected from different tests. Meanwhile, the low variation in the disk diameter, disk and tilt angles may be an outcome of these variables having standard values and no additional changes in their levels.

Skewness is known as a portion of the absence of symmetry in a distribution. A distribution is known a symmetric or a normal if the quantities to the left and right of the middle point appear identical, producing a zero value for impeccable symmetry. A positively skewed distribution tails off to the high end of the scale, while a negative skew tails off to the low end of the scale[46]. Kurtosis is known as a portion of the variance from the peak values in the distribution, relative to its width. For a normal distribution, the kurtosis value will be zero, however, it will be negative for flat distributions, and it will be positive for peaked distributions[46].

As shown in Table 1:

- The plowing speed, disk angle, all showed skewness and kurtosis with positive distributions, thus indicating deviations from a normal distribution;
- The disk diameter showed skewness with a negative distribution and kurtosis with a positive distribution, as well as indicating deviation from a normal distribution;
- The plowing depth, showed skewness and kurtosis with negative distributions, also indicating a deviation from a normal distribution;
- The draft, tilt angle, soil texture index and bulk density of the soil all showed that the skewness had a positive distribution and the kurtosis had a negative distribution, and again, all indicated a deviation from a normal distribution.

3.2 Comparison of error indicators for ANFIS model versus MLR model utilizing testing data set

After training the ANFIS model and building the MLR model, result carried out a comparison of error indicators in the estimation of the draft of a disk plow for the ANFIS model versus the MLR model utilizing 12 points that were not seen in the training data. Figure 8 shows the online distribution of the predicted and actual draft values of a disk plow in the testing data (12 of test data points on X-axis) using the ANFIS model. Clearly, there is little variation in the distribution points.

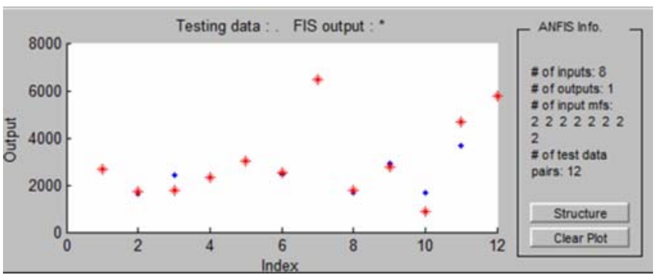

Figure 8 Online distribution of predicted and actual draft values of disk plow in testing data (index on X-axis means data points)

Figure 9 shows the plot correlation between the observed draft values and predicted draft values from the ANFIS and MLR models in the testing stage. It is obvious from Figure 9 that the predicted values from ANFIS are closer to the observed values than those from MLR. Furthermore, Table 4 lists the error indicators for the ANFIS model versus the MLR model when utilizing the testing data set to predict the draft of a disk plow. The mean absolute error (MAE) in the testing stage (Table 4) from the MLR model was 875.7745 N/disk; whereas through the ANFIS model it was 226.5794 N/disk, which was sufficiently small, indicating that the ANFIS model was the better prediction model. The results in Table 4 also show that the RMSE for the MLR model was greater than that for the ANFIS model. This means that the amount of error in the estimation by MLR was greater than the error in the ANFIS model. Thus, it could be stated that the ANFIS model was more effective than the regression method for predicting the draft.

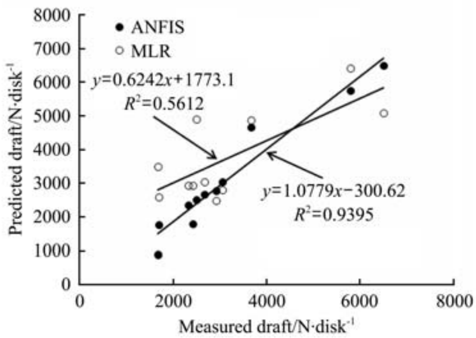

Figure 9 Correlation of predicted and actual data of draft during testing stage

Table 4 Error indicators for ANFIS model versus MLR model utilizing testing data set in predicting draft of disk plow

Error indicator	MLR model (Eq. 19)	ANFIS
MAE/N·disk^{-1}	875.7745	226.5794
$RMSE$/N·disk^{-1}	1103.402	411.3676
R^2	0.5612	0.9395

3.3 Validation of developed ANFIS model using testing data set

To validate the recently developed ANFIS model, the field trial data (soil 1) were employed to predict disk plow draft. Figure 10 depicts the relationships between the plowing speed and the field actual and predicted draft values for the disk plow, showing that the predicted pattern performs like the field pattern (i.e., plowing speed increases, an increase in draft force followed). Moreover, as revealed in Figure 11, the R^2 between the observed data from the field test and the predicted values from the established ANFIS model of the draft was 0.9199, which indicated the accurate prediction of the draft.

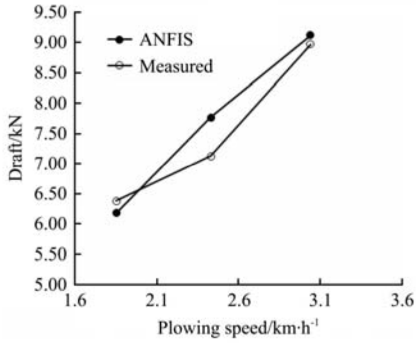

Figure 10 Relationship between plowing speed and measured draft (field data, soil 1) and predicted draft (ANFIS data) of disk plow

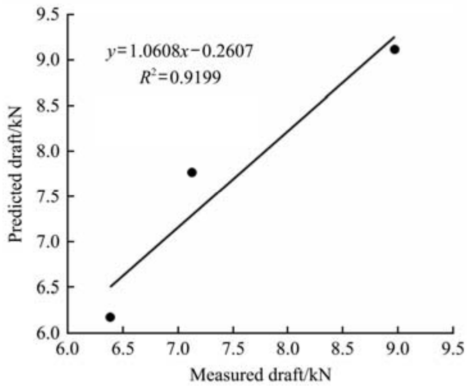

Figure 11 Relationship and coefficient of determination (R^2) between measured draft from field experiments (soil 1) and predicted draft from developed ANFIS model of disk plow

3.4 Validation of developed ANFIS model using other approaches

An additional validation was performed using the spreadsheet developed by Ahmadi[20] to predict the draft of a disk plow by inserting data, such as the soil cohesion, angle of soil internal friction, soil bulk density, radius of the disk, mass of the disk, angle of soil metal friction, disk angle, rake angle, angle of soil displacement on horizontal plane, number of disks, forward speed, overlap percentage of blades, and maximum working depth (Figure 12). In this study, the overlap percentage of the blades was assumed to be 30%, and the angle of soil displacement on the horizontal plane was assumed to be 75°[20]. Moreover, Hendrick[47] developed an equation for the specific draft of a furrow slice for a 66 cm disk, with a 22° tilt angle and 45° disk angle. The specific draft (N/cm^2) is given by the following equation for Davidson loam soil (S is speed, km/h):

$$\text{Specific draft} = 2.4 + 0.045S^2 \tag{20}$$

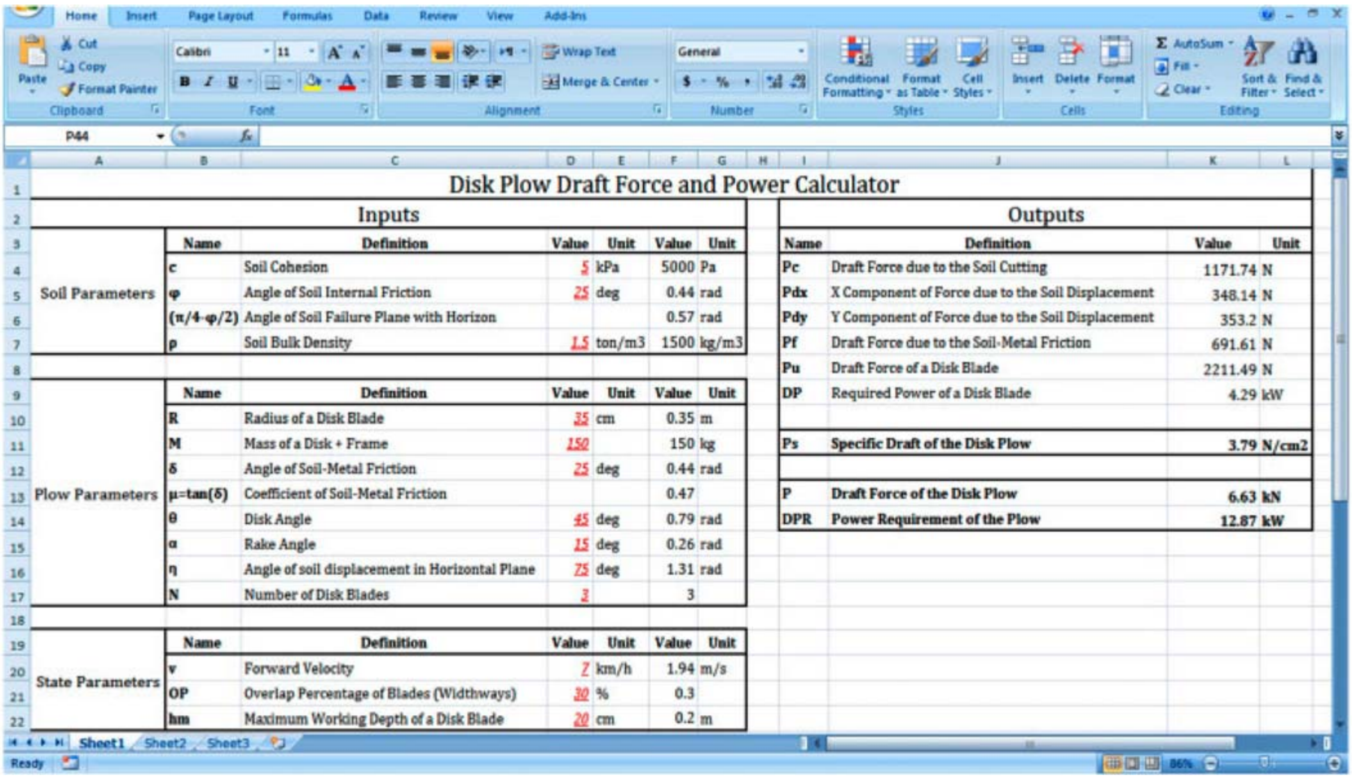

Figure 12 Spreadsheet developed by Ahmadi ([20]2016) for prediction of draft of disk plow

The specific draft data from the Hendrick[47] equation was compared to the measured data (soil 1, soil 2, and soil 3), with the plowing area equal to the plow width multiplied by the plowing depth. A graphical description of the rules created to map the input data (antecedent) with the output (consequent) for the draft in the ANFIS is displayed in Figure 13. As shown, each rule is denoted by a specific row, while variables are signified by specific columns. The first eight columns depict the membership functions for the eight input variables, referenced by the antecedent, or the "if-part", of each rule. The ninth column shows the membership functions used by the consequent, or "then-part", of each rule. The vertical lines in the eight columns show the current data inputs. The bottom plot in the right column signifies the collective of each consequent, whereas the defuzzified output value is denoted by a thick line passing through the aggregate fuzzy set. A graphical window in Figure 13 was utilized to obtain the draft data.

The results of four approaches for disk plow draft prediction (that of Ahmadi[20]; the developed ANFIS model; that of Hendrick[47]; and the MLR model) were compared to the measured draft values for soil 1, soil 2, and soil 3, and the results are tabulated in Table 5. Table 6 lists the relative error values of the actual draft of a disk plow using different approaches for soil 1, soil 2, and soil 3. As recorded in Table 6, the draft predictions for a disk plow were compared to the actual values, and the value of the average relative error is –1.97%, which may be acceptable when compared to the relative error acquired from the other approaches. Therefore, the developed ANFIS model is able to produce an acceptable draft for a disk plow that is within the range of the utilized inputs. The established ANFIS model can improve the prediction accuracy of the draft for disk plow due to the suggested ANFIS model can be engaged as a dominant tool for understanding performance of the draft as influenced by plowing depth and speed, texture index of the soil, initial moisture content of the soil, initial soil bulk density, disk diameter, disk and tilt angles. Additionally, complex and non-linear model such as the ANFIS model probably is able to construct more accurate and powerful relationship between multiple input and output variables[48]. Moreover, higher performances of the intelligent models were sourced from greater degree of robustness and fault tolerance than traditional statistical models[49]. Thus the use of the suggested ANFIS method not only provided new approach and methodology to estimate draft for disk plow, but also extend beyond the high accuracy rate compared to multiple linear regression method.

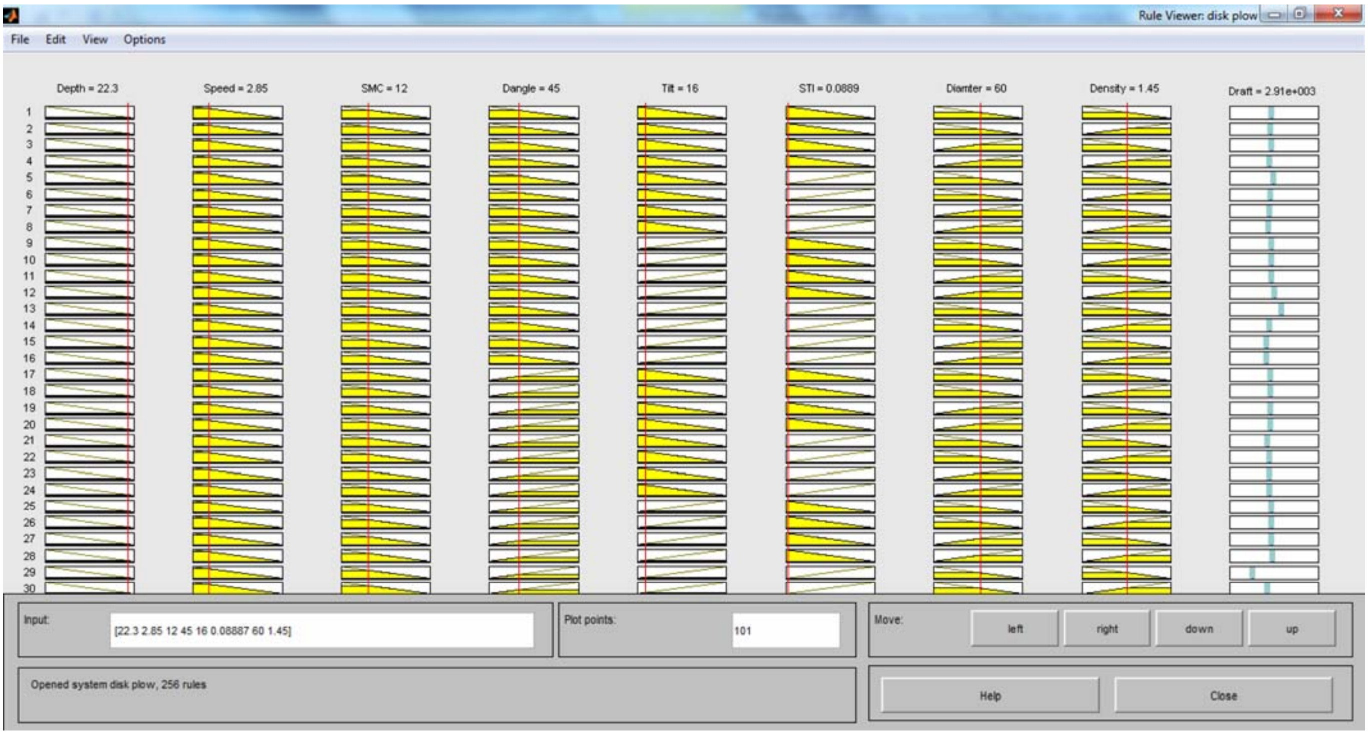

Figure 13 Graphical representations of rules for ANFIS draft model of disk plow

Table 5 Comparison of measured draft (kN) of disk plow to draft values from different approaches

Tests	Measured	Ahmadi[20]	ANFIS model	Hendrick[47]	MLR model (Eq. 19)
Soil 1 (plowing speed = 1.85 km/h)	6.39	8.90	6.18	7.68	8.05
Soil 1 (plowing speed = 2.43 km/h)	7.13	8.96	7.77	8.01	8.22
Soil 1 (plowing speed = 3.04 km/h)	8.97	9.03	9.12	8.46	8.41
Soil 2	9.38	11.29	10.47	6.46	11.56
Soil 3	9.25	9.17	8.40	8.13	13.11

Table 6 Comparison of relative error between measured draft and draft values for disk plow obtained from different approaches

Tests	Relative errors (%)*			
	Ahmadi[20]	ANFIS model	Hendrick[47]	MLR model (Eq. 19)
Soil 1 (plowing speed = 1.85 km/h)	–41.11	3.21	–20.28	–26.02
Soil 1 (plowing speed = 2.43 km/h)	–27.35	–8.98	–12.34	–15.31
Soil 1 (plowing speed = 3.04 km/h)	–2.01	–1.67	5.69	6.29
Soil 2	–20.36	–11.62	31.13	–23.22
Soil 3	0.43	9.19	12.11	–41.68
Average relative error/%	**–18.08**	**–1.97**	**3.26**	**–19.99**

Note: *Relative error (%) = (measured – model)/measured*100.

This study is generally assumed that value of η (field efficiency) to be 0.8 for the primary tillage based on the range of 70% and 85%[50]. The actual field capacity was determined for the tests in soil 1, as shown in Figure 14. The actual field capacity could be increased by increasing the operating speed or implement width, and it would appear that doubling the size or speed would double the capacity[25]. As indicted in Figure 14, increasing the plowing speed leads to an increase of the actual field capacity, which is in agreement with the findings of Zaied et al.[51] and Meselhy[52].

The energy requirements could be determined based on the actual field capacity and draft of a disk plow, and Figure 15 depicts these values for the experimental data in soil 1. It is clear that the required energy values obtained by Ahmadi[20] and ANFIS at a plowing speed of 3.04 km/h were 23.58 kW·h/hm^2 and 23.50 kW·h/hm^2, respectively; the calculated energy from ANFIS was 15.92 kW·h/hm^2 for a plowing speed of 1.85 km/h; and the calculated energy from the field data of soil 1 was 16.45 kW·h/hm^2. At a plowing speed of 2.43 km/h, the calculated energy from ANFIS was 20.02 kW·h/hm^2, and the calculated energy from the field data of soil 1 was 18.37 kW·h/hm^2.

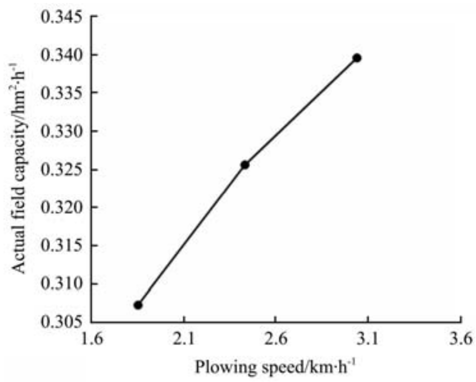

Figure 14 Variation of actual field capacity with plowing speed for data of soil 1

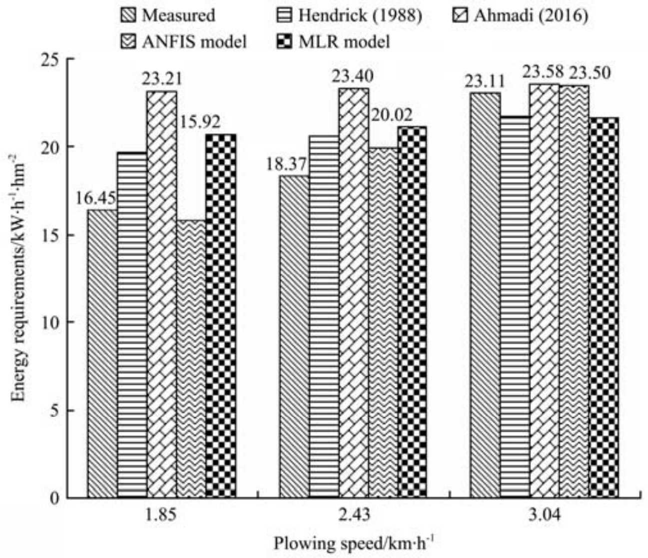

Figure 15 Energy requirements of the disk plow obtained from different approaches for data of soil 1

4 Conclusions

An ANFIS model and MLR model were both applied to estimate the draft of a disk plow. The input variables for the models were the plowing depth and speed, texture index of the soil, initial moisture content of the soil, initial soil bulk density, disk diameter, disk and tilt angles. One of the benefits of the established models was the use of field data to produce the models. The ANFIS model could predict the draft of a disk plow when a triangular membership function was applied with a mean absolute error of 226.5794 N/disk, whereas this value for the MLR model was 875.7745 N/disk using the testing data set. Validation tests of the ANFIS model had positive results. Thus, the established ANFIS model could be successfully used to predict the draft of a disk plow within the ranges of the variables studied.

Acknowledgements

With sincere respect and gratitude, the team of this research would like to express our deep thanks to the Deanship of Scientific Research, Researchers Support Services Unit, Agriculture Research Center, and College of Food and Agriculture Sciences at the King Saud University for the packages of technical support, sponsoring, and encouragement.

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