DEVELOPMENT OF A COMPUTER PROGRAM USING VISUAL BASIC FOR PREDICTING PERFORMANCE PARAMETERS OF TILLAGE IMPLEMENTS

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ABSTRACT

This research effort is looking at alternatives to equation-based modeling; the ability to make predictions without creating equations to describe variable relations satisfies the research goals. A program for predicting performance of tillage implements in visual basic based on trained artificial neural network was developed. The program was designed to predict the required draft and energy of chisel, moldboard and disk plows. Field efficiency for each plow was assumed. The results of the program application are found almost identical with actual performance data of the selected plows. The fuel consumption could be determined through rated PTO power of a tractor. Hence, the developed program can be used to aid decision – makers in selecting the optimum tractor–machine complement size during operation under specific conditions of the soil and both plowing speed and depth. The specifications of each plow were considered as inputs in the program. The benefit of the program is to assist graduate and undergraduate students in agricultural engineering field to estimate data performance of tillage implements.

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INTRODUCTION

In agriculture crop production system, tillage is considered an essential process. However, the required energy for it represents a significant share of the energy needed in the crop production (Askari and Khalifahamzehghasem, 2013). Usually the required draft of a specific tillage implement working under different field and operation settings has measured using particular instrumentation systems (Elashry et al., 1994; Al-Janobi, 2000; Al-Jalil et al., 2001; Adamchuk et al., 2003; Bentaher et al., 2008; Al-Suhaibani et al., 2010; Younis et al., 2010). Such instrumentation systems are considered completely for an exacting tractor and not simply adjustable to other tractors (Al-Suhaibani et al., 2010). On the other hand, the required draft of a specific tillage implement can be measured directly by using strain gage load cells, hydraulic dynamometer or spring dynamometer.   Wide reviews on various instrumentation systems used in measuring the required draft of tillage implements and other performance parameters for such implements are obtainable from literature (Al-Janobi and Al-Suhaibani, 1995 and 1996; Al-Janobi et al., 1997 and 1998; Al-Suhaibani et al., 1994; Al-Suhaibani and Al-Janobi, 1996).

Different draft empirical models developed by statistical analysis to predict the required draft of tillage implements are available in literature (Gee-Clough et al., 1978; Oskoui and Witney, 1982; Oskoui et al., 1982; Elbanna, 1989; El Khadrawy, 1990; Elbanna, 1992; Kheiralla et al. 2004; Sahu and Raheman, 2006; Rashidi et al., 2013.). Draft models could be also developed by dimensional analysis (Olatunji and Davies, 2009; Nkakini and Douglas, 2012; Moeenifar et al., 2013a, 2013b) or by fuzzy table look-up scheme (Mohammadi et al., 2012). Moreover, predicting tractor power requirements could be available using decision support system (Vishal et al., 2013).

The models which are used to predict draft, pull and energy requirements of tillage implements could be built by the help of artificial neural networks   (Hassan and Tohmaz, 1995; Tohmaz and Hassan,1995; Kushwaha and Zhang, 1997; Zhang and Kushawaha,1999; Choi et al.,2000; Al-Janobi et al.,2001; Aboukarima et al. 2003; El Awady et

al.,2003; El Awady et al., 2004; Aboukarima, 2004; Aboukarima and Saad, 2006; Aboukarima, 2007; Roul et al., 2009; Al-Janobi et al., 2010; Lai et al., 2010; Altinisik et al., 2012; Carman and Taner, 2012; Aboukarima, 2013; Saleh and Aly, 2013; Taghavifar and Mardani, 2013a and 2013b; Taghavifar et al., 2013a and 2013b).   One of the reasons in which leads researchers to use artificial neural networks in building models is its powerful estimation and there is no specific material relation between the dependent and independent variables (Alimardani et al., 2009).

In scientific investigations, models could be a good tool to participate in resource management (Graves et al., 2002). In addition, a model enables researchers to manage their theoretical ideas and experimental explanations and to assume the reasonable implications of their investigations (Fishman, 1973). It can also be used in predicting or as forecasting tools (Muthuri, 2004) that help users make sensible educated guesses about future behaviour. As example, in farm machinery field, Sogaard et al. (1996) built a model for optimal selection of farm implements sizes within specific boundary conditions. In addition, other model designed by spreadsheet was developed by Al-Hamed et al. (1994) to estimate tractor performance. Moreover, a program for predicting tractor performance in Visual C++ was also built by Al-Hamed and Al-Janobi (2001). Generally, tractor simulation and prediction models programmed by computer languages could be a successful tool to save time and field experiments (Catalan et al., 2008) and represent a necessarily cost-free tool to the determination of the relative importance of a number of variables affecting actual tractor operation. On the other hand, there are four criteria that can be used to select the preferable model. These are: prediction precision, model simplicity, evenness of parameter estimates and sensitivity of results to change in parameter (Hesse and Keuper, 2001). In spite of these criteria are granted the suitable selection of a model for specific case, a model to evaluate the draft force of farm implements with good accuracy is often complicated (Amara et al., 2013).

Al-Janobi et al. (2010) developed an educational program to assist graduate and undergraduate students to estimate fuel consumption for tillage equipment. It supports to select the appropriate power of an agricultural tractor to operate with a particular tillage implement in specific operation and soil conditions to minimize fuel consumption. The program was written in visual C++ programming language. The program was based on training library of an artificial neural network. The program offers an educational help and clarification to most of the affecting parameters on fuel consumption. The program was validated by comparing predicted fuel consumption with the results obtained during field experiments. The program has proven to be very user-friendly and efficient to meet the requirement.

Hassan et al. (2011) developed a program for predicting performance of agricultural machinery in visual basic. The program predicts field efficiency, field capacity, draft power required to operate machines and PTO power. This program helps machinery management and could be used as educational and research tool. The formulas used in building the program are gathered from literature and the program was written in Visual Basic programming language as user-friendly interactive program. The program provides an intuitive user interface by linking to built-in databases were made available for the standard values of machinery specifications parameters to predict the performance of a selected agricultural machine otherwise, the user is prompt to enter his relevant input data for the model. The program has been statistically validated and proven to be user friendly and efficient.

Pranav et al. (2012) developed user friendly software for predicting the performance of power tiller to meet requirements in educational and research organizations by using visual basic. The software was based on Brixius equations rolling radius, gross traction ratio) and motion resistance ratio and slip was calculated by iteration. The developed software was validated by conducting experiments with a 6.7 kW power tiller. The results simulated by software indicate lower draft and slip in the range of 1-23 and 2-9% with respect to the experimental data.

Although instrumentation systems could be designed for draft measurements to be relatively inexpensive, portable, low maintenance, and easily adaptable to the tractors available at each site (Graham et al., 1990) and availability of different types of dynamometers for measuring such draft of a tillage implement, but the field work is hard and expensive to make a complete field performance data. Besides, draft force varies greatly due to numerous factors including soil condition like moisture content, texture and bulk density, forward speed, depth and tool geometry (Mouazen and Ramon, 2002; Godwin et al., 2007; Rashidi et al., 2013; Mahfoud and Ilham, 2013). Currently visual basic and visual C++ are widely used to develop a computerized tractor simulation and prediction model based that calculates drawbar (Catalan et al., 2008). On the other hand, the visual basic environment facilitates could be used with artificial neural network to implement computerized prediction model for draft requirements. So, it is necessary to have a simple, accuracy and friendly interactive computer program to predict and estimate the required performance data of tillage implements. Thus, this research work was undertaken to develop a program for predicting performance of tillage implements in visual basic based on trained artificial neural network. This program is useful for research and educational purposes as it depends on working and field conditions in wide ranges.

MATERIALS AND METHODS

Draft data collection and calculations

Available draft data of chisel, moldboard and disk plows in literatures, which directly related to the subject, were collected from different literature and field experiments (Project No. 09-SPA876-02, National Plan for Science and Technology King Saud University, Saudi Arabia). The studies in literature executed field or laboratory experiments using the plows in soils having different moistures, bulk densities and textures with different changeable working conditions and plows geometries. Collected data set was consisted of 130 data points for disk plow. However, Godwin and O'Dogherty (2007) made Microsoft Excel spreadsheet that incorporated moldboard plow draft prediction. This spreadsheet is straightforward to use. In the project, this spreadsheet was

used to predict draft requirements of different moldboard plows available in Saudi farms (Table 1) by the help of soil mechanical properties (cohesion, soil internal friction angle, soil metal friction angle and soil adhesion) for different studied regions. After suggesting plowing speed and depth, several draft data were available considering plow specifications (share approach angle, moldboard angle and rake angle). The created moldboard draft data were 3720 rows.

In the project, soil texture index (STI, dimensionless) for moldboard and chisel plows ANN models will be formulated from sand, slit and clay as follows:

$$STI = \frac{log\ (Sa^{Si} + CCa\ )}{100}$$ ………………………...………………… (1)

Where Sa, Si and CCa are % of sand, silt and clay fractions in the soil. However, Microsoft Excel spreadsheet to predict draft and vertical forces of single tool which presented by Godwin and O'Dogherty (2007) was used. It was able to calculate draft and vertical forces for user-desired soil properties and geometrical parameters. These calculations require soil bulk unit weight (specific weight, kN/m^3), (soil cohesion, kN/m^2), (angle of internal friction, degrees) and (angle of soil-metal friction, degrees). In addition to soil properties, this spreadsheet requires geometric and operating parameters of the tool, which are specific to the tool under consideration. For a single tine, relevant geometric parameters are tool width and rake angle. The operating parameters are the depth of operation and the forward speed. In the project, this spreadsheet was used to predict draft requirements of different chisel tools available in Saudi farms by the help of soil mechanical properties obtained in the project for different regions. After suggesting plowing speed and depth, several draft data were available considering plow specifications (tool width and rake angle). The final outcomes of these computations are the predicted values of draft and vertical forces values of 1342 data points. Table (2), Table (3) and Table (4) illustrate range of inputs for ANN modeling for disk, moldboard and chisel plows, respectively.

Table (1). Specifications of moldboard plows available in some Saudi farms.

Item	Plow model				
	ALPVEMA-ARADO IBS14-034E	OVERUM-S 7073-31	Hb1-cd-81791	No model available	EBERHARDT
Country		Sweden			Germany
Share sweep angle	44	44	44	35	35
Moldboard angle (°)	38	39	39	35	35
Point depth (cm)	6	6	5	6	7
Point width (cm)	7	7	6	7	6
Rake angle (°)	20	23	21	22	20
Share width (cm)	32	45	35	40	32
Moldboard length (cm)	86	87	83	87	88

Table (2). Range of inputs for disk plow.

Parameters	Unit	Minimum	Maximum
Disk angle	(°)	40.00	55.00
Tilt angle	(°)	15.00	25.00
Disk diameter	(cm)	53.00	66.00
Plowing speed	(km/h)	1.20	10.00
Plowing depth	(cm)	6.70	23.40
Soil moisture content	(%db)	4.90	28.00
Sand	(%)	9.00	90.85
Silt	(%)	4.00	48.00
Clay	(%)	4.55	70.00
Soil density	(g/cm^3)	1.22	1.67

Table (3). Range of inputs for moldboard plow.

Parameters	Unit	Minimum	Maximum
Moldboard angle	(°)	35	39
Moldboard length	(cm)	83	88
Rake angle	(°)	20	23
Share sweep angle	(°)	35	44
Plowing speed	(km/h)	2	8
Plowing depth	(cm)	12	25
Soil moisture content	(%)	1.3	15.1
Soil bulk density	(g/cm^3)	1.4	1.98
Soil texture index	(---)	0.05779	0.3790

Table (4). Range of inputs for chisel plow.

Parameters	Unit	Minimum	Maximum
Rake angle	(°)	40	60
Tool width	(cm)	6	7
Plowing depth	(cm)	8	30
Plowing speed	(km/h)	2	8
Soil moisture content	(%)	2.75	10.65
Soil bulk density	(g/cm^3)	1.44	1.84
Soil texture index	(---)	0.05779	0.223456

After collection of draft data of disk plow, required energy and unit draft were calculated. The width of cut (bd, cm) may be adjusted on standard disk plows by changing the angle of the disks with respect to forward motion (Dumitru, 2009). In this study, actual width of cut (bd) of a disk can be expressed as (Alam, 1989):

$$bd = \frac{2\cos\beta}{\cos\alpha}\sqrt{d(D\cos\alpha - d)} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots(2)$$

Where β is disk angle (°), α is tilt angle (°), D is disk diameter (cm), d is plowing depth (cm). The total plowing width (Wd, cm) is calculated as:

$$Wd = N \times bd \quad \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots..(3)$$

Where N is the number of disks on the plow. The tillage energy was calculated according to Smith (1993) as follows:

$$Energy\ (kW.h\,/\,ha\,/\,disk) = \frac{(Fd,kN\,/\,disk)\times(V,km/h)\times(1000,m/km)}{(3600,sec/h)\times(EFC,ha/h)}\ \ .....(4)$$

Where Fd is draft force for disk plow and V is plowing speed. Field efficiency is the most frequently used factor in determining the effective field capacity (Lar *et al.*, 2011). Thus, the effective field capacity (EFC) was calculated according to the following equation:

$$EFC\,(ha/h) = TFC\,(ha/h)\times\eta\ \ \dots\dots\dots\dots\dots\dots\dots\dots\dots..(5)$$

where η is the field efficiency and for tillage primary it was ranged from 70 to 85% (Powell, 2000). Field efficiency was assumed to be 0.8. Further, TFC denotes theoretical field capacity and was calculated according to the following equation:

$$TFC\,(ha/h) = \frac{(Wd,m)\times(V,km/h)\times1000}{(10000,m^2\,/\,ha)}\ \dots\dots\dots\dots\dots\dots\dots\dots\dots.(6)$$

Unit draft (UD) is calculated according to the following equation:

$$UD\,(N/cm^2\,/disk) = \frac{Fd,N/disk}{d,cm\times Wd,cm}\ \dots\dots\dots\dots\dots\dots\dots\dots\dots.(7)$$

The developed neural network model for disk plow to predict draft, energy and unit draft was consisted of three layers, the input layer had 10 inputs, the hidden layer had 8 neurons and output layer had 3 parameters (draft, unit draft and energy requirement of disk plows).The inputs were plowing speed, sand content, silt content, clay content, soil moisture content, disk diameter, disk angle, tilt angle and soil density. Minimum and maximum output parameters were 920 and 8000 N/disk for draft, for unit drat, the minimum and maximum values were 0.46 and 3.04 N/disk/cm^2, respectively and for energy requirements, the minimum and maximum values were 8.02 and 29.81 kW.h/ha/disk, respectively.

After collection of draft data of moldboard plow, the required energy and unit draft were calculated as follows:

$$Energy\ (kW.h\,/\,ha) = \frac{(Fm,kN)\times(V,km/h)\times(1000,m/km)}{(3600,sec/h)\times(EFC,ha/h)}\ \dots\dots\dots\dots\dots\dots\ (8)$$

Where Fm is total draft for moldboard plow (kN) and field efficiency is calculated according to Eq. (5) and TFC is calculated according to the following equation:

$$TFC(ha/h) = \frac{(Wb,m) \times (V,km/h) \times 1000}{(10000, m^2/ha)} \quad \text{……………………………..(9)}$$

Where Wb is plowing width of moldboard plow and it was calculated as follows:

$$Wb(m) = bm \times Nu \quad \text{……………………………..……..(10)}$$

Where bm is shear width of moldboard plow (m) and Nu is the number of shares. Unit draft is calculated according to the following equation:

$$UD(N/cm^2) = \frac{Fm,N}{d,cm \times Wb,cm} \quad \text{………………...…..........…..(11)}$$

The developed neural network model for moldboard plow to predict draft was consisted of three layers, the input layer had 9 inputs, the hidden layer had 12 neurons and output layer had 1 parameter (draft of moldboard plow).The inputs were plowing speed, plowing depth, rake angle, share sweep angle, soil moisture content, soil bulk density, soil texture index, moldboard angle and moldboard length. Minimum and maximum values for output parameter were 0.44 and 10.33 kN/body, respectively.

After collection of draft data of chisel plow, the required energy and unit draft were calculated as follows:

The width of chisel plow (W,cm)

$$W = \frac{Nc}{2} \times H \quad \text{…………………………………………….…… (12)}$$

Where Nc is number of tools, H is distance between two tools in the same raw (cm).

Theoretical Field capacity (ha/h):

$$TFC(ha/h) = W(cm) \times Plowing\ speed(km/h)/1000 \quad \text{…………….(13)}$$

Actual Field capacity (ha/hr):

$$EFC(ha/h) = TFC(ha/h) \times \eta/100 \quad \text{……………………………….(14)}$$

Total draft (kN) = Fc * Nc/1000……………………….……………(15)

Where, Fc is draft for chisel tool (N/tool) and tillage energy (kW.hr/ha) can be obtained by:

$$Energy \; (kW.h/ha) = \frac{(Total\; draft, kN) \times (V, km/h) \times (1000, m/km)}{(3600, sec/h) \times (EFC, ha/h)} \quad ....(16)$$

$$Unit \; draft \; (kN/cm^2) = \frac{(Total\; draft, kN)}{(W, cm) \times (d, cm)} \quad …………………………(17)$$

The developed neural network model for chisel plow to predict draft was consisted of three layers, the input layer had 7 inputs, the hidden layer had 10 neurons and output layer had 1 parameter (draft of chisel plow).The inputs were soil moisture content, soil bulk density, soil texture index, rake angle, plowing depth, plowing speed and tool width. Minimum and maximum values for output parameter were 137.4 and 6076.7 N/tool, respectively. The minimum and maximum value of field efficiency which feed to the software was 70 and 85%, respectively.

Considerations for computer program development

There have been several research activities on ANNs over the years (Hwang, 2001; Medeiros and Pedreira, 2001; Zhang, 2001). ANNs have been successfully used for a variety of tasks in many fields of agriculture and become an acceptable tool for prediction. Furthermore, ANNs are used for quantitative modeling for researchers (Alhassan and Misra, 2011). The number of published papers related to ANN in agricultural field of scientific journals proves the importance and wide acceptability of it. One of the major characteristics of ANNs is that it serves as a promising alternative tool for forecasters. This is so, because its inherent nonlinear structure is particularly useful for capturing complex underlying relationships which can be found in many real world problems. In addition, ANNs are used today because apart from its versatility as tool for forecasting applications in nonlinear structured problems, they are good for modeling linear processes (Alhassan and Misra, 2011).

On the other hand, hybrid prediction techniques for farm management are the order of the day, which involve a combination of data driven models and knowledge driven models. So, in this research paper ANN prediction tool has been generated with visual basic GUI to predict the performance

parameters of three common tillage implements for farm machinery management purposes within permissible tolerances. The prediction such parameters is done using multilayered feed forward network using standard back propagation method. Multilayered feed forward network is known as a supervised network because it requires a desired output in order to learn. The goal of this type of network is to create a model that correctly maps the input to the output using historical data so that the model can then be used to produce the output when the desired output is unknown. Besides, the back propagation algorithm is an iterative gradient algorithm designed to minimize the mean-squared error between the desired output and the actual output for a particular input to the network (Lendaris, 2004). Basically, back propagation learning consists of two passes through the different layers of the network: a forward pass and backward pass. During the forward pass the synaptic weights of the network are all fixed. During the backward pass, on the other hand, the synaptic weights are all adjusted in accordance with an error-correction rule (Lippmann, 1987). This algorithm may be found elsewhere (Lendaris, 2004). Back propagation is easy to implement, and has been shown to produce relatively good results in many applications. It is capable of approximating arbitrary non-linear mappings. The success of back propagation methods very much depends on problem specific parameter settings and on the topology of the network (Leonard, 1990).

In this research, training ANN models was accomplished using commercially available Qnet 2000 (Vesta Services, 2000). It is a software program for constructing, training and recalling predictions using neural networks. This package comes with a graphical user interface for constructing and training back-propagation neural networks. The software also comes with a Dynamic Link Library (DLL) file that provides software commands that can be used to send and receive data from the neural networks within the Visual Basic programming environment (Brown, 2005). However, execution of a trained network is just the process of feeding an array of inputs to the network and receiving back the appropriate array of outputs. This is handled by the Qnetsolv.dll that is part of Qnet2000. This integration can be performed by programmers who utilize programming languages that support standard Windows DLL access like Visual Basic programming environment. However, there is a dynamic program flow between the DLL file of the software shell and the

definition file generated by the trained neural network. A front end Graphical User Interface (GUI), created in Visual Basic integrates the definition file through the relevant Dynamic Link Library and calls the trained neural network as and when necessary to give predictions once the inputs are entered in the Visual Basic form.

Program development

Microsoft Visual Basic was selected as the programming language for building the developed program for tillage performance parameters predictions. This selection because it can be compiled into an executable program for rapid execution, is compatible with integrating the ANN training data set and is the language most familiar to the developer. However, Visual programming provides a set of screens, object buttons, scroll bars, and menus. The objects can be positioned on a form, and their behaviours are described through the use of a scripting language associated with each one. The program is an interactive program where the user is prompt to enter the relevant input data for the model. Figures (1) through (7) show screenshots of the Graphical User Interface (GUI) for performance parameters of three tillage implements (chisel plow, disk plow and moldboard plow). These figures illustrate inputs and outputs GUI for the three implements.
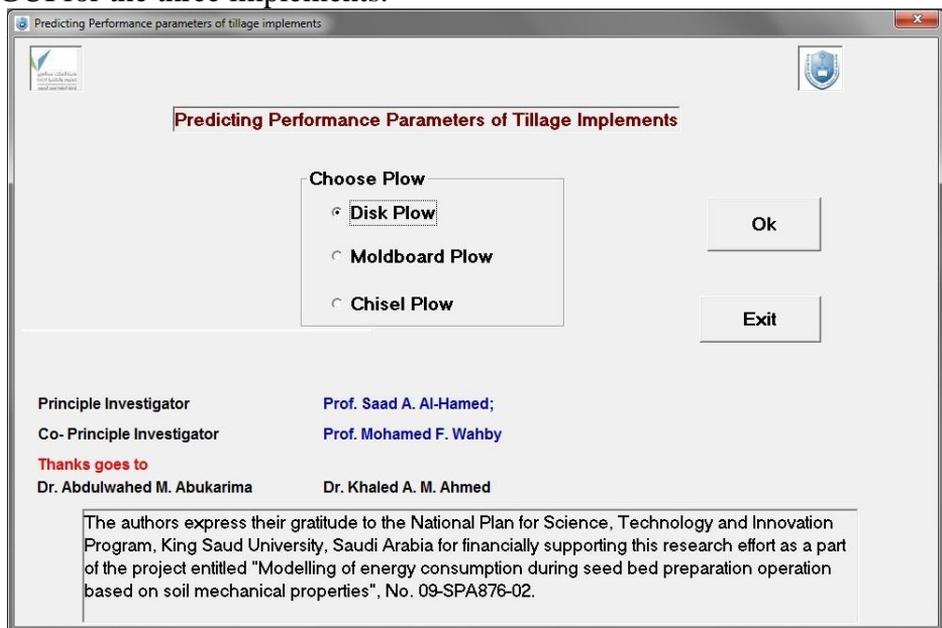
Figure (1). Screenshot of the first screen of the software for prediction of the performance parameters of tillage implements.

Figure (2). Screenshot of GUI inputs for disk plow.

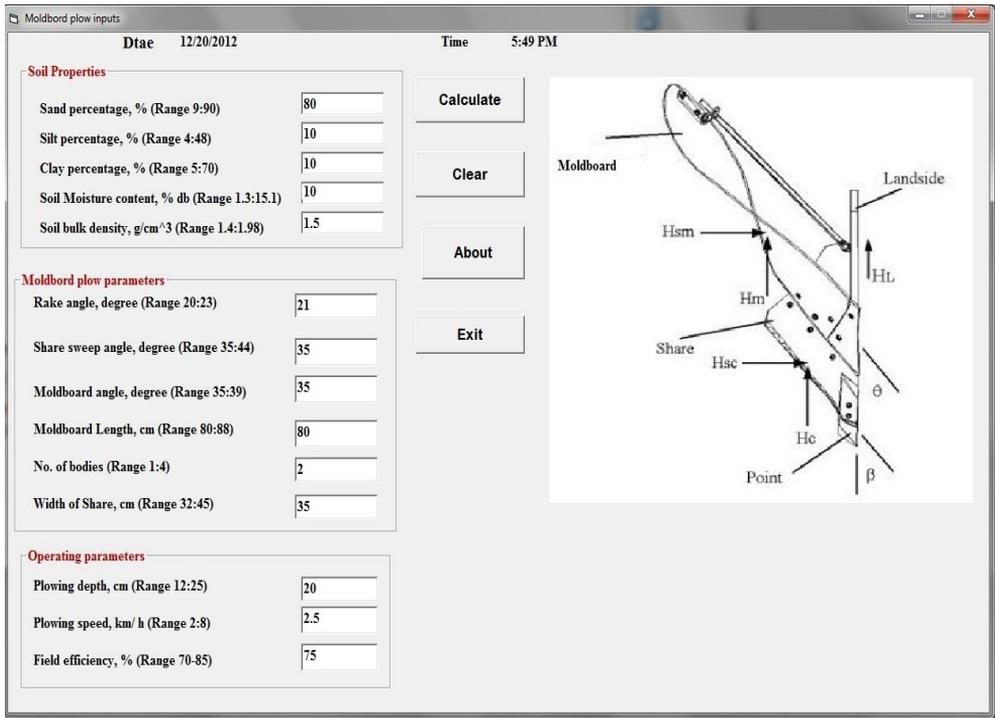Figure (3). Screenshot of GUI of output parameters for disk plow.

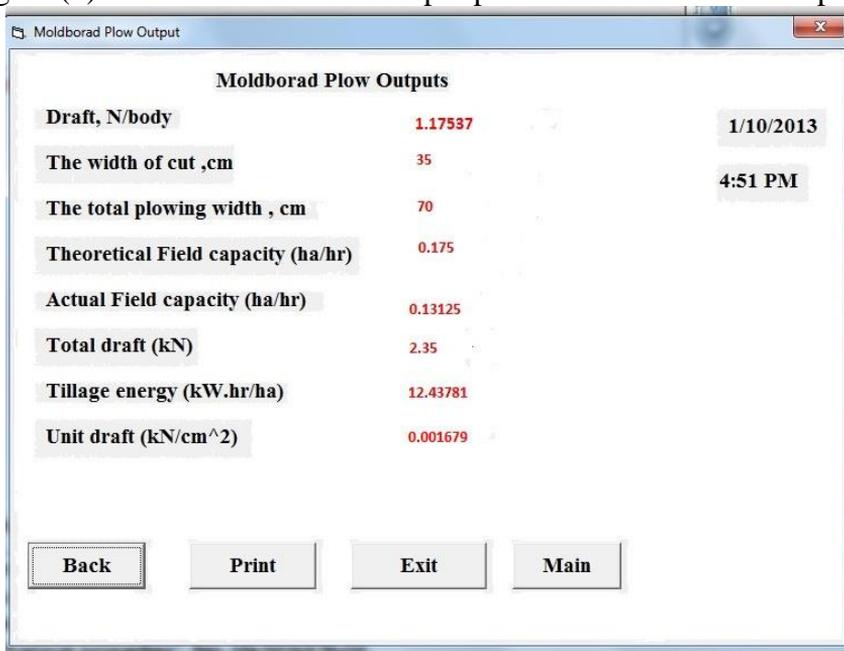Figure (4). Screenshot of GUI of input parameters for moldboard plow.

Figure (5). Screenshot of GUI of output parameters for moldboard plow.
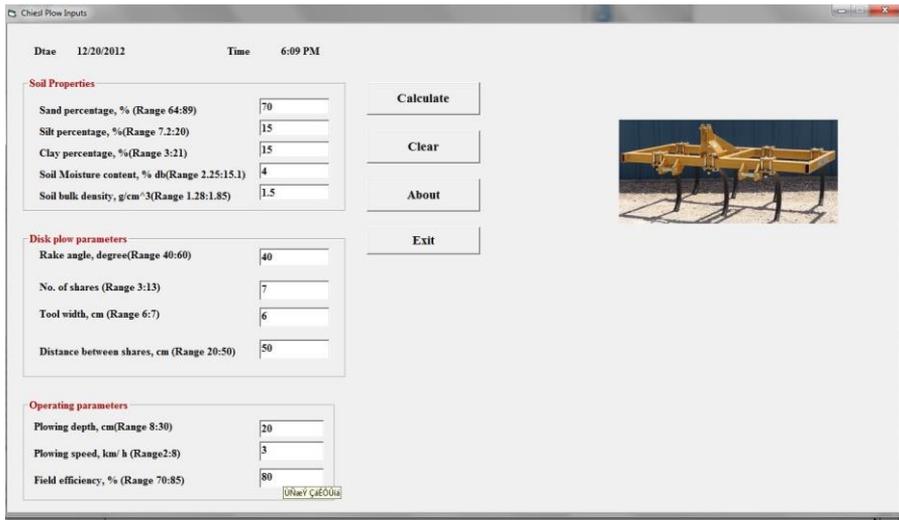
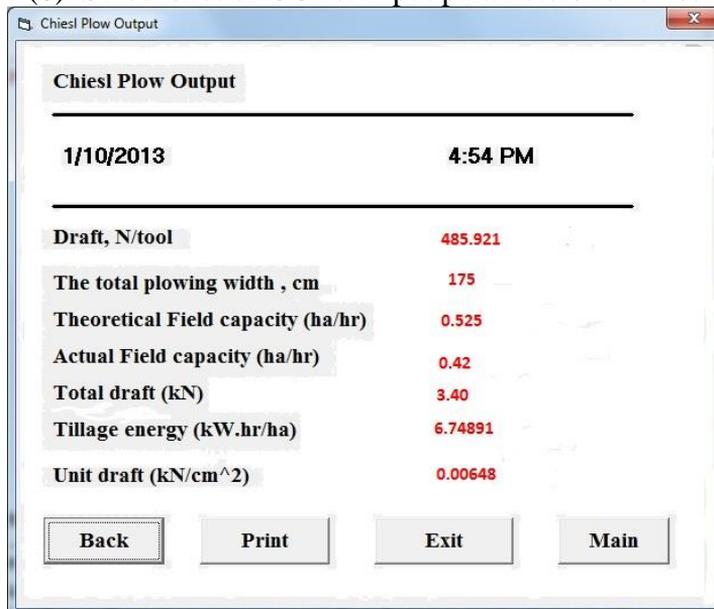Figure (6). Screenshot of GUI of input parameters for chisel plow.

Figure (7). Screenshot of GUI of output parameters for chisel plow.

Program validation

Once any model is built, it must be validated before use (Brown, 2005). A validation test means that the model accurately represents the real world system. To correctly validate a model, the actual system is tested over the range of values that the model will be used to predict. If acceptable agreement between the test data and the model is obtained that means, the

model is validated. Field experiments were conducted using the three plows to get actual draft data at different texture, plowing speed, and depth, moisture content and bulk density for specific plow. Details of these experiments are offered in Al-Hamed and Wahby (2013).

For chisel plow, the field experiments were conducted using a chisel plow with 13 shanks. The characteristics of the soil for such experiments were depicted in Table (5) and the working conditions are illustrated in Table (6). The shank width was 7 cm and the rake angle was 55 degree.

Table (5). The characteristics of the soil for field experiments using a chisel plow with 13 shanks.

Soil-metal friction angle	21.66°	Silt	12.4%
Soil internal friction angel	36°	Soil cohesion	19.62 kPa
Clay	3%	Sand	84.6%
Soil bulk density	1.67 g/cm^3	Soil adhesion	10.72 kPa
Soil moisture content	7.5 % db		

Table (6). The raw data for field experiments using a chisel plow with 13 shanks.

Plowing speed (km/h)	Plowing depth (cm)	Measured total draft (kN)
2.50	15.1	4.11
2.68	15.2	4.42
3.38	15.2	5.31

For moldboard plow, the field experiments were conducted using a moldboard plow had rake angle of 20 degree, share sweep angle of 44 degree, moldboard angle of 38 degree and moldboard length of 86 cm. The characteristics of the soil for experiments using a moldboard plow with 2 bodies are illustrated in Table (5). The working conditions for moldboard plow are illustrated in Table (7).

For disk plow, the field experiments were conducted using Nardi, mounted category II, weight 362 kg, Italy, model MF 38, serial No. TDPE48/D, with 3 disks with 36 cm disk diameter and distance between disks was 60 cm, the disk angle and tilt angle were measured and they

were 45° and 16°, respectively. Characteristics of the soil in the experimental using disk plow are depicted in Table (8) and the working conditions are illustrated in Table (9).

Table (7). The raw data for field experiments using a moldboard plow with 2 bodies.

Plowing speed (km/h)	Plowing depth (cm)	Measured draft (kN)
2.69	21	3.81
2.95	23	4.31
3.08	18	3.33
3.57	25	5.43
3.87	18	3.68
4.32	22	4.89
4.56	16	2.85
4.76	20	4.64
5.83	22	5.85
5.88	25	6.83
6.28	18	3.57
6.51	20	4.50

Table (8). Characteristics of the soil in the experiments using disk plow.

Items	Unit	Value
Sand	(%)	83.2
Silt	(%)	9.8
Clay	(%)	7.0
Soil bulk density	(g/cm^3)	1.52
Soil moisture content	(% db)	6.44

Table (9). Raw data of the field tests during plowing with disk plow.

Plowing speed (km/h)	Plowing depth (cm)	Measured draft (kN)
1.45	23	5.09
2.27	23	5.43
2.84	23	5.86

RESULTS AND DISCUSSION

In the testing phase for chisel plow draft requirements ANN prediction model, standard deviation, bias, maximum error and correlation coefficient were 116.774 N/tool, -14.042 N/tool, 773.347 N/tool and 0.992, respectively. Also, in the testing phase for disk plow draft, unit drat and energy requirements ANN prediction model, standard deviation, bias, maximum error and correlation coefficient were 794.465 N/disk, -0.997 N/disk, 2029.314 N/disk and 0.934, respectively for draft. For unit draft, standard deviation, bias, maximum error and correlation coefficient were 0.583 N/disk/cm^2, 0.016 N/disk/cm^2, 1.797 N/disk/cm^2 and 0.993, respectively. For energy requirements, standard deviation, bias, maximum error and correlation coefficient were 2.793 kW.h/ha/disk, -0.175 kW.h/ha/disk, 7.229 kW.h/ha/disk and 0.915, respectively. Meanwhile, in the testing phase for moldboard plow draft ANN prediction model, standard deviation, bias, maximum error and correlation coefficient were 0.25748 kN/body, 0.00097 kN/body, 1.31518 kN/body and 0.988, respectively. More details about training and testing such models are seen in Al-Hamed and Wahby (2013).

The developed software was used to predict the performance of plows at different operating conditions. It can predict additional values within the range of the training data set. After feeding the inputs to the software, the output parameter could be obtained and compared to measured data. For moldboard plow, the predicted draft from the developed program was compared to the results of field experiments where the effect of depth and speed on the horizontal (draft) forces of a general purpose moldboard plow were recorded in open field conditions. Figure (8) depicted the relationship between predicted drafts from the developed program and measured by field experiments for a moldboard plow. Meanwhile, Figure (9) depicted the relationship between predicted drafts from the developed program and measured by field experiments for a disk plow. Also, Figure (10) depicts the relationship between predicted drafts from the developed program and measured by field experiments for a chisel plow.
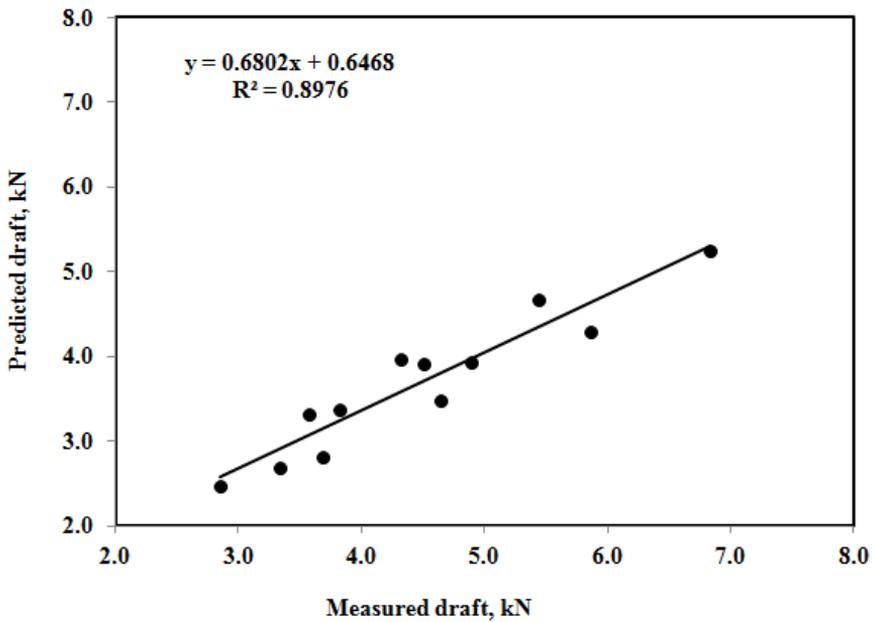
Figure (8). The relationship between predicted drafts from the developed program and measured by field experiments for a moldboard plow.
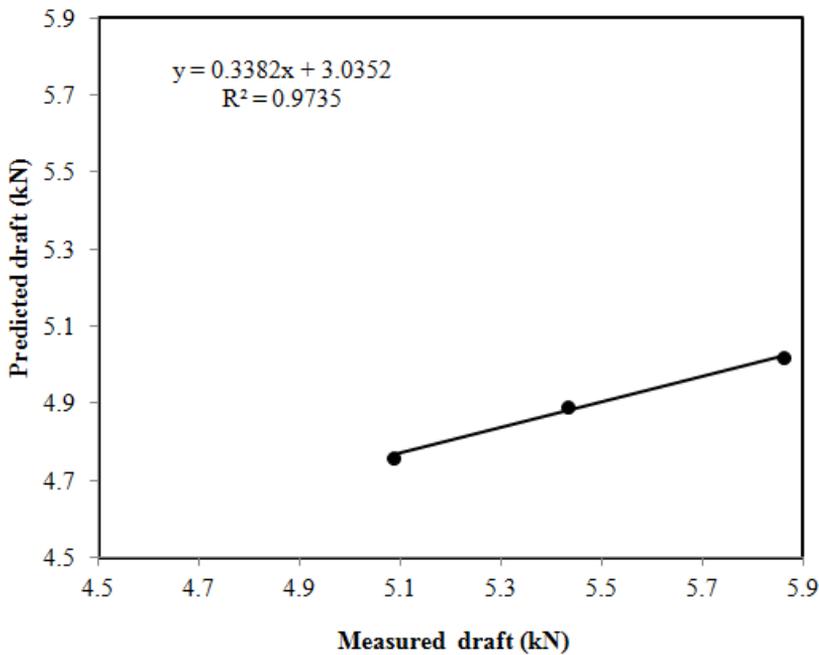

Figure (9). The relationship between the actual data of a disk plow from field experiments and the predicted values from the developed program.
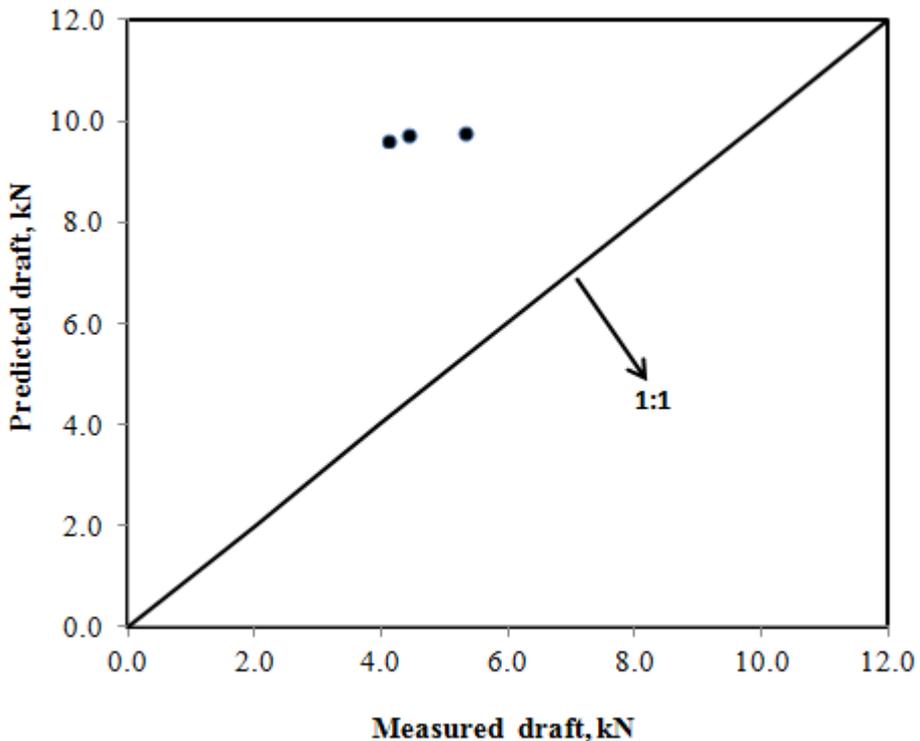
Figure (10). The relationship between predicted drafts from the developed program and measured by field experiments for a chisel plow.

By examining Figure (8) and Figure (9), it is obvious good agreements between measured and predicted draft from the developed program as confirmation from coefficients of determination (R^2) as shown in the figures which are around 0.9.

CONCLUSION

A program in visual basic was written based on trained ANN models to predict drat data of three tillage implements namely chisel, disk and moldboard plows. This predication could be done at varying operating and soil conditions. The program mainly predict the draft, unit drat and energy. The program was validated for its operational behavior using real experimental data. The results found to be satisfied for draft of all plows as confirmation from coefficients of determination (R^2) which are roughly 0.9. Hence, it is expected that the developed program package can be used

to estimate tractor power to match such implements by simple calculations from the predicted draft.

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الملخص العربي

تطوير برنامج حاسب آلي باستخدام لغة البيسك المرئية
للتنبؤ بمتغيرات أداء آلات الحرث

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في هذه الدراسة تم البحث عن بدائل للنماذج الرياضية المعتمدة على معادلات وتكون لها القدرة على التنبؤ دون بناء معادلات لوصف العلاقات التي تربط المتغيرات بعضها البعض. تم بناء برنامج يعتمد على لغة البيسك المرئية للتنبؤ بمتغيرات الأداء لمعدات الحرث الأساسية والعلاقات بين المتغيرات تم الحصول عليها من خلال تدريب نموذج شبكة عصبية اصطناعية. اعتبرت مواصفات كل محراث كمدخلات في البرنامج وقد تم تصميم البرنامج لتوقع متطلبات الطاقة وقوى الشد لمعدات الحرث (المحراث القلاب المطرحي، المحراث القلاب القرصي، والمحراث الحفار). تم فرض الكفاءة الحقلية لكل محراث. وبينت النتائج عند التحقق من أداء البرنامج أن البيانات متطابقة تقريبًا مع بيانات الأداء الفعلي للمحاريث المحددة. ويمكن من خلال البرنامج تحديد استهلاك الوقود لمعدة الحرث من خلال معرفة القدرة على عمود الإدارة الخلفي للجرار المستخدم مع المحراث. ويمكن اعتبار البرنامج المطور وسيلة مساعدة في اتخاذ القرار عند اختيار معدة حرث وجرار في ظل ظروف محددة من التربة وسرعة الجرار وعمق الحرث المطلوب. وفائدة هذا البرنامج هو لمساعدة طلاب الدراسات العليا والبكالوريوس في مجال الهندسة الزراعية ومهندسي الميكنة الزراعية لتقدير متغيرات الأداء لآلات الحرث.

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¹أستاذ ـ قسم الهندسة الزراعية، كلية علوم الأغذية والزراعة. جامعة الملك سعود، السعودية.

²باحث أول، معهد بحوث الهندسة الزراعية، مركز البحوث الزراعية. حاليًا يعمل كأستاذ مساعد بجامعة شقراء بالمملكة العربية السعودية.

³باحث، معهد بحوث الهندسة الزراعية، مركز البحوث الزراعية. حاليًا يعمل كأستاذ مساعد بجامعة الملك سعود بالمملكة العربية السعودية.