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Prediction of Specific Draft of Different Tillage Implements Using Neural Networks

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Abstract

A Multilayer Perceptron with error backpropagation learning algorithm was used to build neural network model to predict specific draft (kN/m) of different tillage implements from the field data. The neural network model was trained and tested with different sites, tillage implements, plowing depths, and forward operating speeds as input parameters and the measured specific draft as output parameter. The architecture of the neural networks 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 65000 training runs that gave minimum mean squared error equals to 0.0004 during training process. The results showed that the variation of measured and predicted specific draft was small and the correlation coefficient was 0.987 and mean squared error between measured and predicted specific draft was 0.1445.

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Introduction

The availability of draft requirement data of tillage implements is an important factor in selecting suitable tillage implements for a particular farming situation. Farm managers and consultants use draft requirement data of tillage implements in specific soil to determine correctly the proper tractor size. Also, using accurate draft data can only minimize ownership and operating costs of both tractors and implements. Therefore, prediction of implement draft requirement is important for tractor selection and implement matching. Many studies have been conducted to measure draft and power requirements of tillage implements under various soil conditions (Al-Janobi and Al-Suhaibani, 1998; Bashford et al. 1991, Harrigan and Rotz, 1994; Mckyes, 1984; Yasin et al.1991 and Grisso et al. 1994). ASAE Standards (1994) provide mathematical expressions for draft and power requirements for tillage implements in several soil types as part of the ASAE Data D497. Implement width, plowing depth, and forward speeds are the main factors that affect specific draft of a tillage implement. Draft per unit width or cross-sectional area of the tilled zone is a function of soil type and forward speed at which the implement is pulled.

Neural Networks are computational systems whose architecture and operation are inspired from our knowledge about biological neural cells (neurons) in the brain. Neural Networks can be described either as mathematical and computational model for non-linear function approximation, data classification, clustering and non-parametric regression or as simulations of the behavior of collections of model biological neurons (Ruan et al., 1995). These are not simulations of real neurons in the sense that they do not model the biology, chemistry, or physics of a real neuron. They do, however, model several aspects of the information combining and pattern recognition behavior of real neurons in a simple yet meaningful way. Neural modeling has shown incredible capability for emulation, analysis, prediction, and association.

Biological models have inspired technology of neural Networks. The building blocks of neural network are neurons or processing elements. Neurons operate by receiving inputs from individual dendrites. These inputs are weighted according to the synapses and the resulting quantities are summed. If the sum is greater than the threshold for the neuron, the neurone executes a transfer function on the weighted sum and passes the value onto the next neuron.

The operation of a processing element parallels its biological equivalent with synapses being replaced by connection weights. The processing elements are combined into layers. The parallel structure of the neural network distinguishes it from traditional serial processing computers. This results in some of the fundamental properties of neural networks. The learning or training phase of a neural network typically requires paired input-output data. The inputs are fed into the network, and transferred through the network layers. Ultimately a predicted output is calculated. This predicted output is subsequently compared with the actual output and the connection weights between the processing elements are modified to minimize the deviation between the predicted and actual output. This process continues until a defined accuracy has been reached. During this training phase, many factors of neural network structure, such as the number of hidden layers and the number of nodes in each layer, are adjusted by a trial and error approach to obtain the optimum network (Ruan et al. 1995).

Applications of neural networks in agricultural engineering and biological industries are still in its infancy. However, some research works have already shown great promise. Noguchi et al. (1993) studied the optimal control of agricultural vehicles by neural networks system through nonlinear controller. The results showed that, the output of neural networks were in good agreement with the experimental data, and were more accurate than the output of the physical model neglecting slip angle.

Hassan and Tohmaz (1995) used the neural networks to evaluate the tractive performance of a rubber-tired skidder operating on soft organic soil in the Coastal Plain region of North Carolina. They used three tire sizes inflated at each of three inflation pressures (69, 103, and 172 kPa). They used a neural network consisted of 4 neurons/input layer, 5 neurons/first hidden layer, 3 neurons/second hidden layer, and 1 neuron/output layer (4-5-3-1). The results indicated that, the neural network simulation of the pull-load relationship was in close agreement with the statistical model of the actual pull-load data.

Sato et al. (1993) investigated the possibility of using neural networks for operator's voice recognition under tractor noise. The neural networks were initially trained to recognize input voice and noise, and later during recognition, it compared the learned signals and test signals to distinguish between the tractor noise and operator's voice. All investigations were carried out at a fixed tractor noise level at 2500 rpm of the engine and it was observed that the neural networks could be successfully used to recognize the operator's voice under the tractor noise.

Kanali (1997) made prediction of axle loads induced by sugarcane transport vehicles using statistical and neural network models. Inputs to the networks were payloads and empty trailer axle loads and the outputs were the measured trailer and tractor rear axle loads. The results showed that the neural network model achieved 70% prediction as compared with 65% prediction achieved by the statistical model.

Kushwaha and Zhang (1997) studied the soil-tool interacting system and used the radial basis function neural networks to recognize soil-tool response and evaluate the system performance. They used two neural networks, in the first one, the inputs included soil types, five tools, and operating speed and draft was the output. In the second neural networks, they used soil types, tools, soil moisture, depth, and speed as inputs and the outputs were draft, specific energy, and overall energy efficiency. The overall results showed that, the neural networks gave a good prediction of tool response to the system inputs.

Other potential applications for neural networks have also been discussed by researchers (Muttiah and Engel, 1991; Bolte, 1989; Zhuang and Engel, 1990; Verdenius et al. 1997; Yang et al. 1996; Moshou et al. 1997 and Zaidi et al. 1999).

The objective of this paper is to apply the Mulitlayer Preceptron (MLP) neural networks to predict specific draft for tillage implements relating to varying initial soil conditions, splowing depth, and forward operating speed.

Materials and methods

Tillage experiments

A set of primary tillage implements comprising chisel plow, an offset disk harrow, a moldboard plow, and a disk plow were used over a wide range of forward speed and plowing depths. Implement specifications are given in Table (1). Al-Suhaibani and Al-Janobi (1997) have performed a number of field experiments of tillage operation using those implements at various plowing depth and forward operating speed. The experiments were conducted on sandy loam soil in two fields with different initial conditions of moisture content and cone index. The characteristics of tested field are given in Table (2).

Table (1): Specifications of tillage implements used.

Tillage implement	Symbol	Width* ,m	Specifications
Chisel plow	P1	2.1	Heavy duty type capable of accommodating 13 shanks arranged in two rows. 355 mm between shanks in each row and 450 mm between rows. Massey Ferguson (Denmark), model MF 38. Serial No. L4078. Width of shank 70 mm and shank stem angle 55°.
Moldboard plow	P2	1.15	General purpose type. Three bodies in the frame each of width 360 mm. Overum-S (Sweden), model 7073331.
Offset disk harrow	P3	1.8	Thirty six disks each of 510 mm diameter, 18 each in two rows, inclined to the direction of travel, with 210 mm between disks in each row. Massey Ferguson (Denmark), model MF 38. Serial No. L4082.
Disk plow	P4	1.115	Three disks each of 660 mm diameter with tilt angle of 22°, disk angle of 45° and 600 mm between disks. EBRO (Spain), model ADE 300.

* actual width.

Table (2): Soil characteristics of the tested fields.

Test fields	Symbol	Sand	Silt	Clay	Moisture content*	Cone index*
		%	%	%	%, d.b	kPa
Field 1	F1	55	27	18	8.3-13.4	1204-2160
Field 2	F2	79	11	10	7.3-10.4	480-1278

* at depth of 70-210 mm.

Neural network architectures

The NeuroSolution software version 3.0 from NeuroDimension, Inc. was used for the neural network analysis. This software provides the user with an easy to use system to organize and process the data and gives the user the choice to select from several network architectures. Multilayer Perceptron (MLP) with the error backpropagation (BP) learning algorithm was used in this study. Demuth and Beale (1998) provide the complete description of MLP and BP.

Using the data provided by Al-Suhaibani and Al-Janobi (1997) and the binary coding, each input parameter had only two distinct values: 0 and 1 for tillage implements and two fields, whereas plowing depth and forward operating speed had numeric values.

The input processing elements in neural networks were F1, F2, P1, P2, P3, P4, plowing depth, and forward operating speed and the output was specific draft. The architecture of the neural network employed is shown in Fig. (1).

The hidden and output layers have sigmoid transfer functions in neural networks model. The learning rule was momentum with 0.9 and step size 1.0. The number of hidden layers and the number of nodes in each layer were adjusted by a trial and error approach to obtain the optimum network.

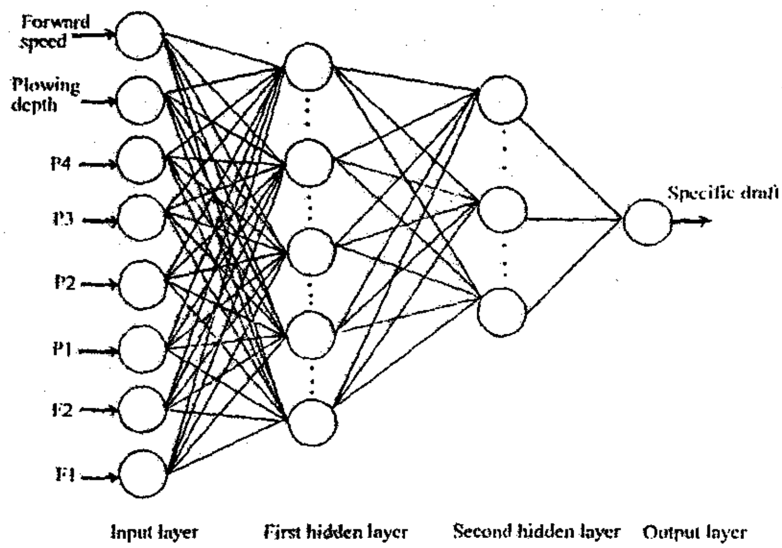

Fig. (1): The architecture of the neural networks.

The optimum solution was decided based on minimizing the difference between the neural networks and the desired outputs. The mean squared error (MSE) and linear correlation coefficient (r) were used for the determination of neural network performance. As the networks learn, its MSE value decreases, and the closer the value is to zero the better the convergence. The mean squared error (MSE) for all input patterns is:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(x_i - y_i)^2 \qquad (1)$$

where:

x_i = measured specific draft , kN/m .

y_i = predicted specific draft by neural network , kN/m

n = total number of patterns.

Results and discussion

The optimal values of neural network parameters such as number of hidden layers and number of nodes in each hidden layer needed to be determined. The data was separated into two groups. A total of 59 cases which is about two-third of the data was set as training data and the rest for testing. Several neural networks model were trained with various design including number of hidden layers and number of nodes in each hidden layer. The selection of the optimum model was based on minimizing the difference between the neural network results and the desired output. The best model in this study was a neural network consisted of two hidden layers with 24 nodes in the first hidden layer and 12 nodes in the second layer.

The MSE was decreasing with increasing of learning iteration (epoch). The best results were achieved at 65000 training runs, which gave minimum MSE equals to 0.0004 during training process. Fig. (2) shows the error curve for training process. After the training process preformed, the neural network was tested and the predicted specific draft from neural network was compared with measured values and error analysis performed. The MSE between measured and predicted specific draft was 0.1445 and the linear correlation coefficient was 0.987. The higher correlation coefficient indicates that the predicted specific draft by neural network with experimental values is excellent. Fig. (3) shows the variation of measured and predicted specific draft of tillage implements for different data points. The relatively lower correlation was observed and this is probably due to the slightly higher experimental variations found. So, the neural network predicted specific draft well.

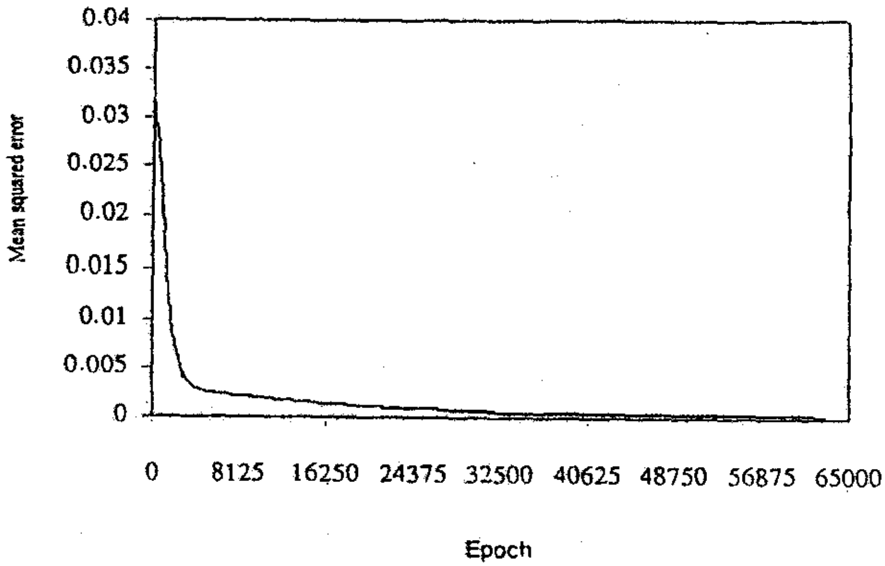

Fig. (2): Error curve for training, showing learning runs (epochs) plotted against mean squared error.

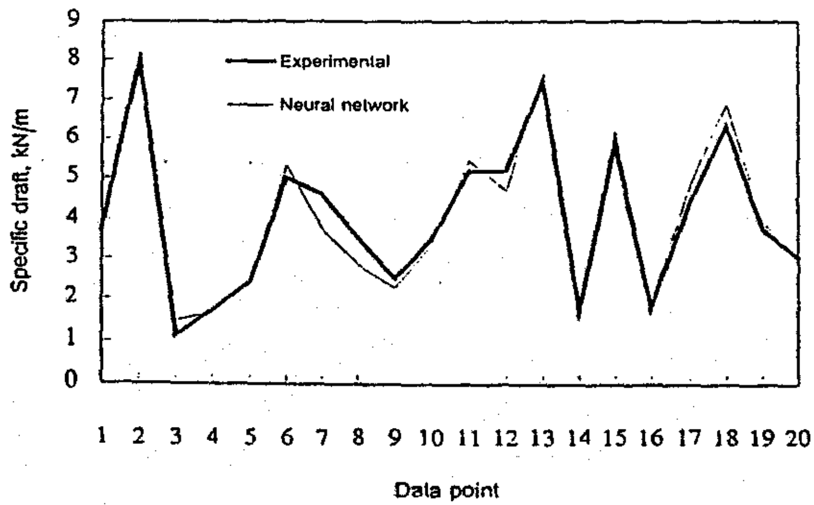

Fig. (3): Relationship between experimental and predicted specific draft.

Conclusion

In neural networks modeling applications, the number of hidden layers, the number of neurons in the hidden layer, and learning iterations need to be optimized before using the neural networks. In this study, a Multilayer Perceptron with error backpropagation learning algorithm was used to construct neural network model to predict the specific draft (kN/m) of four different tillage implements from the field data. The neural networks were trained and tested with different sites, tillage implements, plowing depths, and forward operating speeds as inputs and the measured specific draft as output. The neural network model consisted of two hidden layers with 24 nodes in the first hidden layer and 12 nodes in the second.

The hidden and output layers have sigmoid transfer functions in neural network model and the output layer transfer function was sigmoid and the learning rule was momentum with 0.9 and step size 1.0. The best results during training process were achieved at 65000 training runs that gave minimum mean squared error equals to 0.0004. The proposed neural network model, by testing, indicated that there is a small variation of measured and predicted data with linear correlation coefficient equals to 0.987 and mean squared error between experimental and predicted specific draft equals to 0.1445.

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الملخص العربي

التنبؤ بالشد النوعي لمحاريث مختلفة باستخدام الشبكات العصبية

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يهدف هذا البحث إلى التنبؤ بالشد النوعي (كيلو نيوتن/متر من عرض المحراث) لآلات مختلفة لتمهيد مرقد البذرة باستخدام الشبكات العصبية (Neural networks). حيث استخدمت طريقة بيرسبترون ذات التغذية المتعددة (Multilayer Perceptron) وطريقة التعليم الخلفية (Backpropagation) لبناء وتدريب واختبار هذه الشبكة العصبية . نفذ عدد من التجارب بهذه الآلات في حقلين مختلفين من ناحية المحتوى الرطوبي، دليل مخروط التربة ومكوناته من نسب الرمل والطين والسلت وتم حساب الشد النوعي عند سرعات أمامية وأعماق حرث مختلفة.

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تكونت الشبكة العصبية من أربعة طبقات واحدة للمدخلات، اثنتين مختفيتين وواحدة للمخرجات. شملت طبقة المدخلات حقلين مختلفين أجريت فيهما التجارب، أربعة أنواع من آلات تمهيد مرقد البذرة، عمق الحرث، وأخيراً السرعة الأمامية. واحتوت الطبقة المختفية الأولى على ٢٤ عنصراً بينما احتوت الطبقة المختفية الثانية على ١٢ عنصراً أما طبقة المخرجات فشملت الشد النوعي لآلات تمهيد مرقد البذرة. استخدم نظام الترميز ٠ ، ١ لحقلي التجارب وأنواع آلات تمهيد مرقد البذرة . تم تدريب الشبكة عند معدل تعليم قدره ٠,٩ بخطوة مقدارها ١,٠ باستخدام ٦٥٠٠٠ مكررة وتم استخدام متوسط مربع الخطأ (MSE) ومعامل الارتباط الخطي (r) بين قيم الشد النوعي المقاسة والقيم المتنبأ بها للدلالة على أداء الشبكة العصبية المقترحة. بينت النتائج أن الشبكة العصبية المقترحة أعطت أقل متوسط مربع للخطأ (MSE) وقدره ٠,٠٠٠٤ أثناء عملية التدريب مما يدل على أن الشبكة العصبية المقترحة قد تم تدريبها بشكل جيد.

عند اختبار الشبكة العصبية المقترحة كانت قيم معامل الارتباط الخطي (r) ومتوسط مربع الخطأ بين قيم الشد النوعي المقاسة والمتنبأ بها باستخدام الشبكات العصبية هي ٠,٩٨٧ و ٠,١٤٤٥ على الترتيب. هذه النتائج توضح أنه يمكن التنبؤ بقيم الشد النوعي (كيلو نيوتن/متر من عرض المحراث) لأنواع مختلفة من آلات تمهيد مرقد البذرة، محراث حفار، محراث قلاب مطرحي، محراث قلاب قرصي و مشط قرصي باستخدام الشبكات العصبية بطريقة صحيحة وذلك تحت ظروف مختلفة من التشغيل مثل السرعة الأمامية وعمق الحرث وذلك عند إجراء الحراثة على أنواع مختلفة من الترب الزراعية.