A comparative study between mathematical models and the ANN data mining technique in draft force prediction of disk plow implement in clay loam soil

Seyed Mojtaba Shafaei, Mohammad Loghavi, Saadat Kamgar*

(*Department of Biosystems Engineering, School of Agriculture, Shiraz University, Shiraz 71441-65186, Iran*)

Abstract: This paper communicates prediction of required draft force of disk plow implement during tillage operations. The well-known mathematical model proposed by American Society of Agricultural and Biological Engineers (ASABE), multiple linear regression (MLR), and data mining model, based on artificial neural network (ANN), were employed for this purpose. Input variables of the models were considered as forward speed of 2-6 km·h^{-1} and plowing depth of 10-30 cm. Development details of the models have been documented in the paper. On account of statistical performance criteria, the best ANN model with coefficient of determination of 0.971, root mean square error of 0.762 kN, mean absolute percentage error of 1.886% and mean value of absolute prediction residual errors of 0.968 kN was better performed than the ASABE and MLR models for prediction of required draft force. The ANN modeling results also showed that simultaneous or individual increment of forward speed and plowing depth caused nonlinear increment of draft force. The well-developed ANN model should be considered operational to predict draft force as an essential step towards proper selection of combination of tractor and disk plow implement.

Keywords: plowing depth, forward speed, tillage operations, artificial neural network, tractor power

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1 Introduction

Horizontal component of force generated by tractor to pull tillage implement within soil is known as draft force. Draft force of implement is a major factor in matching of tractor with implement in different tillage operations. Determination of proper size and power of tractor required to perform tillage operations with specific implement is obtained based on draft force data (Kumar et al., 2016). Hence, availability of draft force data for a specific tillage implement in particular farm situation is vital in this realm.

Magnitude of draft force is influenced by operational variables such as soil conditions, forward speed, plowing depth, and implement geometry (Kepner et al., 2005). Determination of draft force data under wide range of field conditions is a time consuming and costly job. Therefore, investigators preferred to find relationship between draft force and operational variables, using available modeling techniques, in order to extend discrete experimental results towards integral applicable results with limited trials.

In this context, a mathematical model suggested by American Society of Agricultural and Biological Engineers (ASABE) is a well-known model which is initially used by researchers to predict draft force of implements in tillage operations. The model performs based on parameters of soil, forward speed, machine/implement width, and plowing depth (ASABE, 2015).

Literature review indicated that draft force of some

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***Corresponding author: Kamgar, Saadat,** Ph.D., Assistant Professor, Department of Biosystems Engineering, School of Agriculture, Shiraz University, Shiraz, Iran 71441-65186. Tel: 98 07132287114. Fax: 98 07132286104. Email: kamgar@shirazu.ac.ir.

tillage implements were predicted well by the ASABE model in various types of soil over the past years (Ismail and Burkhardt, 1993; Harrigan and Rotz, 1995; Askari and Khalifahamzehghasem, 2013; Ranjbarian et al., 2017). Due to inadequate ability of the ASABE model in prediction of draft force of some implements in particular soils, previous authors intended to focus their studies on multiple linear regression (MLR) modeling of draft force (Harrison and Reed, 1962; Mamman and Oni, 2005; Al-Suhaibani et al., 2015). They found that the MLR model performed better than the ASABE model to predict draft force of desired tillage implement in target soil. Some available published documents revealed that draft force changed nonlinearly as affected by forward speed and plowing depth in a specific tillage system. Therefore, the MLR model could not successfully predict draft force in these conditions. Thus, other modeling techniques with ability of nonlinear mapping between multiple input and output parameters were examined by researchers to achieve better results in comparison with mathematical modeling techniques.

One of well-known nonlinear models performed based on data mining technique is artificial neural network (ANN). The ANN was originally established based on structure of biological neural system. The ANN models are adaptable intelligent systems capable of finding nonlinear relationships between input and output data sets. A trained ANN based on available observation data can be applied in the same situations for future works. This outstanding feature leads to employment of the ANN model in many fields of agricultural studies in recent years. Details of development aspects of the ANN modeling technique can be found in the literature (Taghavifar and Mardani, 2014a; Taghavifar and Mardani, 2014b; Shafaei et al., 2015; Taghavifar and Mardani, 2017; Shafaei et al., 2018a; Shafaei et al., 2018b). A probe into some published papers showed applications of the ANN in prediction of implement draft force based on field conditions (Aboukarima and Saad, 2006; Aboukarima, 2007; Alimardani et al., 2009). Furthermore, previous attempts indicated that the ANN model was proposed to predict draft force of tillage tools in controlled soil bin facility (Choi et al., 2000; Roul et al., 2009; Akbarnia et al., 2014).

In south regions of Iran, disk plowing is commonly performed by farmers as primary tillage operations in clay loam soils. In general, there have been no published results about draft force prediction of disk plow implement in clay loam soil on the basis of concurrent changes of plowing depth and forward speed. Therefore, current study was conducted to assess predictive ability of the ASABE, MLR, and ANN models for direct prediction of draft force of disk plow implement in clay loam soil. The best model with the highest predictive ability presented in the study results would be served in agricultural machinery managements to optimize matching situations of disk plow implement with available tractors in the country.

2 Materials and methods

2.1 Tillage site

An experimental farmland with clay loam soil texture (35% sand, 30% silt and 35% clay) and flat topography located at Bajgah Agricultural Research Station of Shiraz University (North West of Shiraz city, Iran) was used to carry out the research. A sampled container of farmland soil was collected and dried in a convection oven at 105± 1°C to reach the constant weight. Moisture content of the sampled soil was then determined as mass reduction during drying procedure divided by dry mass of the soil based on Equation (1) (SAA, 1977).

$$MC = \frac{W_w - W_d}{W_d} \times 100 \tag{1}$$

Where, W_w is mass of initial soil (g); W_d is mass of dried soil, and MC is moisture content of the sampled soil (d.b%). To eliminate measurement error, the tests were completed in triplicate for 30 cm topsoil layer and mean value was used. The moisture content of farmland soil was found to be 8.84 d.b%. To perform the tests, total of 27 farm plots with specific determined size (30 m × 15 m) were selected in the farmland.

2.2 Tractor and disk plow implement

An 81 kW 4WD Massey Ferguson 399 (MF-399) tractor manufactured by ITM company, Iran, was used in this research. To accurately measure and record draft force data, a digital instrumentation system consisted of a load cell transducer (model: NS4-5t, manufacture: Mavin, country: China, accuracy: 2.5 N) and a data acquisition board with data collection rate of 10 Hz was mounted on the tractor. Engineering aspects, and theoretical and experimental considerations of the system design are reported by Karparvarfard and Rahmanian-Koushkaki (2015), and Shafaei et al. (2018c). The simple method for draft force measurement of implement during tillage operations officially proposed by Regional Network for Agricultural Machinery (RNAM) (RNAM, 1995) was generally considered in the study.

A 120 cm wide mounted-type disk plow implement (model: TAKA 165, manufactured by TAKA, Iran) consisted of three disk bottoms mounted on a toolbar and equipped with a gauge wheel was used for the field trials. Prior to the trials, to minimize parasitic forces on the implement attached to the tractor, it was leveled using top and lift links of the tractor. Initial checkout of the tractor and the implement was also performed at base station (Figure 1).

Figure 1 The disk plow implement attached to the tractor at base station

2.3 Field trials

All field trials were carried out with three replications on a half day on Jun 5, 2016. In the field, before each test plot, a practice area was considered to achieve desired levels of plowing depth and forward speed. Desired plowing depths were practically gained through adjustment of three-point linkage height of the tractor. To obtain desired forward speeds, combination of tractor gears was used while the tractor in 2WD mode was travelling in a practice area. Three experimental levels of plowing depth (10, 20 and 30 cm) and forward speed (2, 4 and 6 km h^{-1}) were examined. Required draft force of the disk plow implement for each combination of plowing depth and forward speed was accurately measured and recorded by the digital instrumentation system. According to the RNAM method, the unpowered tractor-implement was pulled by an auxiliary tractor (model: 4450, manufactured by John Deere, USA) while, the load cell transducer of the digital instrumentation system was horizontally located between two tractors. Schematic of the method is graphically given by Rahmanian-Koushkaki et al. (2015). The experiments were conducted with the implement at desired plowing depths and forward speeds. Obtained force data was recorded as gross traction forces. The experiments were also repeated at desired forward speed and raised position of the implement. The recorded force data was considered as rolling resistance force of the tractor wheels. Subsequently, required draft force of the disk plow implement was computationally obtained by means of the following Equation (2).

$$DF=H-R \tag{2}$$

Where, DF is draft force (kN); H is gross traction force (kN), and R is rolling resistance force (kN).

2.4 Statistical descriptions

To determine draft force changes as affected by forward speed and plowing depth, obtained draft force data for the disk plow implement was statistically analyzed by applying some statistical parameters (mean, standard deviation, coefficient of variation, and coefficient of non-uniformity). The following equations describe formulation of the statistical parameters (Shafaei and Kamgar, 2017).

$$M=\frac{1}{N}\sum_{i=1}^{i=N}DF_i \tag{3}$$

$$SD=\frac{1}{N}\left[\sum_{i=1}^{i=N}(DF_i-M)\right]^{1/2} \tag{4}$$

$$CV=\left(\frac{SD}{M}\right)\times 100 \tag{5}$$

$$CNU=\left(\frac{DF_{\max}-DF_{\min}}{M}\right)\times 100 \tag{6}$$

Where, M is draft force mean, N is number of used data; DF_i is ith sampled draft force (kN); SD is standard deviation (kN); CV is coefficient of variation (%); CNU is coefficient of non-uniformity (%); DF_{max} is maximum of draft force (kN), and DF_{min} is minimum of draft force (kN).

2.5 Development of the models

2.5.1 Mathematical models

The ASABE and MLR models (Equations (7) and (8), respectively) were developed to predict required draft force of the disk plow implement during tillage operations. The values of experimental forward speed and plowing depth in accordance with specific soil and the implement parameters were fed to the model and corresponding draft force values for each combination of forward speed and plowing depth were obtained. The specific soil and implement parameters were extracted from the ASABE standard (ASABE, 2015).

$$DF = F_i[A + B(FS) + C(FS)^2]W \times PD \tag{7}$$

$$DF = a_0 + \sum_{i=1}^{i=n} a_i x_i \tag{8}$$

Where, F_i is a dimensionless soil texture adjustment parameter; A, B and C are machine-specific parameters; FS is forward speed (km.h^{-1}); W is machine width (m); PD is plowing depth (cm); a_0 is the MLR model constant; x_i is the ith MLR model variable, a_i is the ith MLR model coefficient, and n is number of variables. In this study, the MLR model was developed on the basis of two variables (forward speed and plowing depth).

2.5.2 ANN model

A classic ANN architect (multi-layer perceptron (MLP) network) with three layers of neuron (an input layer, one hidden layer, and output layer) was designed to predict draft force based on two input variables of plowing depth and forward speed. Schematic architect of designed ANN model is presented in Figure 2. The MLP network is the most popular ANN model in engineering problems in term of nonlinear prediction. The MLP network adjusts its biases and weights based on error-back propagation algorithm to diminish prediction error. In this method, input layer is mapped to hidden layer using input transfer function. Hidden layer is similarly mapped to output layer using output transfer function. There are many general transfer functions, namely unit step, linear, gaussian, exponential, sine, logistic, logarithm, and tangent, used in the ANN models.

In the present study, forward speed (3 levels) and plowing depth (3 levels) were chosen as input parameters. The draft force data were selected as target parameter in output layer. Data set was randomized and partitioned into 70%, 15% and 15%, respectively, for training, validation, and testing the designed network. The different parameters of network (input and output transfer function, number of neurons in hidden layer, and training cycles) were optimized to attain the best structure for developed ANN model using STATISTICA 10 software.

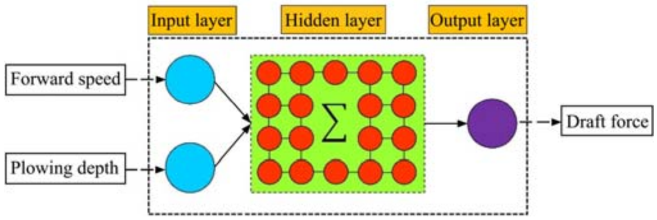

Figure 2 Schematic architect of designed MLP network for predicting draft force

2.6 Statistical assessment of models

Performance of the ASABE, MLR and ANN models developed for prediction of draft force was evaluated based on different statistical criteria. To determine modeling accuracy, regression analysis (coefficient of determination), was conducted between predicted and measured draft force data using Equation 9. Moreover, to determine absolute and relative mean of modeling error, root mean square error (RMSE) and mean absolute percentage error (MAPE), were calculated according to Equations (10) and (11), respectively (Shafaei et al., 2016a; Shafaei et al., 2016b; Shafaei et al., 2017a).

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{i=N} (DF_{meas,i} - DF_{pre,i})^2}{\sum_{i=1}^{i=N} (DF_{meas,i} - DF_{measave})^2} \right) \tag{9}$$

$$RMSE = \left[\frac{1}{N} \sum_{i=1}^{i=N} (DF_{pre,i} - DF_{meas,i})^2 \right]^{0.5} \tag{10}$$

$$MAPE = \frac{100}{N} \sum_{i=1}^{i=N} \left(\frac{|DF_{pre,i} - DF_{meas,i}|}{DF_{meas,i}} \right) \tag{11}$$

Where, R^2 is coefficient of determination; N is number of used data; $DF_{meas,i}$ is ith measured draft force (kN); $DF_{pre,i}$ is ith predicted draft force (kN), and $DF_{measave}$ is average of measured draft forces (kN).

2.7 Performance comparison of models

To determine modeling residual error mean, mean value of absolute prediction residual errors (MVAPRE) of the models was calculated, based on Equation (12), for each developed model. To select the best model for proper prediction of draft force, a comparative trend was performed among the statistical performance criteria of developed models. The best model with the highest predictive ability for draft force prediction was found in accordance with the highest coefficient of determination and the lowest values of the RMSE, MAPE, and MVAPRE.

$$MVAPRE = \frac{1}{N}\sum_{i=1}^{i=N} | DF_{pre,i} - DF_{meas,i} | \tag{12}$$

3 Results and discussion

3.1 Statistical descriptions

The calculated statistical parameters for required draft force of the disk plow implement during tillage operations are tabulated in Table 1. According to the table, minimum and maximum draft forces were found in the lowest (FS=2 km h^{-1} and PD=10 cm) and highest (FS= 6 km h^{-1} and PD=30 cm) levels of variables, respectively. The high values of coefficient of variation and coefficient of non-uniformity reported in the table indicate that draft force changed considerably as the levels of plowing depth and forward speed varied.

Table 1 Statistical parameters obtained for required draft force of the disk plow during tillage operations

Mean (kN)	Standard deviation (kN)	Minimum (kN)	Maximum (kN)	CV (%)	CNU (%)
11.393	4.220	4.910	22.01	37.041	150.092

3.2 Validation of developed models

3.2.1 Mathematical models

The statistical performance criteria, constant and coefficients of the ASABE and MLR models developed to predict required draft force of the disk plow implement during tillage operations are summarized in Table 2. According to the table, inappropriate values of the statistical performance criteria imply that draft force was poorly predicted by the ASABE and MLR models through the experimental conditions. Figure 3 depicts mismatched relationships between measured and predicted draft forces. In case of the ASABE model, it could be due to mismatch of studied soil properties with the soil parameters which is presented in the ASABE standard (ASABE, 2015). In case of the MLR model, it could be attributed to nonlinear changes of draft force as result of concurrent changes of forward speed and plowing depth. Although the MLR model could not properly predict draft force, statistical significance of the constant and coefficients of the model indicated that draft force was a function of plowing depth and forward speed.

Table 2 Constant, coefficients and statistical performance criteria of the mathematical models developed to predict draft force

Model	a_0	a_1	a_2	R^2	RMSE (kN)	MAPE (%)	MVAPRE (kN)
ASABE	–	–	–	0.852	1.282	5.267	1.623
MLR	–2.144*	0.369*	1.687*	0.897	1.097	3.464	1.552

Note: *Significant at 0.01 probability level (P<0.01).

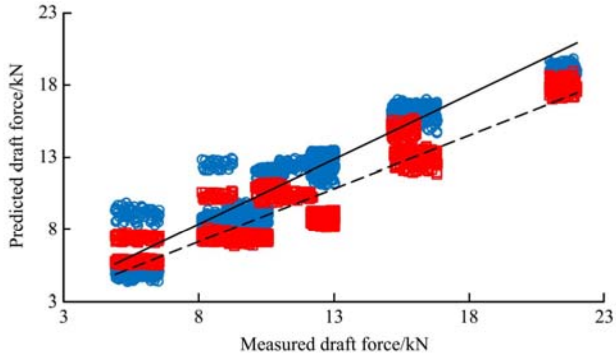

Figure 3 Comparison between measured and predicted draft force by the mathematical models ● the ASABE and ■ MLR model

3.2.2 ANN model

The architecture parameters and values of statistical performance criteria of selected twenty ANN models developed to predict required draft force of the disk plow implement during tillage operations are presented in Table 3. The boldfaced line in the table represents the best model with the highest predictive ability (R^2=0.971, RMSE=0.762 kN and MAPE=1.886%). As it can be seen in the table, the best ANN model was the one with structural parameters of 6 neurons in hidden layer, 374 training cycles, exponential and tangent transfer function in input and output layers, respectively. According to the acceptable values of the statistical performance criteria, the best ANN model was able to properly predict draft force. Figure 4 shows mapping between predicted and measured values of draft force by the best ANN model. The figure represents well-matched relationship between predicted and measured draft force data. Figure 5 depicts random distribution of prediction residual errors of the best ANN model for draft force prediction, revealing no specific trend. It was also found that the MVAPRE and standard deviation were 0.345 kN and 0.260 kN, respectively. Therefore, prediction residual error of the best ANN model was not sensitive to measured data.

Comparison between results of this study and previous works (Taghavifar et al., 2013; Taghavifar and Mardani, 2014c; Taghavifar and Mardani, 2015) indicated excellent predictive ability of the ANN model for estimation of Agricultural and Biosystems Engineering objects.

Table 3 The architecture parameters and statistical performance criteria of selected twenty ANN models developed to predict draft force

The number of neurons in hidden layer	The number of training cycles	Transfer function		R^2	RMSE (kN)	MAPE (%)
		Input	Output			
5	525	exponential	exponential	0.935	1.336	2.632
4	537	logistic	tangent	0.922	1.598	2.697
4	377	exponential	logistic	0.909	1.132	2.365
3	456	tangent	exponential	0.950	1.103	2.231
6	768	tangent	logistic	0.926	1.523	2.659
7	323	logistic	exponential	0.949	1.364	2.502
5	742	exponential	tangent	0.935	1.402	2.665
10	350	logistic	tangent	0.970	0.863	1.952
9	535	exponential	logistic	0.954	1.036	2.230
6	377	tangent	tangent	0.964	0.978	2.136
10	684	tangent	logistic	0.935	1.368	2.541
4	768	logistic	exponential	0.964	0.954	2.069
4	379	tangent	logistic	0.967	0.994	2.003
3	555	exponential	exponential	0.960	0.978	2.223
6	**374**	**exponential**	**tangent**	**0.971**	**0.762**	**1.886**
7	684	sine	tangent	0.964	0.966	2.102
5	234	sine	logistic	0.931	1.423	2.590
8	323	sine	tangent	0.933	1.451	2.652
5	742	sine	sine	0.947	1.123	2.296
7	890	sine	sine	0.952	1.103	2.320

Note: The boldfaced line represents the outperforming model

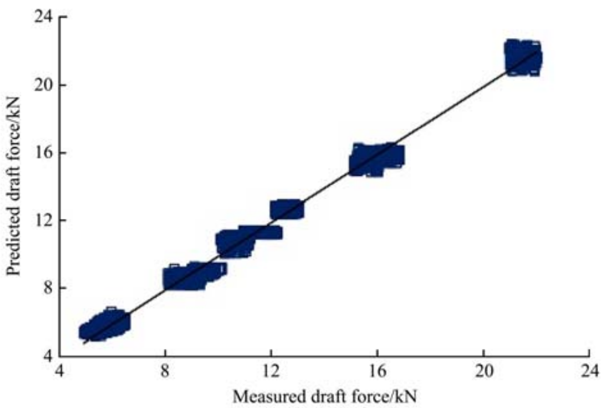

Figure 4 Mapping between predicted and measured values of draft force of the disk plow implement by the best ANN model

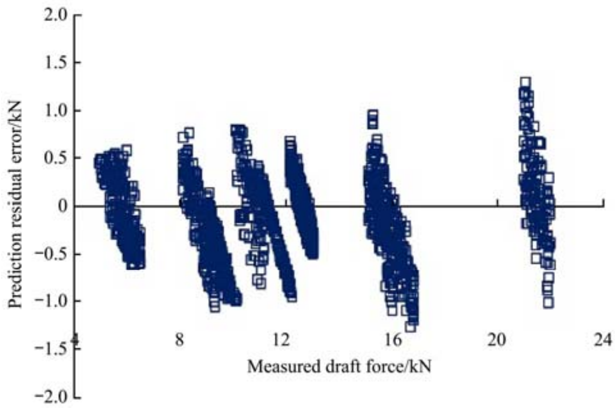

Figure 5 Distribution of prediction residual error of draft force modeling by the best ANN model

3.3 Performance comparison of the models

Comparison of the statistical performance criteria of the mathematical models (ASABE and MLR) and the best developed ANN is graphically depicted in Figure 6. According to the figure, the best ANN model with higher value of R^2, and lower values of the RMSE, MAPE, and MVAPRE was better rated than the ASABE and MLR models for prediction of required draft force of disk plow implement during tillage operations. Therefore, it can be stated that the best ANN model developed in this study was sufficient enough for prediction of draft force directly based on simultaneous changes of forward speed and plowing depth in the experimental range of 2-6 km.h^{1} and 10-30 cm, respectively.

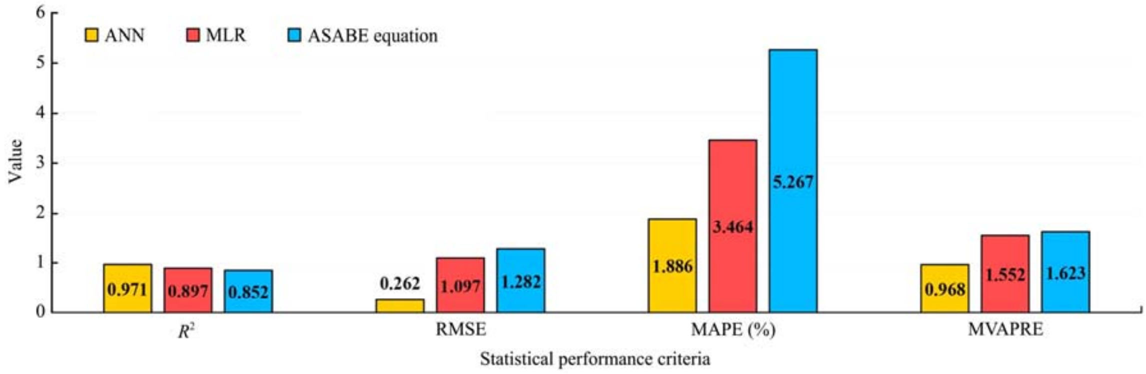

Figure 6 Comparison between the statistical performance criteria of assessment of the ASABE, MLR, and ANN models for draft force prediction of the disk plow implement during tillage operations

3.4 Draft force prediction

To study draft force behavior of the disk plow implement during tillage operations, the corresponding ANN surface plot was served to illustrate interrelationship between draft force, and plowing depth and forward speed (Figure 7). As it can be appreciated in the plot, the ANN model nonlinearly responses to input variables. It is also inferred that draft force increased as plowing depth was raised from 10 to 30 cm. Any increment of plowing depth leads to the increase of soil volume cut, dispersed and moved. Accordingly, higher draft force is required to plow higher soil volume (Al-Suhaibani and Ghaly, 2013). It can be also mentioned that increment of forward speed from 2 to 6 km h^{-1} resulted in draft force growth. Soil particles intend to gain higher acceleration as forward speed rises. The higher acceleration forces result in increase of normal loads acting on the implement disks. When the normal load increases, frictional force and thereby, draft force increases (Kepner et al., 2005).

Comparison of the ANN modeling results of the present study with some previous published results reported by Naderloo et al. (2009), Shafaei et al. (2017b), and Shafaei et al. (2018d) for other plow implements, respectively, implied the same trend of the increasing effect of plowing depth on draft force. Meanwhile, the increasing effect of forward speed on draft force obtained in this study for disk plow implement was in agreement with those presented by Cullum et al. (1989) and Novák et al. (2014) for one-way disk with seeder and cultivator, respectively.

Figure 8 graphically shows results of the ANN modeling for the dual interaction effect of forward speed and plowing depth on draft force of the disk plow implement during tillage operations. According to the figure, it is comprehended that the dual interaction effect of forward speed and plowing depth on draft force was congruent. As it can be seen in the figure, the congruent increasing dual interaction effect of plowing depth in the range of 10-30 cm along with forward speed in the range

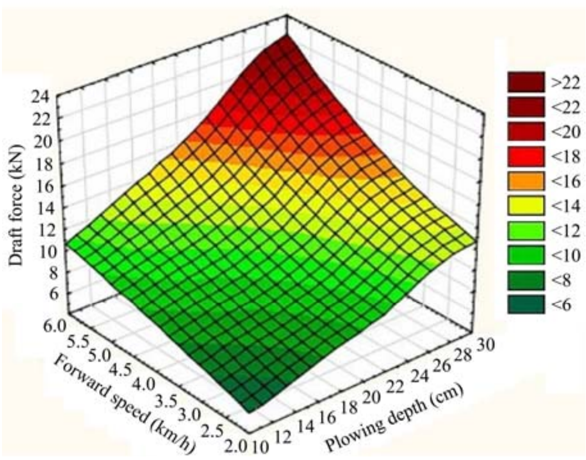

Figure 7 The ANN prediction of draft force of the disk plow implement during tillage operations

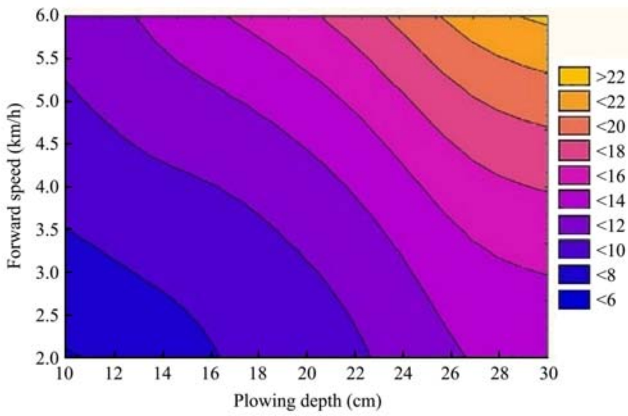

Figure 8 The dual interaction effect of forward speed and plowing depth on draft force of the disk plow implement during tillage operations

of 2-6 km h^{-1} lead to integrated growth of draft force from the lowest bound (<6 kN) to the highest bound (>22 kN). The positive dual interaction effect of plowing depth and forward speed on draft force was also reported in previous studies by Al-Suhaibani and Ghaly (2010), and Al-Suhaibani et al. (2010) for medium size and super heavy chisel plow implement, respectively, in a sandy soil.

4 Conclusions and recommendations

This paper was dedicated on the modeling of required draft force of the disk plow implement during tillage operations in clay loam soil as affected by forward speed and plowing depth. Potential of the mathematical models (ASABE and MLR) and the ANN data mining model for high accuracy prediction of draft force was assessed. According to the acceptable statistical performance criteria of R^2=0.971, RMSE=0.762 kN, MAPE=1.886% and MVAPRE=0.968 kN obtained for the well-developed ANN model, it was realized that the ANN model was proper than the mathematical models. The ANN promising results demonstrated that draft force nonlinearly increased as forward speed and plowing depth increased. It is concluded that the proposed ANN model can be used as a powerful tool to better understand draft force behavior as influenced by forward speed and plowing depth. The applicable ANN modeling results obtained in the study are recommended to be practically used by the farmland managers in regions with similar soil texture for proper selection of tractor type for pulling the disk plow in a high-efficiency manner.

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