Modeling of draft force variation in a winged share tillage tool using fuzzy table look-up scheme

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Abstract: Currently Artificial Intelligence (AI) methods such as fuzzy computing have great importance in both modeling and control. The main purpose of this research is to explore the intelligent way to model soil-tool interaction for a winged share tillage tool. A Fuzzy Inference System (FIS) model, with Mamdani min-max method and 24 rules was developed based on table look-up scheme in order to predict draft requirements of two winged share tillage tools in a loam soil under varying operating conditions. Tests were taken in soil bin. The trials were conducted in different working depths and working speeds of winged shares. The input parameters of the FIS were working depth, working speed and share width. The output from the FIS was the draft requirement of the winged share. The results of the developed FIS were compared with the test data of experimental results. The coefficient of determination of relationships was found 0.92 and Root Mean Squares of Errors (RMSE) was 0.33 for draft force. Such results indicate that the developed FIS 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.

Keywords: fuzzy inference system, Mamdani, look-up scheme, winged share, draft

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1 Introduction

The winged shares tillage tools are growing more important in design of reduced tillage systems because of their benefits in comparison to traditional tillage tools such as mouldboard plows. Prediction of tillage tools forces is of value to designers and managers of cultivation equipment to achieve the best matching of implement size to tractor power.

The effects of design parameters (such as geometric shape) and working parameters (such as working depth) of implements on soil-tool interaction have been studied by researchers using empirical and semi empirical methods (Desbiolles et al., 1997; Kheiralla et al., 2004; Wheeler and Godwin, 1996; Zhang and Kushwaha, 1995).

In recent years, the methods of Artificial Intelligence (AI) such as fuzzy computing and neural network have been used in the different field of agricultural applications such as modeling of soil-machine and soil-tillage tool interaction (Kushwaha and Zhang, 1998; C□arman, 2008). Fuzzy logic is a rule-based system that enables a human expert to construct a prediction model by specifying some key input/output relations through linguistic rules, between which the fuzzy logic inference engine then interpolates to complete the prediction

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function. One of the main advantages of fuzzy logic is that compared with traditional methods, it is more capable of specifying relation between fuzzy and non-uniform input variables to a single output in uncertain dynamic processes.

Principles steps in application of Fuzzy Inference System (FIS) to model input/output relations are:

1. Fuzzify inputs
2. Apply Fuzzy Operator
3. Apply Implication Method
4. Aggregate All Outputs
5. Defuzzify

The first step is to take the inputs and determine the degree to which they belong to each of the appropriate fuzzy sets via Membership Functions (MFs). Membership functions give the scaled value of definite number values that are defined by linguistic labels such as low, medium, high, etc.

The input to the fuzzy operator is two or more membership values from fuzzified input variables. The output is a single truth value.

The input for the implication process is a single number given by the antecedent, and the output is a fuzzy set. Implication is implemented for each rule.

All processes included in steps 2 and 3 are based on IF-THEN rules that provide a transition between input and output fuzzy sets.

The rules must be combined in some manner in order to make a decision. Aggregation is the process by which the fuzzy sets that represent the outputs of each rule are combined into a single fuzzy set. The input of the aggregation process is the list of truncated output functions returned by the implication process for each rule. The output of the aggregation process is one fuzzy set for each output variable.

The aggregate of a fuzzy set encompasses a range of output values, and so must be defuzzified in order to resolve a single output value from the set. The input for the defuzzification process is a fuzzy set (the aggregate output fuzzy set) and the output is a single number. Bisector calculation is one of the popular defuzzification methods in which a vertical line divides the region of output fuzzy set into two sub-regions of equal area in order to obtain a single number that is the value of output variable related to input variables.

The aim of this study is to investigate the relationship between some working and design parameters of winged share to draft force requirement, and the construction of FIS for modeling of soil-tillage tool interaction based on the Mamdani approach. Test data collected from soil bin experiments were used to evaluate the fuzzy models.

2 Materials and methods

Two winged share tillage tools were used in this study. They consisted of a leg which has a chisel at the bottom, wings attached to both sides of the leg and two flanges for linking tillage tool to implement toolbar. Their input variables included widths of 440 and 660 mm, working depths of 150, 200, 250 and 300 mm and working speeds of 1.5, 3 and 6 m s^{-1}. An overview of the winged share used in this study is shown in Figure 1. The geometrical specifications of winged shares used in the study are given in Table 1.

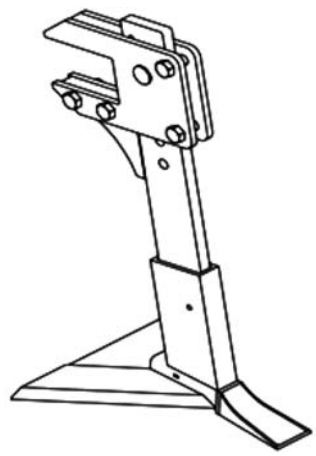

Figure 1 Winged share with leading chisel

Table 1 Geometrical specifications of winged share tillage tools

	Narrow share	Wide share
Wing width	440 mm	660 mm
Chisel width	50 mm	60 mm
Wing rake angle	40 degree	40 degree
Chisel rake angle	30 degree	30 degree
Leg height	600 mm	650 mm
Leg width	20 mm	30 mm

Experiments were conducted in the soil dynamics laboratory of the Agricultural Engineering Research Institute (AERI), Karaj, Iran. The equipment consists of an indoor soil bin of 27 m length, 1.7 m width and 1 m depth, a soil processing trolley with a levelling blade and compaction roller, a power transmission system and a force measuring equipment.

The soil bin was filled with a one-meter-thick layer of loam according to the USDA textural classification of soils. The soil processing trolley was used for processing the soil in order to achieve uniform soil condition as desired for test-run throughout the soil bed. Before each test run, three random soil cores (50 mm diameter, 50 mm length) were taken for measuring initial soil moisture content and dry bulk density at 4 depth range based on working depth and then mean values were calculated. To determine the cohesion and the angle of internal friction of the soil, the direct shear test was used (Mckeys, 1985). Some physical and mechanical properties of soil are shown in Table 2.

Table 2 Physical and mechanical properties of loam soil used in the study

Parameter	Mean value
Soil composition	
Sand (0.05-2.0 mm)	33.28%
Silt (0.002-0.05 mm)	45.84%
Clay (<0.002 mm)	20.88%
Moisture content	13.23%
Bulk density(db)	1.41 g/cm^3
Cohesion	0.41 kg/cm^2
Angle of internal friction	35 degree
Penetration resistance	1500 kPa

In order to determine the draft requirement of the winged shares, completely randomized factorial experiment with four working depths (150, 200, 250 and 300 mm) and three working speeds (1.5, 3 and 6 m s^{-1}) were conducted for two winged share tillage tools. Each treatment was replicated three times. Thus, a total of 72(4×3×2×3) test runs were done. The force measuring equipment included a tillage tool dynamometer (comprising an Extended Octagonal Ring Transducer (EORT)) and a data acquisition system (Godwin, 1975) that was mounted to a tractor (MF 399) as shown in Figure 2.

The data were recorded (25 samples per second) for each treatment and mean values of each replication were used for computation and analysis. Analyze of variance (ANOVA) was performed on the data to test the effects of input parameters (i.e. working depth, working speed and share width) on output (i.e. draft force) and statistical inferences were made at the probability of 5% level.

Figure 2 Force measuring equipment used in the study

For modeling of relations between inputs and output, the fuzzy logic toolbox from MATLAB 7.10 was used. For implementation of FIS, working depth (WD) of winged share, working speed (WS) and share width (SW) were used as input parameters and draft force (DF) was used as output.

Mamdani max–min inference System for formulating the mapping from given inputs to an output using fuzzy logic was used. The structure of used FIS is shown in Figure 3 schematically.

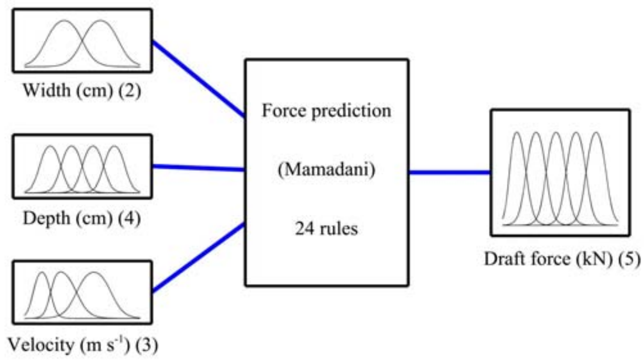

Figure 3 Fuzzy inference system structure

In the fuzzification step, the linguistic variables very low (VL), low (L), medium (M), high (H) and very high (VH) were used. In comparison to other types of membership functions, the product of two sigmoidally shaped membership functions (psigmf) resulted in the most accuracy and was used for both input and output variables. The number of membership functions and their initial values is determined based on the system knowledge and the experimental conditions.

Consider the design of a fuzzy system with two inputs (x_1, x_2) and one output (y) system. Further, there are n data points in the training set. In order to generate fuzzy rules with fixed membership functions, fuzzy partition of input and output variables are defined. Then for each of the n input-output pair, one fuzzy rule is generated. This result in the initial fuzzy rule base as following (Mendel, 2001; Liu et al., 2003):

$$(x_1^p, x_2^p, y^p) \Rightarrow Fuzzy\,Rule \quad p = 1, 2, ..., n \tag{1}$$

From each input-output pair, one fuzzy rule can be generated. In some cases the fuzzy sets may overlap. In order to assign the appropriate membership functions to the variables in each data pair, the common practice is that the fuzzy variable is assigned the membership function that produces the maximum membership value. In this process the degree of each fuzzy rule is calculated. Further, the number of fuzzy rules generated by the input-output pairs is usually large and inconsistent and redundant rules are inevitable. In order to remove inconsistent and redundant rules, the rule having the largest degree is adopted. There is an improved selection approach in which a reliability factor is calculated in order to remove inconsistency and redundancy.

Specifically, for each given set of k rules with the same antecedent parts, the reliability factor is defined as (Liu, Kwan and Foo, 2003):

$$\text{Reliability Factor}(RF) = \frac{K_1}{K} \tag{2}$$

where, K_1 = Number of redundant rules; K =Total number of the redundant and inconsistent rules having the same antecedent part.

The reliability factor is then used as a weighting factor for computing the effective degree for each rule degree as follows (Liu, Kwan and Foo, 2003):

$$\text{Effective Degree } (D_{eff}) = D * RF \tag{3}$$

where, D = Rule degree.

The final fuzzy rule-base can now be compiled by choosing the rules with the largest effective degrees. For the redundant and inconsistent rules, the effective degree is given by (Liu, Kwan and Foo, 2003):

$$D_{eff}(\max)=\max(D_{eff(i)}),\ i=1,2,\ldots,n \tag{4}$$

where, D_{eff} = effective degree, and n is the number of membership function.

The units of the used factors were: WD (cm), WS (m s^{-1}), SW (cm) and DF (kN). Total of 24 fuzzy rules were formed that Parts of it are shown in the Table 3.

For example, Rule 1 and Rule 24 can be interpreted as follows.

Rule 1: If SW=L, WD = L and WS = L then DF = VL, i.e. if the share's SW, WD and WS are low, then share's DF is very low.

Rule 24: If SW=H, WD = VH and WS = H then DF = VH, i.e. if the share's WD is very high and SW and WS are high and, then share's DF is very high.

Table 3 Fuzzy inference system rules

Rules	Input variables						Output variable
	SW		WD		WS		DF
Rule 1	L		L		L		VL
Rule 2	L		L		M		VL
...		AND		AND		THEN	
Rule 20	H		H		M		H
…							
Rule 24	H		VH		H		VH

The membership functions of input and output parameters were obtained from the experiment conditions and the determined rules. For example membership functions of working depth (WD) were given as following formula:

$$\mu_L(WD) = f_1(x, a_1, c_1) \times f_2(x, a_2, c_2);$$

$$a_1 = 1.099,\ c_1 = 12.5,\ a_2 = -1.099,\ c_2 = 17.5 \tag{5}$$

Where the function $f_i(x, a_i, c_i)$ is expressed as:

$$f_i(x, a_i, c_i) = \frac{1}{1 + e^{-a_i(x - c_i)}};\ i = 1, 2 \tag{6}$$

The other membership functions of working depth (WD) were expressed as:

$$\mu_M(WD) = f_1(x, a_1, c_1) \times f_2(x, a_2, c_2);$$

$$a_1 = 1.099,\ c_1 = 17.5,\ a_2 = -1.099,\ c_2 = 22.5 \tag{7}$$

$$\mu_H(WD) = f_1(x, a_1, c_1) \times f_2(x, a_2, c_2);$$

$$a_1 = 1.099,\ c_1 = 22.5,\ a_2 = -1.099,\ c_2 = 27.5 \tag{8}$$

$$\mu_{VH}(WD) = f_1(x, a_1, c_1) \times f_2(x, a_2, c_2);$$

$$a_1 = 1.099,\ c_1 = 27.5,\ a_2 = -1.099,\ c_2 = 32.5 \tag{9}$$

where, $\mu(WD)$ is the membership degree of working depth at each linguistic variables. In order to determine two parameters a_i and c_i, the experimental data and defined rules were used.

The membership functions of test variables are shown in Figure 4 and 5.

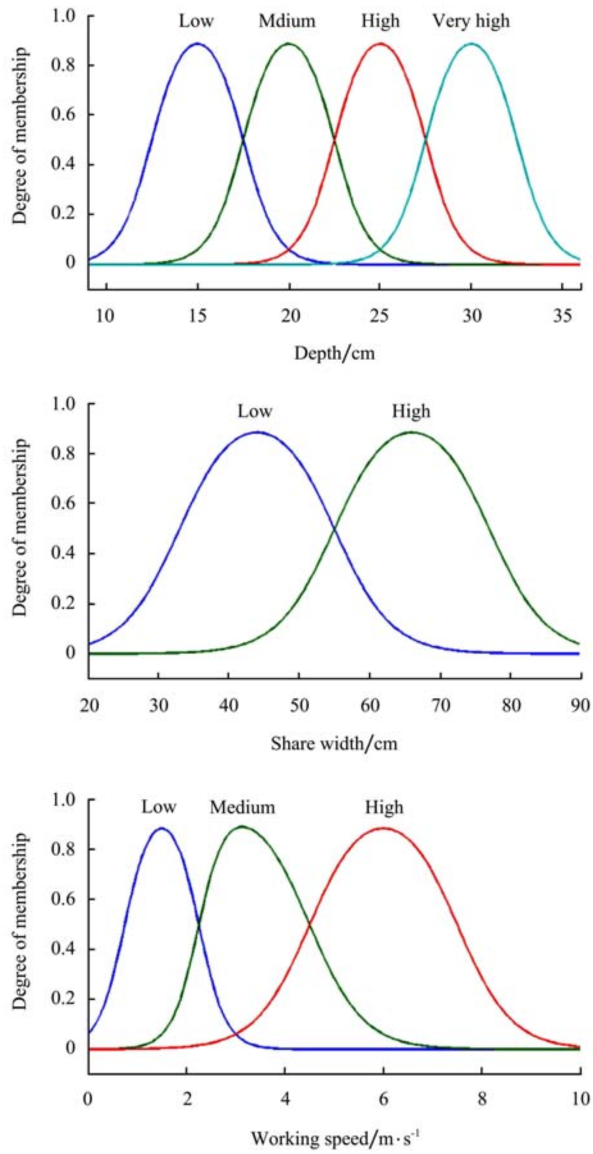

Figure 4 Input variables

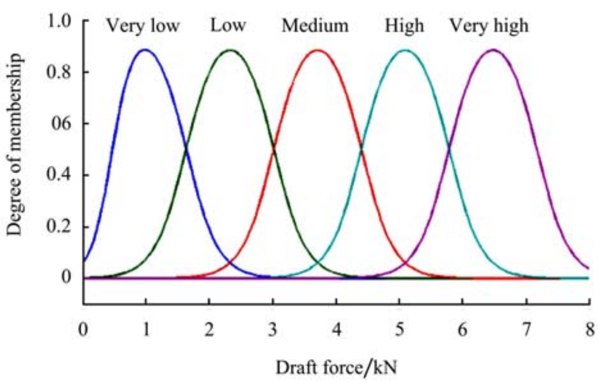

Figure 5 Output variable

In the second step degrees to which input data matched the condition of the fuzzy rules were calculated and then fuzzy operator was applied to calculated degrees. Outputs of this step were single values for each rule.

In the third step the rules conclusions based on degree of matching were calculated according to clipping method. This method cuts off the top of the output membership function whose value is higher than the degree of matching.

In the fourth step the inference results of rules were combined by superimposing all fuzzy conclusions for each rule. The output of the aggregation process was one fuzzy set for output variable.

In the last step of FIS implementation, the crisp value of output variable was calculated from the aggregate output fuzzy set. In defuzzification process the bisector method was used. The bisector is the vertical line that will divide the region of output fuzzy set into two sub-regions of equal area.

The detail information of inputs and output and used methods in each step of Fuzzy Inference System (FIS) implementation to model input/output relations are shown in Table 4.

Table 4 Details of used methods in FIS implementation

Number of inputs	3
Number of output	1
Number of rules	24
And Method	'min'
Or Method	'max'
Implication method	'min'
Aggregation method	'sum'
Difuzzification method	'bisector'

In order to determine the relative error (□) of FIS, the following equation was used:

$$RMSE = \sqrt{\frac{\sum (y_p - y_o)^2}{n}} \tag{10}$$

where, n is the number of observations; y_p is the predicted value and y_o is the measured value.

3 Results and discussion

Analysis of variance (ANOVA) was performed to investigate the effects of input parameters on output parameter variation that results are shown in Table 5.

For each winged share the results showed that working speed, operating depth and share width affected the draft force of share significantly at 5% level of probability ($p < 0.05$). Greater depths and widths provide more reaction force of soil at the interface. Moreover higher forward velocities result in increasing the draft force because of increased acceleration of disturbed soil and sliding resistance on tillage tool surface (Spoor, 1969).

Table 5 Analysis of variance of the test variables effects on the draft force

Source	Sum of Squares	df	Mean Square	F	Sig.
Treatment	131.847a	23	5.73	29.42	0
width	52.62	1	52.62	270.04	0
velocity	7.82	2	3.91	20.07	0
depth	59.88	3	19.96	102.43	0
width * velocity	0.26	2	0.13	0.67	0.51
width * depth	9.93	3	3.31	16.98	0
velocity * depth	0.98	6	0.16	0.84	0.54
width * velocity * depth	0.36	6	0.06	0.31	0.93
Error	9.35	48	0.19		
Total	141.20	71			

Note: a. R Squared = 0.934 (Adjusted R Squared = 0.902).

The interaction between the width and depth was also statistically significant at 5% level of probability ($p < 0.05$). Mean values of draft force versus working depth at different levels of other input variables is shown in Figure 6. The draft force varied from 1.10 to 6.13 kN. The greatest value of draft force was obtained at a working depth of 30 cm and working speed of 6 m s^{-1}. Approximately, a decreased of 33% at share width caused a 43% decreased of the draft force.

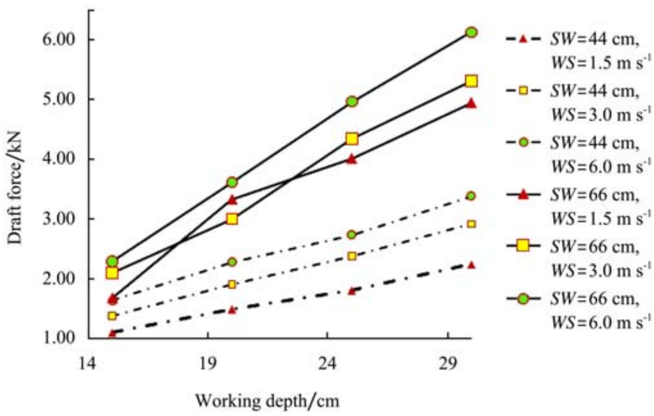

Figure 6 Measured values of draft force versus working depth

In order to investigate prediction capability of FIS model, 66% of experiment data used to train model, randomly, and the other remained experiment results used to test the developed model.

The results of FIS implementation for prediction of inputs-output relations are shown in Figures 7 and 8 for two winged shares. These surfaces were extracted from the spatial interpretation of fuzzy "IF-THEN" rules using test data.

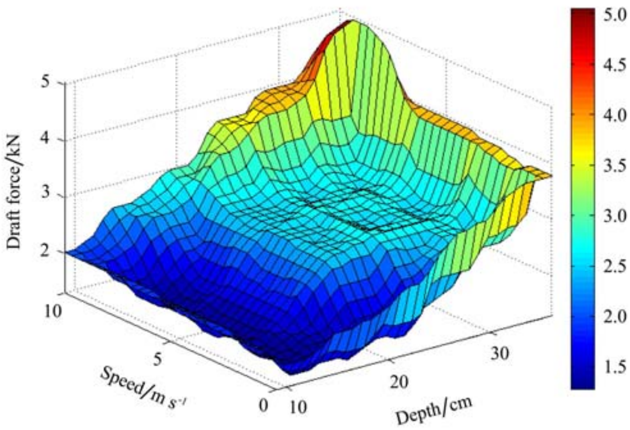

Figure 7 Evaluation surface of FIS for narrow share (440 mm)

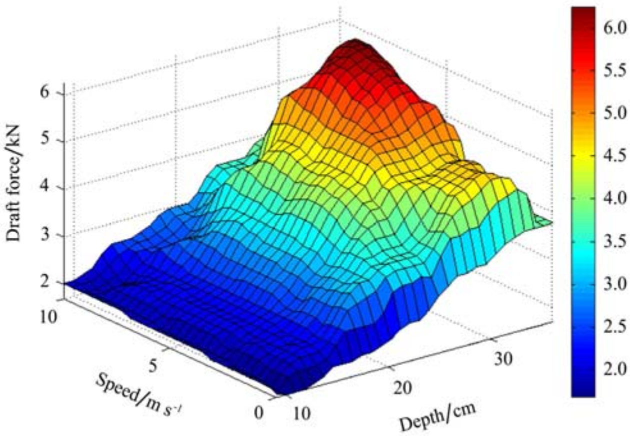

Figure 8 Evaluation surface of FIS for wide share (660 mm)

The results of the developed FIS were compared with the test data of experimental results. The correlation between measured and predicted values of draft force in different working conditions was given in Figure 9. The coefficient of determination of relationships was found 0.92 and Root Mean Squares of Errors (RMSE) was 0.33 for draft force which was in good agreement with experiment results.

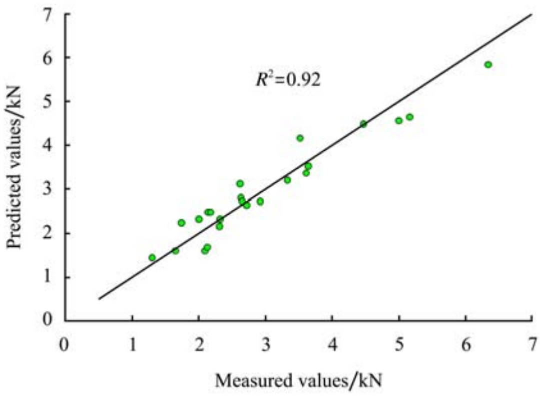

Figure 9 Correlation between measured and predicted (from FIS) values of draft force

4 Conclusion

Prediction of draft force is necessary for power requirements of tillage tools. In comparison to other predictive modeling techniques, fuzzy models have the advantage of being simple (relations between input and output parameters can be developed in a linguistic-based rule base) and robust (rules can be easily created independent of system training). In this study fuzzy table look-up scheme was employed to predict draft force of a winged share tillage tool. In this paper, according to evaluation, performance of the developed fuzzy knowledge-based model was found to be valid. The low variability between the measured and predicted draught values over the range of test variables implies that Mamdani max–min inference System was able to suitably model complex soil–tool interaction under the selected experimental conditions. The developed model could be considered as an alternative and practical tool for soil-tool interaction modeling because it can handle fuzzy and non-uniform variables under actual field conditions and can be used as a reference for further tillage studies. This system can be developed further with increasing the knowledge rules from one side and with implementation of other AI methods such as Takegi-Sugeno and ANFIS (Adaptive Neuro-Fuzzy inference System) method to the system from the other side.

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