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Predicting the draught requirement of tillage implements in sandy clay loam soil using an artificial neural network

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A 5–9–1 artificial neural network (ANN) model, with a back propagation learning algorithm, was developed to predict draught requirements of different tillage implements in a sandy clay loam soil under varying operating and soil conditions. The input parameters of the network were width of cut, depth of operation, speed of operation, soil moisture content and soil bulk density. The output from the network was the draught requirement of the individual tillage implement. The developed model predicted the draught requirement of mouldboard plough, cultivator and disk harrow with an error $< 6.5\%$ when compared to the measured draught values, whereas the American Society of Agricultural and Biological Engineers (ASABE) equation predicted these draught values with an error $> \pm 30\%$. Such encouraging results indicate that the developed ANN model for draught prediction could be considered as an alternative and practical tool for predicting draught requirement of tillage implements under the selected experimental conditions in sandy clay loam soils. Further work is required to demonstrate the generalised value of this ANN in other soil conditions.

1. Introduction

For conventional tillage, most of the farmers in India utilise their available tillage implements with a range of tractor powers, consequently there is often improper matching of the tractor and its implement resulting in under loading of tractor and hence, poor efficiency (Alam, 2000). The draught of tillage implements plays a vital role in developing more efficient tillage systems by selecting suitable combinations of tractor and implement. The availability of data on the draught requirement of tillage implements is an important factor while selecting suitable tillage implements for a particular farm situation. However collecting draught data under wide range of field conditions is a tedious and time consuming job. Therefore, draught prediction models are required to predict the draught of tillage implements under different soil and operating conditions. The magnitude of draught is affected by soil type and its condition, tool characteristics, working speed and depth (Reed, 1937; Gill and Vanden Berg, 1968; Kydd *et al.*, 1984; Grisso *et al.*, 1996; Al-Janobi and Al-Suhaibani, 1998; ASAE Standard, 2003). A number of other variables are also required to be considered while analysing the draught requirements of tillage implements. Some of these additional variables, listed by Glancey *et al.* (1989), were static and dynamic components of soil shear strength, coefficient of soil–metal friction, soil density and implement geometry. The relationship between the draught of plane tillage tools and speed of operation in different soils has been found to be linear, second-order polynomial, parabolic and exponential (Rowe and Barnes, 1961; Siemens *et al.*, 1965; Luth and Wismer, 1971; Godwin and Spoor, 1977; Godwin *et al.*, 1984; McKyes, 1985; Swick and Perumpral, 1988; Gupta *et al.*, 1989).

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Nomenclature

A, B, C and D	soil and implement parameters; Godwin et al. (2007) draught equation
A_1, B_1, C_1	machine specific parameters; ASABE draught equation
B_F	bending force in the lower link, kN
C_F	compressive force in the top link, kN
d	depth of operation, m
D_1	implement draught; ASABE equation, N
eh	computed error at hidden layer neuron
eo	computed error at output layer neuron
Fi	dimensionless soil texture adjustment parameteri is 1 for fine, 2 for medium, 3 for coarse textural soil
H_t	total draught force, kN
L	learning rate
N_c	number of training cycles
nh	number of neurons in hidden layer
R^2	coefficient of determination
S	speed of operation, km h^{-1}
T	tillage depth, cm
T_F	tensile force in the lower link, kN
Th	threshold parameter of hidden layer
To	threshold parameter of output layer
tol	tolerance limit
U	synaptic joint weights between input and hidden layer
v	forward velocity, m s^{-1}
W	synaptic joint weights between hidden and output layer
W_1	machine width, m or number of rows or tools
X	independent parameters
Y	dependent parameter
yh	computed output of hidden layer
yo	computed output of output layer
θ	angle of lower link in the horizontal plane, °
φ	angle of lower link in the vertical plane, °
β	angle of top link in the horizontal plane, °
γ	angle of top link in the vertical plane, °
ρ_w	dry bulk density

Subscripts

D	deviation from mean
M	mean value
max	maximum value of corresponding parameters
min	minimum value of corresponding parameters
minps	pseudo-minimum percentage error

Abbreviation

ANN	artificial neural network
ASABE	American Society of Agricultural and Biological Engineers
BP	back propagation
CI	cone index
DAS	data acquisition system
EORT	extended octagonal ring transducer
MSE	mean squared error
PE	percentage error
PTO	power take-off
RBF	radial basis function
TLRNN	time lagged recurrent neural network

These differences in the findings are the result of the variations in inertia required to accelerate the sandy soil and also the variation of the effect of shear rate on the shear strength and the effect of shear rate on soil–metal interaction properties in clay soils. Draught requirements of agricultural implements show considerable spatial variability due to variations in soil properties and the fracturing of soil. Hence, a larger area of land is necessary to obtain a representative mean draught value for a given soil type and condition. Sahu and Raheman (2006) conducted laboratory experiments with scale-model tillage implements (mouldboard plough, cultivator and disc gang) in sandy clay loam soil at 10– 12% moisture content. They observed that the draught requirement of all the tillage implements was significantly affected by speed, depth, width of cut, soil moisture content and soil cone index (CI) while the characteristic lengths of implement (curvature and length for mouldboard and tyne, and concavity for disk) and soil bulk density were found to be non-significant.

A number of empirical polynomial/multi-linear regression models have been developed in the past by several researchers for the prediction of draught of tillage implements (Wang *et al.*, 1972; Collins *et al.*, 1978; Gee-Clough *et al.*, 1978; Kepner *et al.*, 1982; Kydd *et al.*, 1984; Upadhyaya *et al.*, 1984; Grisso *et al.*, 1996; Kheiralla *et al.*, 2004; Sahu and Raheman, 2006). However, most of these models are often subjected to multi-colinearity problems and their application is limited to those soils and implements conditions for which they were developed. Most recently, Godwin *et al.* (2007) reported the following relationship between the draught, speed and depth of operation for mouldboard plough:

$$H_t = \left(Ad^2 + Bd\right)v^2 + \left(Cd^2 + Dd\right) \quad (1)$$

where, H_t is the total draught force, kN; d is depth of operation, m; v is forward speed, ms^{-1}; The values of the constants A, B, C and D determined from this analysis were specific for the particular soil and plough body geometry. According to ASABE standards (ASAE, 2003),

$$D_1 = W_1 T\left[F_i\left(A_1 + B_1(S) + C_1(S^2)\right)\right] \quad (2)$$

where, D_1 is implement draught, N; F is dimensionless soil texture adjustment parameter; i is 1 for fine, 2 for medium, 3 for coarse textural soil; A_1, B_1, C_1 are machine specific parameter; S is speed of operation, km h^{-1}; W_1 is machine width, m or number of rows or tools; T is tillage depth, cm. This draught prediction equation is used in most parts of the world and the reported variability for this equation ranges within ±50%. This variability is too large to be used for selecting the suitable power of tractors.

A few regression equations have been developed to predict the draught of any tillage implement with respect to the draught of reference tillage implement in the same soil at a given depth or speed (Glancey and Upadhyaya, 1995;

Glancey et al., 1996; Desbiolles et al., 1997; Sahu and Raheman, 2006). However, in order to allow prediction of draught of other tillage implements a large number of experiments are required for the reference tillage tool operating in the desired soil condition. As the draught requirement of implements is an important parameter for the selection of suitable size of implement and the power of the tractor, it is most essential to have a suitable model that can accurately predict draught data under field conditions. Hence, it is necessary to think of alternative approaches to predict the draught of implements under field conditions. In the present work, an attempt has been made to develop soft computing based techniques, i.e., a feed-forward artificial neural network (ANN) to model the draught of various implements.

A few researchers have attempted to develop ANN models to predict the draught of tillage implements. Zhang and Kushwaha (1999) developed a radial basis function (RBF) neural network to predict draught of narrow blades using operating speed, tools and soil types as input parameters. The data for the development of the model were obtained by conducting tests in three field sites using 5 different narrow blades with operating speed was in the range of 5 – 60 km h^{-1}. The tests indicated that the characteristics of draught-speed relation varied greatly with tools and soil types. They reported that the developed neural network model for the draught prediction had good generalisation ability in the sense of interpolation within the range of input parameters. The soil characteristics (moisture content and bulk density), width of cut and depth of operation of the implement were not considered as the input parameters in this model. Choi et al. (2000) developed a time lagged recurrent neural network (TLRNN) to predict dynamic draught of three kinds of tillage tools using tool shapes, shearing force and CI of soil as input parameters. An ANN model was reported to be a promising modelling method for calculating dynamic draughts. Al-Janobi et al. (2001) developed a multilayer perception with error back propagation (BP) learning algorithm based neural network model to predict specific draught of a chisel plough, an offset disc harrow, a mouldboard plough and a disc plough using sites (soil properties), tillage implements, ploughing depths and forward operating speeds as input parameters and the specific draught as output parameter. The architecture of the ANNs consisted of two hidden layers with 24 nodes in the first hidden layer and 12 nodes in the second layer. The hidden and output layers have a sigmoid transfer functions in neural networks model and the learning rule was momentum with 0.9 and step size 1.0. The best result was achieved at 65 000 training runs that gave minimum mean squared error (MSE) equals to 0.0004 during the training process. The results showed that the variation of the measured and the specific draught was small with a correlation coefficient of 0.987 and the MSE between measured and predicted specific draught was 0.1445. This model was site-specific model since it does not consider any variation in the soil properties.

Considering the above, and to overcome the problems associated with analytical and empirical methods of predicting draught of different tillage systems, an attempt was made to develop an ANN model for predicting the draught requirement of tillage implements, such as mouldboard ploughs, cultivators and disc harrows for different soil physical conditions, namely, moisture content and bulk density.

2. Experimental method and materials

To develop the ANN model, a large amount of data related to draught of different tillage implements (mouldboard plough, cultivator and disc harrow) under different operating and soil conditions were obtained by conducting laboratory and field tests. To obtain draught values under uniform soil conditions, the laboratory tests were carried out in the soil bin of the Agricultural and Food Engineering Department, Indian Institute of Technology, Kharagpur, India (Fig. 1).

2.1. Soil bin

The soil bin comprised a stationary bin, a carriage system, implement and soil processing trolleys, a power transmission system, a control unit and instrumentation (Fig. 1). The bin was 15.0 m long, 1.8 m wide and 0.6 m deep. Two rails, one on top of each side of the bin wall, were used for supporting the soil processing and the implement trolleys. The soil processing trolley comprised a frame, rotary tiller, levelling blade and roller to till, level and compact the soil, respectively to obtain the desired cone penetration resistance. A sprayer was used to apply water on the soil to maintain the desired average moisture content. The different speeds of operation were obtained by choosing suitable gears of a gear reduction unit coupled to the input shaft of the revolving drum, which was attached to soil processing trolley with stainless steel rope. A control unit, placed outside the soil bin, controlled the direction of movement of the soil processing trolley. The testing implement was mounted on the frame of the implement trolley, where screw jack arrangements were provided to vary the depth of operation.

2.2. Soil bed preparation in the soil bin

The experiments were conducted using a remoulded sandy clay loam soil. The average moisture content of soil during the tests was 10.5% dry basis (d.b.) with a maximum variation of ±1.2% d.b. Before the experiments, the soil bed was prepared to achieve the desired/required levels of cone

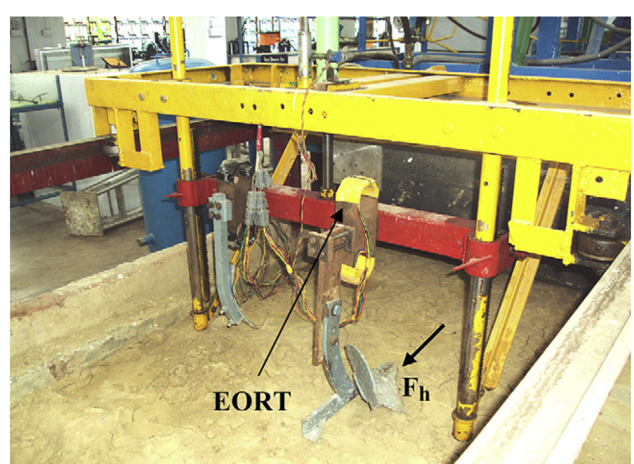

Fig. 1 – Arrangement of EORT in the soil bin for laboratory tests.

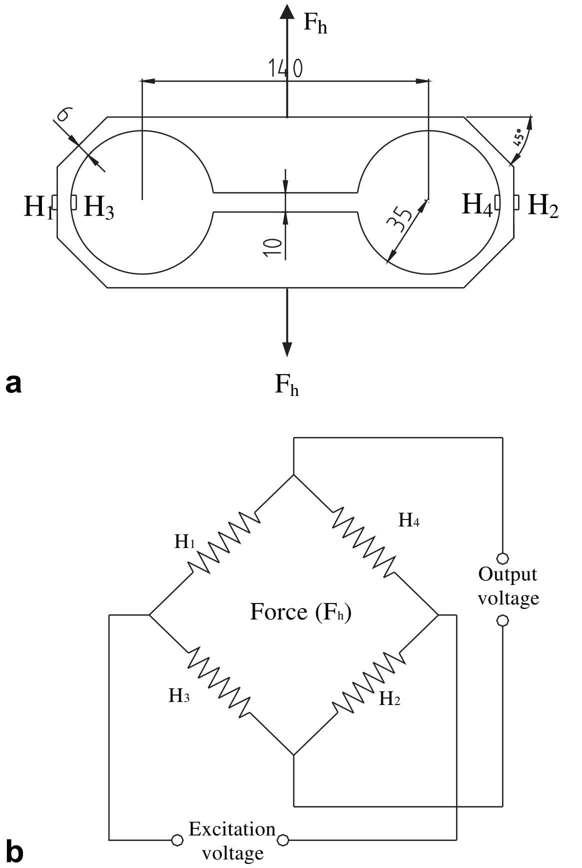

Fig. 2 – Measurement of draught of tillage implements in the soil bin: (a) strain gauge arrangements in EORT; (b) Wheatstone bridge circuit.

penetration resistance and bulk density. Firstly, the tiller was used to pulverise the soil after water was sprayed as desired. Then, the soil was levelled with the levelling blade and compacted by the roller to the desired cone penetration resistance and bulk density in layers. At the end of each soil preparation, a hand-operated soil cone penetrometer was used to measure the cone penetration resistance to a depth of 0.15 m at intervals of 0.025 m at six locations in the soil bin following the procedures outlined in the ASABE Standards (ASAE Standard, 2000). The locations were 2 m apart along the centre of the bin and were selected to check the soil condition near the start of the soil bed, in the middle and towards the end. At each of these locations, two samples were taken across the bin (0.5 m apart) using a core sample and a hand-operated soil cone penetrometer. The locations were chosen so as not to interfere with the tillage tests. To ensure soil uniformity, soil bed preparation was repeated if the cone penetration resistances and bulk densities varied significantly from each other.

2.3. *Experimental layout*

Experiments were conducted in the laboratory for three tillage tools (a single furrow mouldboard plough; one, two and three-tine cultivators; and a disc gang) in medium (CI of 856 ± 68 kPa, ρ_w of 1360 ± 57 kg m^{-3}) and soft soil conditions (CI of 472 ± 38 kPa, ρ_w of 1170 ± 25 kg m^{-3}) at four forward speeds, three depths for mouldboard plough, cultivator and disc gang with two replications for each combination. The levels of these variables are given in Table 1.

Field experiments were conducted for three prototype tillage implements (two furrow mouldboard plough, nine-tine cultivator and a double gang of seven disc offset disc harrow) with 37 kW 2wheel-drive tractor in hard and soft soil conditions at four forward speeds, two depths of operation (0.15 and 0.2 m for the mouldboard plough, 0.1 and 0.15 m for the cultivator and offset disc harrow) with two replications for each combination. All field tests were conducted in sandy clay loam soil. A fallow area of approximately 0.6 ha was selected after rainy season as hard soil condition (CI of 1298 ± 118 kPa, ρ_w of 1600 ± 90 kg m^{-3}). On another plot of 0.6 ha, the medium

Table 1 – Experimental plan (variable levels) for soil bin and field experiments.

Variables		Levels
Independent variables		
Soil bin		
(i) Tillage tools	3	mouldboard plough (cutting width of 0.1, 0.15 and 0.25 m) cultivator (cutting width of 0.2, 0.4 and 0.6 m) offset disk harrow (cutting width 0.09, 0.337 and 0.367 m)
(ii) Speed of operation	4	1.2, 2.2, 3.2, 4.2 km h^{-1}
(iii) Depth of operation		0.05, 0.075, 0.1 m
(iv) Soil condition	2	medium (average CI: 856 ± 68 kPa; ρ_w: 1360 ± 57 kg m^{-3} and moisture content 10.5 ± 1.2%) Soft (472 ± 38 kPa, average ρ_w: 1170 ± 25 kg m^{-3} and moisture content 10.8 ± 0.5%)
Field experiments		
(i) Tillage implements	3	mouldboard plough (cutting width of 0.6 m) cultivator (cutting width of 2.1 m) offset disk harrow (cutting width of 1.6 m)
(ii) Speed of operation	4	in the range of 3–8 km h^{-1}
(iii) Depth of operation	2	in the range of 0.1–0.25 m
(iv) Soil condition	2	hard (average CI: 1298 ± 118 kPa; ρ_w: 1600 ± 90 kg m^{-3} and, moisture content 12.5 ± 0.8%) medium (average CI: 856 ± 68 kPa; ρ_w: 1170 ± 25 kg m^{-3} and moisture content 11.2 ± 0.5%)
Dependent variables		
Draught		for both soil bin tests as well as field experiments

soil condition (CI of 856 ± 68 kPa, ρ_w of 1360 ± 57 kg m^{-3}) was achieved by ploughing once followed by discing twice and cultivating twice. Before the experiments, the bulk density, moisture content and CI data of the plots were collected. They are summarised in Table 2.

2.4. *Instrumentation*

2.4.1. *Laboratory*

In the laboratory the draught requirements of different tillage implements were measured using an extended octagonal ring transducer (EORT) as shown in Fig. 2a. This transducer was designed and fabricated for a maximum force of 3 kN following the design procedure of Godwin *et al.* (1993) and O'Dogherty (1996). For Measuring draught, four electrical strain gauges, each of 120 Ω and 2.6 gauge factor, were mounted on the octagonal faces of the transducer ring to form the Wheatstone bridge configurations, which was connected to a Spider 8 data acquisition system (DAS) (Fig. 2b). The transducer was attached to the front side of the cross bar of the screw jack arrangement provided in the implement trolley. The testing implement was mounted to the EORT at the front.

After fixing the desired depth of operation and selecting a gear for particular speed, the implement trolley along with tillage implement was pulled by the soil processing trolley in the soil bin. Using the calibrated EORT, the draught required to pull the implement into the soil were measured at different soil and operating conditions. The data for draught of tillage implement were continuously acquired by the measuring system. Simultaneously, to calculate the speed of operation, the time taken to cover a fixed distance of 10 m was recorded using a mechanical stopwatch.

2.4.2. *Field experiments*

The draught requirement of tillage implement in the field was measured with an instrumented three point linkage of tractor and a schematic view is shown in Fig. 3. For axial force measurement in the lower links, eight strain gages were used. Four gauges, each of 120 Ω and 2.6 gauge factor were active and mounted directly on the theoretical neutral axis of lower links and four dummy gauges were mounted on a separate mild steel plate (Fig. 4a and b). Gauges R_1, R_1', R_2 and R_2' were so oriented (placed opposite to each other on the theoretical neutral axis) that these were only sensitive to tensile force (F_a and F_a') and insensitive to bending force (F_b and F_b'). Any axial force in the lower links could be measured with gauges connected in the Wheatstone bridge arrangement as shown in Fig. 4c. Similarly, for compensation of lateral forces in the lower links, the gauges R_1 and R_1' and R_2 and R_2' were positioned in such a way that if any lateral force existed, such as when striking a hard structure, the resultant force was not affected by such a force. This is made possible by providing a rigid link between the lower link arms so that they could move together producing tension in gauge R_1 and R_2 and compression in gauge R_1' and R_2' or *vice versa*, with no influence on the bridge balance. The important point to note is that the strain gauges were mounted on the lower links where the cross sections of the two arms are equal.

For measuring bending forces in the lower links, eight strain gages (S_1, S_1', S_2, S_2', S_3, S_3', S_4 and S_4') were used. In this case, all gauges were active and mounted directly on the top and bottom surfaces of the links. Since, all the eight gauges were strained to same amount when subjected to axial force; the output of the Wheatstone bridge circuit was not affected by the tensile force. Thus, all active gauges were sensitive to bending force only. Bending force caused tensile stress in gages S_1, S_1', S_2 and S_2' and compressive stress in gages S_3, S_3', S_4 and S_4'. Using these strain gages, a Wheatstone bridge circuit as shown in Fig. 4d was made to measure the bending force.

Normally, the top link is subjected to a compressive range of forces during tillage. It is subjected to bending force due to friction on the ball swivel joints, eccentricity and due to the link itself. Although bending forces in these links are small, greater accuracy can be obtained by replacing the conventional turn buckle with a strain gauge equipped proving ring. The link tie tubes were welded to the proving ring clamp assembly. The proving ring was designed and fabricated from mild steel ring for a maximum force of 10 kN considering the design procedure of Godwin *et al.* (1993) and O'Dogherty (1996). A schematic view with the detailed dimensions of the proving ring has been given in Fig. 5a. Four electrical strain gages each of 120 Ω and 2.6 gauge factor were mounted on the proving

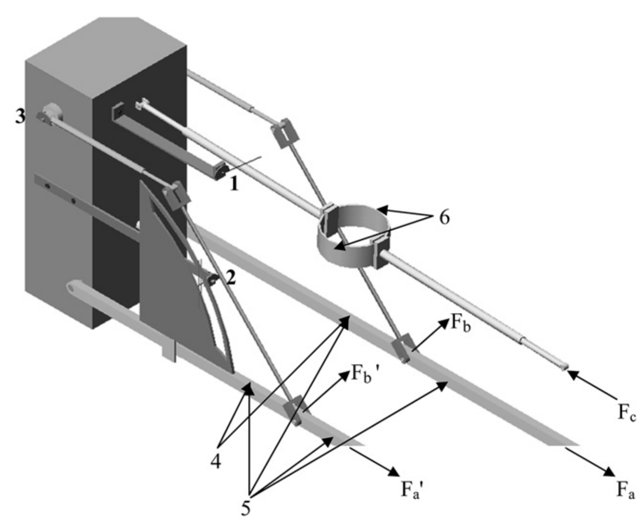

Fig. 3 – Instrumented three point linkage for measurement of force and angle of links indicating positions of strain gages and potentiometers: (1) vertical angle for top link; (2) horizontal angle for lower link; (3) vertical angle for lower link; (4) strain gauge positions for axial force; (5) strain gauge positions for bending force; (6) strain gauge positions for top link compressive force.

Table 2 – Mean and deviation of soil bulk density, moisture content and cone penetration data in the field before experiments.

Soil condition	Dry bulk density Kg m^{-3}	Moisture content % (d.b.)	Cone penetration resistance kPa
Hard	1600 ± 90	12.5 ± 0.8	1298 ± 118
Medium	1170 ± 25	10.8 ± 0.5	856 ± 68

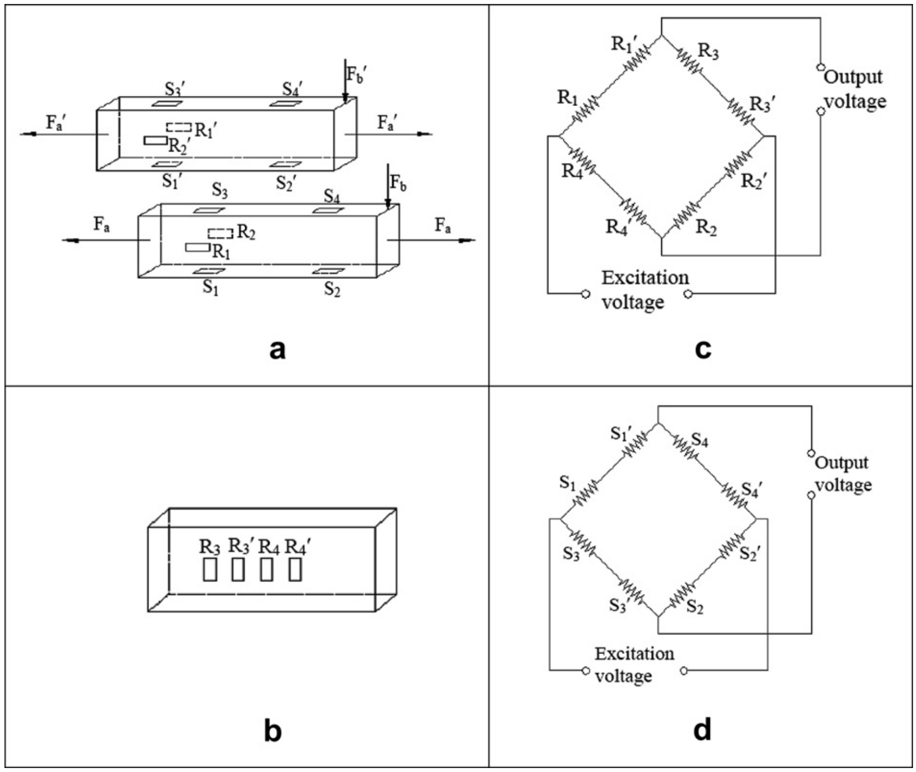

Fig. 4 – Strain gauge arrangements for axial and bending force measurement in lower links of a tractor: (a) arrangement of strain gauges on lower links; (b) arrangement of dummy gauges on a plate; (c) circuit diagram for axial force measurements in lower links; (d) circuit diagram for bending force measurements in lower links.

ring and connected to the Wheatstone bridge configuration as shown in Fig. 5b to measure the compressive force. Any compressive force, F_c would cause gauges A and B to have like strains, while gauges C and D would have opposite strains with no effect on the bridge balance so long as the amount of strain in gauges A and B and in gauges C and D were equal. This was verified by application of a large bending moment on the member with no effect on the bridge balance.

Further 5 kΩ rotary potentiometers were fixed one each at power take-off, on the rocker arm of tractor hydraulic system and at the side of power take-off (PTO) in a fabricated frame as shown in Fig. 3 for measuring the vertical angle made by the upper link, vertical and horizontal angles made by the lower link, respectively. The shafts of the potentiometers were allowed to rotate freely. Calibrations of the rotary potentiometers were carried out with known angles of the links of tractor. Output voltages corresponding to the angles of the links were recorded with the DAS.

Finally, the draught values were computed using the measured outputs as parameters in the following equation.

$$H_t = T_F\cos\theta\,\cos\varphi + B_F\cos\varphi\,\sin\theta - C_F\,\cos\beta\,\cos\gamma \qquad (3)$$

where H_t is draught, kN; T_F is tensile force in the lower link, kN; B_F is bending force in the lower link, kN; C_F is compressive force in the top link, kN; θ is angle of lower link in the horizontal plane; φ is angle of lower link in the vertical plane; β is angle of top link in the horizontal plane; γ is angle of top link in the vertical plane.

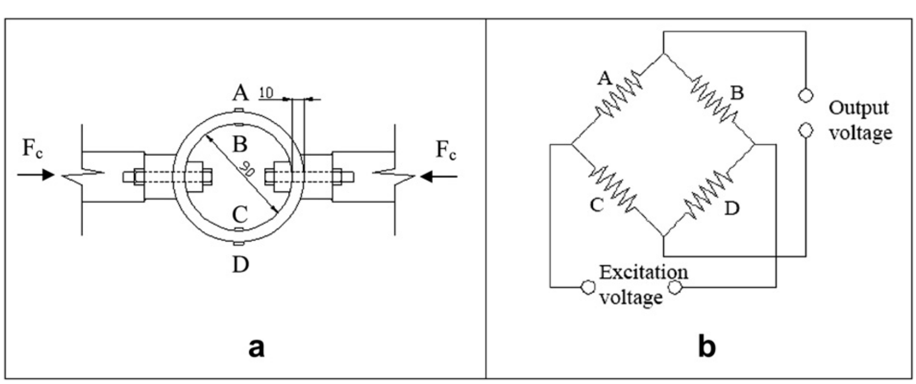

Fig. 5 – Force measurement in top link of a tractor three point linkage system: (a) strain gauge arrangement in proving ring to replace turn buckle in top link; (b) circuit diagram for axial force measurement.

3. Development of neural network model

Agricultural systems, such as soil-tool systems, are quite complex and uncertain and hence they can be considered as ill-defined systems, characterised by non-linearity, time-varying properties and many unknown factors. Therefore, it is essential to make certain assumptions for quantifying the complex relationships between the input and the output of a system based on analytical methods. ANN, mimicking the function of biological brains, has been reported to be an effective alternative for modelling complex systems in agriculture based on their input and output data. The prediction of dependent parameters has been found to be on a par with or better than statistical models (Hassan and Tohmaz, 1995; Kanali, 1997; Kushwaha and Zhang, 1998). With their high learning abilities, ANNs capable of identifying and modelling the complex nonlinear relationships (or behaviours) that occur between the inputs and the outputs of a system without requiring a complete knowledge of the governing laws. The advantage of using neural networks over statistical methods lies in their abilities to automate the process of model selection and also their ability to model nonlinear mapping. Among the various types of existing ANN approaches, a multilayer feed-forward neural network (as shown in Fig. 6) with BP algorithm and gradient descent learning rule, which has become most popular in engineering applications was used in this study. The network comprised one input layer, one hidden layer and one output layer. Independent variables were the width of cut (X_1), depth of operation (X_2), speed of operation (X_3), soil moisture content (X_4) and soil bulk density (X_5). The dependent variable was draught (Y). While developing ANN model, available data were divided into two sets at random, one set (75% of the data) was used for training of the model and the other set (remaining 25%) was used for validation of the model. The neural network model was developed in MATLAB 7 (The Math Works, Inc., Natick, MA, US) environment. The sigmoid transfer function was used in the hidden layer and output layer. The algorithm used for training the ANN is shown in Fig. 7. In the present case, normalisation (coding) of the input data sets (i.e., X_1, X_2, X_3, ... X_5) was carried out within the range of −1 and +1, while the output data sets (i.e., Y) was between 0 and +1. X_{max}, X_{min} and x, represented, respectively the maximum, minimum and coded value of an input variable X. The coded value of X_{max} was +1 and that of X_{min} was −1. The relationship between X and x could be expressed by the following equations (Rajasekaran and Pai, 2004).

$$X_M = (X_{max} + X_{min})/2 \tag{4}$$

$$X_D = (X_{max} - X_M) \tag{5}$$

$$x = (X - X_M)/X_D \tag{6}$$

$$X = x \times X_D + X_M \tag{7}$$

The relationship between actual Y and coded values y of the dependent variables was developed such that the coded value

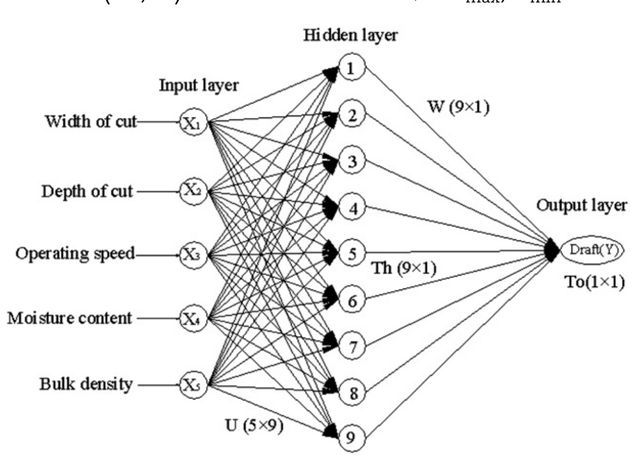

Fig. 6 – Architecture of developed multilayer feed-forward neural network for draught prediction.

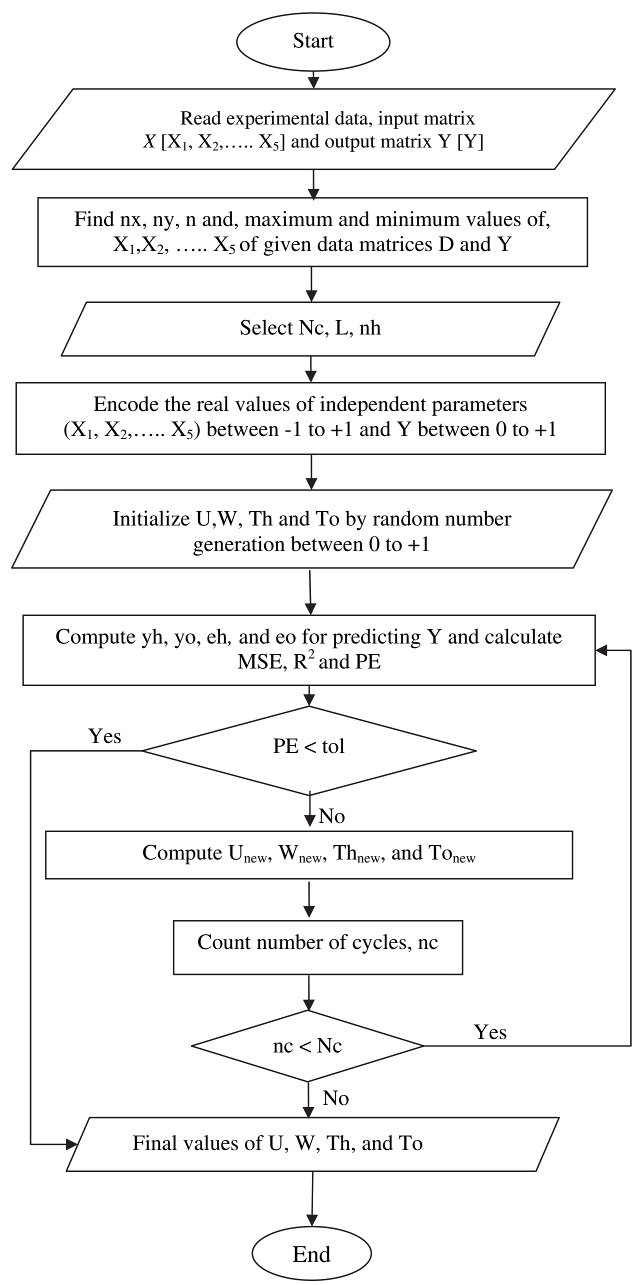

Fig. 7 – Algorithm for training the ANN model.

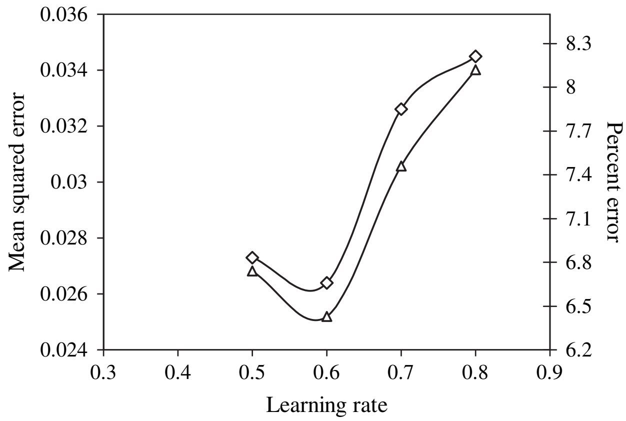

Fig. 8 – Computed mean square error: (◇) and percent error; (△) of ANN model at different *L* during training.

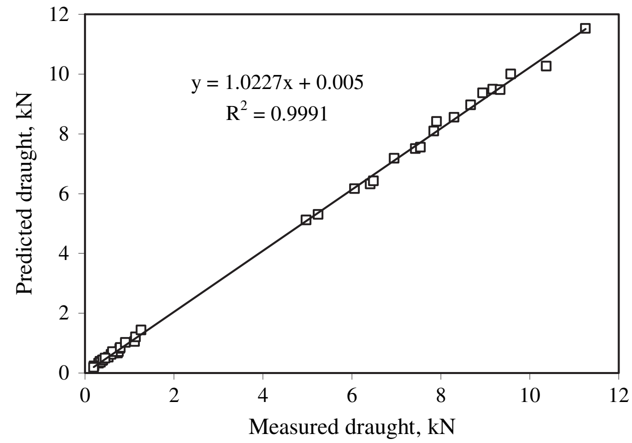

Fig. 10 – Comparison of measured and predicted draught values at *L* = 0.6 (training data).

of Y_{max} was 0. A parameter Y_{minps} representing pseudo-minimum of actual minimum Y_{min} was introduced as given below:

$$Y_{minps} = Y_{min} - (Y_{max} - Y_{min}) \quad (8)$$

The relationship between Y and y then could be expressed as:

$$Y_M = (Y_{max} + Y_{min})/2 \quad (9)$$

$$Y_D = (Y_{max} - Y_M) \quad (10)$$

$$y = (Y - Y_M)/Y_D \quad (11)$$

$$Y = y \times Y_D + Y_M \quad (12)$$

Inputs and outputs of the system determined the number of neurons in the input and output layer of the network, respectively. Thus, input and output layers had five and one neurons, respectively. The number of neurons in the hidden layer was usually set at less than twice the number of neurons in the input layer (Rajasekaran and Pai, 2004). For single hidden layer networks, although there are a number of rules of thumb to obtain the best number of hidden layer nodes, the best approach found was to start with a small number of nodes and to slightly increase the number until no significant improvement in model performance is achieved. In this study, both the learning rate(*L*) and the number of neurons were decided by running the model with varying *L* (0.5– 0.8) and numbers of nodes (5– 11) in the hidden layer. The training cycles were varied from 5000 to 60 000 during training and it was found that after 50 000 cycles, the level of error reached a minimum and there was no further reduction in error was achieved. During training of the network, input–output pairs were presented to the network and weights of the synaptic joints between input-hidden layer and hidden-output layer were adjusted to minimise the error between actual and predicted values. PE between the actual and the predicted values of dependent variable was reduced gradually with completion of each of the computation cycle. After completion of training, the final adjusted connection weights were fixed and the model was validated using a new set of data, which was not used during the training. Of the several numerical indicators, the two important ones selected for the present study were MSE and PE and are as given below:

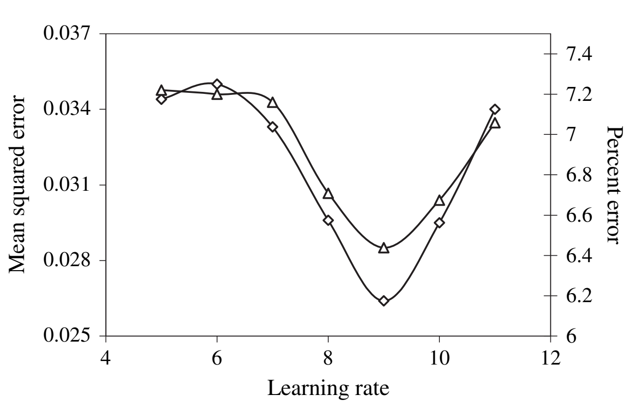

Fig. 9 – Computed variation of error with variation in number of neurons in the hidden layer of ANN model during training: (◇) mean square error; (△) percent error.

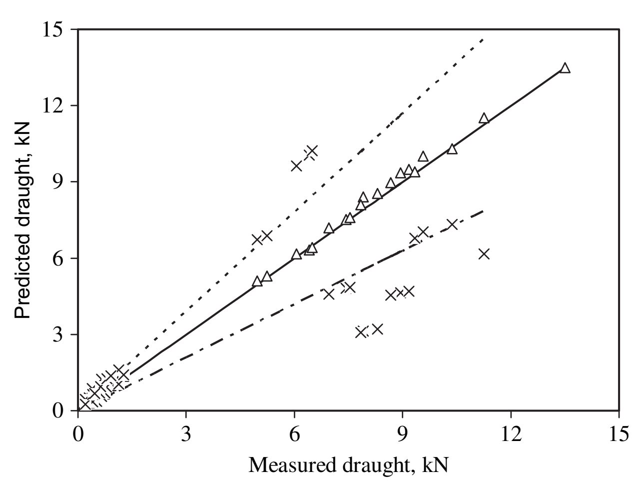

Fig. 11 – Comparison of measured and predicted draught values of tillage implements with validating data: (Δ) ANN model; (×) ASABE Eqn.; (---) +30%; (– - –) −30%.

Table 3 – Draught parameters considered for predicting draught of tillage implements by ASABE equation.

Tillage tool	Width/ Units	Machine parameter			Soil parameter
		A_1	B_1	C_1	F_2
Mouldboard	m	652	0.0	5.1	0.70
Cultivator (Primary tillage)	Tools	46	2.8	0.0	0.85
Offset disc harrow (Primary tillage)	m	364	18.8	0.0	0.88

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(\mathrm{Yi} - \mathrm{Yi}')^2 \tag{13}$$

$$\mathrm{PE} = \frac{1}{n}\sum_{i=1}^{n}\frac{|\mathrm{Yi} - \mathrm{Yi}'|}{\mathrm{Yi}} \times 100 \tag{14}$$

where Yi is the measured draught, kN and Yi$'$ is the predicted draught, kN.

A total 163 sets of draught data were used in the present study. Out of this, 122 sets were used for training the feed-forward BP neural network with gradient decent method of learning and 41 sets were used for validation of the developed neural network. To have wide range of operating speeds, data selected for training and validating the developed ANN model comprised both laboratory and field measurements. In the laboratory tests, the implements could not be operated beyond 4.5 km h^{-1} because of practical limitations.

4. Results and discussion

The ANN model was developed by training the network with various combination of *L* and number of neurons in the hidden layer. Among the number of combinations, a *L* of 0.6 and 9 neurons in the hidden layer resulted in the lowest MSE and PE values. The variation in the MSE and PE with variation in *L* for the prediction model of mouldboard plough is shown in Fig. 8, when 9 numbers of neurons were considered in the hidden layer. When the *L* was $<$0.6, the search process was too slow and 60 000 cycles were found to be insufficient to obtain the low MSE, whereas at $L > 0.6$, the increments in the search process was too large and it did not reach optimum values with low MSE. Similarly, variations in the MSE and PE for mouldboard plough with varying numbers of neurons in the hidden layer are shown in Fig. 9, when a *L* of 0.6 was considered. The lowest value of MSE (0.0264) and PE (6.4380) were observed when the *L* was 0.6 and 9 neurons were considered in the hidden layer. A similar trend was observed for ANNs developed for other implements. Hence, the final network was developed with 9 neurons in the hidden layer. It was trained with *L* of 0.6. The measured and predicted draught values are compared in Fig. 10 for the validation data sets. Good agreement between measured and predicted draught values was found with a coefficient of determination (R^2) of 0.99, indicating that the ANN model had successfully learnt from the training data set to enable correct interpolation.

The experimental draught values for the different tillage implements (validating data) were compared with the draught values predicted by the ANN model as well as by the ASABE equation in Fig. 11. The draught parameters considered for predicting draught of tillage implements by ASABE equation are as listed in Table 3. The agreement between the predicted and measured draught values was greater for the ANN model than the ASABE equation. The variations were $>\pm30\%$ of the measured values using the ASABE equation as compared to $<6.5\%$ using the ANN. This low variation, which is within the acceptable range, confirmed the reliability of the network in predicting the draught requirement of different tillage implements in a sandy clay loam soil. However, more studies are required for other soils to make it a generalised ANN model.

5. Conclusions

Based on the results of this study, the following specific conclusions were drawn:

1. A 5–9–1 neural network was capable of predicting draught requirement of tillage implements in sandy clay loam soil under varying operating and soil conditions as indicated by high R^2 (0.99), low MSE (0.0264) and low PE (6.4%).
2. The low variability between the measured and predicted draught values over the range of tillage implements implies that the multilayer feed-forward neural network with BP algorithm and gradient descent learning rule was able to suitably model complex soil–tool system under the selected experimental conditions.

Further work is required to demonstrate the generalised value of this ANN model for the selected tillage implements operating in other soil conditions.

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