APPLICATION OF A NEURAL NETWORK TO DYNAMIC DRAFT MODEL

Yeong Soo Choi, Kyou Seung Lee, Won Yeop Park
Research Associate Professor Research Assistant
Department of Bio-mechatronic Engineering
Sung Kyun Kwan University, KOREA

ABSTRACT

This study was conducted to predict the drafts of various tillage tools with a model tool and a neural network. Drafts of tillage tools were measured and a time lagged recurrent neural network was developed. The neural network had a structure to predict dynamic draft, having a function of one step ahead prediction. The results showed the model tool draft had linear relations with high coefficient of determinations to the drafts of the tillage tools. Also, the drafts of tillage tools were successfully predicted by the developed neural network.

Key words : Neural network, Draft, Model tool, Prediction.

INTRODUCTION

One of the major objectives of tillage is to provide optimum environmental conditions for plant grows. More than 2 million hectares are estimated to be stirred or turned each year in Korea. To plow this soil once requires 8~12 million liters of diesel or gasoline fuel. It is apparent that the improvement of tillage tool design can enable to reduce mechanical energy and labor requirements and to optimize the soil conditions.

There has been a marked upsurge in tillage tool design of research since about 1950. No reliable attempt for tillage tool design has been made to describe soil failure patterns or the mechanisms of soil failure because soil has ununiformity and different characteristic according to fields. Most studies on the tillage tool design have focused mainly on reporting experimental findings under certain conditions with specific parameters.

The reactions of soils to forces applied by tillage tools are affected by compression resistance, shear resistance, adhesion, and frictional resistance. These are all dynamic properties changed through movement of the soil. In analyzing draft, mean value has been usually used to represent the draft measured over an entire experimental range. Dynamic draft model can be used to analyze mechanics of tillage and to design optimal tillage tool.

Shearing force and cone index are widely used to represent physical property of a soil in predicting draft. It is known that soil failure in measuring shearing force and cone index is different from the failures by tillage tools. In order to predict draft closer to actual draft, it is necessary to develop new measuring device whose mechanics of soil failure is similar to the mechanics by tillage tools (Lee, 1996).

The main objective of this study was to develop a neural network for the prediction of tillage tool draft. The neural network can be used to analyze the dynamic draft in designing a model tool for predicting the drafts of tillage tools. Specific subobjectives of this study were: 1) measure drafts of model tool and tillage tools; 2) find relations between model tool draft and tillage tool drafts by linear regression method; 3) develop a neural network for the dynamic prediction of tillage tool drafts.

MATERIALS AND METHODS

Tillage tools

Tillage tools used in this study were a moldboard plow, a janggi, and a model tool. Table 1 gives the specifications of the moldboard plow and the janggi. Figure 1 shows the view of the model tool.

Soil bin

Measurement of tillage tool drafts were carried out in the soil bin installed in the Soil-Machine System Lab at the Bio-mechatronic engineering department of Sung Kyun Kwan University. This soil bin is 1m wide, 0.7m deep, and 12m long. A steel cable wound on a motor-driven pulley pulled a tool carrier and a soil processing carriage supported by wheels on the tracks which were mounted on the top of the walls of the soil bin. The tool carrier was designed so that tillage tools could be assembled in it according to the hitch types of tillage tools. Test soil was a sandy loam. Table 2 gives physical properties of the test soil.

Data acquisition system

The main components of data acquisition system were a load cell, a rotary encoder, a strain amplifier, and a PC(IBM PC compatible, 100MHz Pentium processor) with PC Lab card. The load cell with a nominal rating of 5kN(kyowa Co.) could measure tensile or compressive force. The rotary encoder(E6A-CS100) was used to measure the tillage speed and generates 100 pulses/revolution. The strain amplifier(DPM-311A, kyowa Co.) used to amplify the signal generated from the load cell has the maximum gain of $100 \times 100 \mu\varepsilon$, and its output voltage is $\pm$ 5V. The PC Lab card had an A/D converter and a counter for counting pluses generated from the rotary encoder. The A/D converter had a resolution of 12 bit, and its A/D conversion time was $9 \mu s$.

Draft measurement

Before the run of each experiment, the following preparations were made in an attempt to ensure that the same soil conditions were maintained in all tests: the soil was pulverized, stirred, and leveled by the soil processing carriage. The soil processing carriage had a rotary tiller, a leveler, and a roller. First preparation was done to pulverized the soil with the rotary tiller at the depth of 20cm, approximately equal to the maximum tillage depth in fields. Second preparation was done to level the soil with the leveler. Last, the soil was compacted twice with the roller. Order and the number of times for the preparations were kept to be same in all experiments.

Drafts were measured at three levels of tillage depth 8, 12, and 16cm. In all tillage depths, tillage speed, replications, and sampling time were 0.49m/s, three, and 0.14sec, respectively.

Neural network structure

In order to develop the dynamic draft model, a time lagged recurrent neural network(TLRNN) was constructed so that the model can process time series data. The TLRNN developed in this study is identical to a feedforward neural network(FFN) in structure, but is trained by using the backpropagation through time algorithm as stated by Werbos, et al (1992). Backpropagation through time modifies the conventional backpropagation algorithm by viewing a network's recall of a time sequence as a cascaded neural network where each cascade step represents one time step in the time series. This results in backpropagation through a network of thousands of layers. Conventional backpropagation works by minimizing an error, $e(t)$ between a predictive value and an actual value at each time step t. Backpropagation through time modifies the parameters to minimize the function

$$E(t) = \sum_{\tau=0}^{\tau=t} e^2(t) \tag{1}$$

The function $E(t)$ represents a total error over considered time sequence. Since the TLRNN is identical to the FFN in structure, the FFN was used as a starting point for training the TLRNN. This greatly reduced training time to convergence.

Figure 2 shows the construction of TLRNN. The procedure for implementing TLRNN was as follows:

1. A starting with an initial weight set and initializing the network with real values of inputs (if necessary) and output $y(t)$, predicted $y(t+1)$, used the predicted value to predict $y(t+2)$, and so on to the end of the time sequence. This prediction is called one step ahead prediction and is expressed as follows:

$$y(t+1)=f\ [y(t), y(t-1), y(t-2), \ldots, y(t-n)] \tag{2}$$

Where, n is the number of previous values of y.

2. At each time step, The weight updates were calculated based on backpropagation algorithm.
3. The weights were updated by averaging over time all the weight updates and using a very small learning rate.

Training of the neural network

The initial weight values were selected randomly and determined by regular backpropagation at initial stage of the training. Then the weights of the neural network were modified with the way of backpropagation through time.

To speed training, several modifications were made to the network as suggested by Fahlman(1990). First, in order to eliminate "flat spots" that occur during training because of a small derivative value for the sigmoid functions, a constant offset of 0.1 was added to the calculation of the derivative. This modification has been shown to cut learning time almost in half. Second, a tangent function was performed on the mean squared at the output before being backpropagated. This improved training speed by put more emphasis on training patterns with large errors over small errors. Last, the weights to the network were averaged over all training patterns (batch learning). All inputs and outputs were scaled to between 0.1 and 0.9 before training.

RESULTS AND DISCUSSION

Drafts of tillage tools

Many researchers have reported that periodical soil failure and the peak of draft appear as a tillage tool advances (Kepner, 1972. Osman, 1964), and the draft varies within the range of $\pm 30 \sim 50\%$ for its mean value.

The drafts measured at the tillage depth, 12cm and the tillage speed of 0.49m/s were plotted in Figure 3 in order to represent the change in the tillage tool drafts. The figure shows the janggi draft had similar peaks to the moldboard plow draft; however, the model tool draft was different from them. This result indicated that soil failure by the model tool was different from the failures by the moldboard plow and the janggi. It was considered the difference was caused from the shapes of the tools. Comparing to the moldboard plow and the janggi, the model tool was symmetric in shape and had a narrow tillage width. It was considered that the soil failure caused by the model tool resulted not from the compression and the shear but from the cutting of soil.

Statistical regression model of model tool draft to tillage tool drafts

Linear regression models were derived to find relations between the tillage tool drafts and the model tool draft. Drafts were measured at three experimental levels of tillage depth 8cm, 12cm, and 16cm. The tillage speed was 0.49m/s at all depths. The values used to find the regression models were the mean values at each experimental level. Table 3 shows all drafts of tillage tools had linear relations with high R^2 to the model tool draft. All the results showed the mean drafts of tillage tools could be predicted by the mean draft of the model tool.

Dynamic draft model with the neural network

The neural network was trained with the drafts measured at tillage speed 12cm. This depth was almost same with the practical tillage depth in Korea. The data measured for three replications was randomly split up into the three groups, keeping sequences of time in order to evaluate continuous prediction: one for parameter modification, one for termination of training, and one for determining the performance of the neural network.

Mean squared error (MSE) was used to evaluate the performance of the trained neural network.

Prediction of moldboard plow draft : The number of nodes in input layer determines how many inputs are necessary for the best draft prediction, explained in equation (2). Optimal number of nodes helps to understand the frequency of the draft. The number of nodes in the hidden layer determines only a performance of the network.

In order to find the effect of the number of nodes in input layer and hidden layer, the performance of the network was evaluated based on MSE after the same training iteration. Table 4 gives the results after 16,000 iterations for the moldboard plow draft. As shown in the table, minimum MSE appeared when the number of nodes in the input layer and the hidden layer were 4 and 9, respectively. Further training proceeded with the selected structure until MSE reached at an acceptable value.

Figure 4 shows the result of one step ahead prediction by the trained network. MSE after 56,000 iterations was 0.0108. The change of draft predicted by the network was very similar to that of the measured draft. This result indicated it was possible to model the dynamic draft of the moldboard plow by the TLRNN. The frequency of the measured draft was not corresponding to the number of furrows.

In moldboard plow draft, mean values of the measured draft and the predicted draft were 32.3Kgf and 32.4Kgf, respectively.

Prediction of janggi draft : Table gives the results after 5,000 iterations for the selection of the number of nodes in case of the janggi draft. Minimum MSE appeared when the number of nodes in the input layer and the hidden layer were 7 and 12, respectively. The network was well trained when the number of node was more than the number of the moldboard plow model in the input layer . It was observed from this result that the period of soil failure by the janggi was longer than the period by the moldboard plow.

Figure 5 shows the result of one step ahead prediction after 80,000 iterations. Mean values of the measured draft and the predicted draft were 32.3Kgf and 32.4Kgf, respectively. Also, MSE after training was 0.0102.

Prediction of model tool draft : Table 6 gives the results after 10,000 iterations for the selection of the number of nodes. The network with 4 and 9 nodes in the input layer and the hidden layer was chosen. The network with 8 nodes in the input layer had lower MSE than the selected network; however, it was thought 8 nodes could not reflect real period of the draft. It was observed that the period of soil failure by the model tool was similar to the period by the janggi.

Figure 6 shows the result of one step ahead prediction after 35,000 iterations. Mean values of the measured draft and the predicted draft were 33.6Kgf and 33.9Kgf, respectively. Final MSE was 0.01.

CONCLUSIONS

Dynamic draft model is necessary to analyze mechanics of tillage and to design optimal tillage tool. A model tool was designed to predict tillage tool draft. Linear regression models of the model tool draft to the tillage tool drafts were derived. Also, a neural network was developed to predict the dynamic drafts of the model tool and tillage tools.

All drafts of tillage tools had linear relations with high R^2 to the model tool draft, which indicated the mean drafts of tillage tools could be predicted by the mean draft of the model tool. The dynamic drafts of tillage tools such as the moldboard plow, the janggi, and the model tool were acceptively modeled by the developed neural network (TLRNN).

FUTURE WORK

The ultimate goal of this study is to apply a neural network to analysis of the effect of tillage tool on soil failure. Authors are developing the neural network model of the model tool draft which can predict tillage tool drafts. Also, new data has been being measured that will allow an analysis of the frequency of soil failure.

REFERENCES

1. Fahlman, S. 1988. Faster-learning variations on back-propagation: an empirical study. *Proceedings of the 1988 Connectionist Models Summer School.* New York, NY: Morgan Kaufmann.
2. Kepner, R. A., R. Bainer., and E. L. Barger. 1972. Principles of farm machinery. *AVI Publishing Co.*
3. Lee, K.S., S.C. Cho, W.Y. Park, and B.G. Kwon. 1996. Draft Prediction of tillage Implement by Model Tool. *Proceedings of the KSAM '96 Conference,* pp.203-208.
4. Osman, M.S. 1964. The Mechanics of soil cutting blades. *Journal of Agricultural Engineering Research.* 9(4):313-328.
5. Werbos, P., T. McAvoy and T. Su. 1992. Neural networks, system identification, and control in the chemical process industries. *Handbook of Intelligent Control: Neural, Fuzzy and Adaptive Approach,* 1992 edition. D. White and D. Sofge, editors. New York, NY: Multiscience Press, Inc.

Table 1. Specifications of the tested tillage tools(Janggi and Plow)

Implement	Max. shear lift angle (degree)	Setting angle shear (degree)	Setting angle wing (degree)	Width of shear (cm)	Weight (kg)	Moldboard type
Janggi	51.3	40.9	63.0	23.4	17.5	5-fork
Moldboard plow	21.3	42.2	55.3	15.5	7.5	Cylindrical

Table 2. Physical properties of test soil

Composition Sand (%)	Silt (%)	Clay (%)	Texture	Internal friction angle (degree)	Cohesion (Kg_f/cm^2)	Adhesion (Kg_f/cm^2)
54.4	36.8	8.8	Sandy loam	57.07	8.41	3.791

Soil-metal friction angle (degree)	Moisture content (%, d.b.)	Cone index (Kg_f/cm^2)	Bulk density (g/cm^3)
41.715	11.719	1.094	1.351

Table 3. Relations between model tool and tillage tools

Regression equation	R^2
$Y_{JA} = 1.152 \times X_M + 13.965$	0.9742
$Y_{PL} = 0.936 \times X_M + 12.830$	0.9598

Y_{JA} : Janggi draft
Y_{PL} : moldboard plow draft
X_M : model tool draft

Table 4. Effect of the number of nodes on the network performance (moldboard plow)

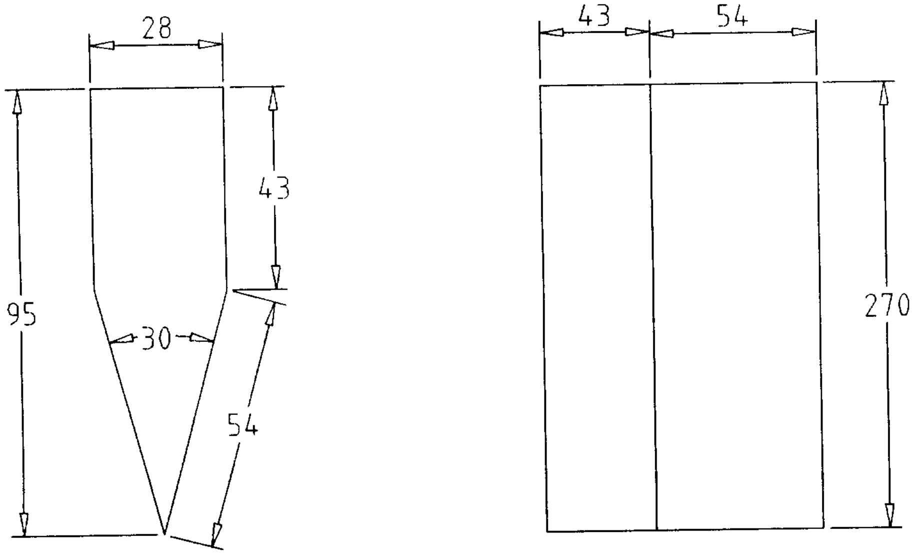
	Case 1	Case 2	Case 3
Node no. in input layer	4	6	6
Node no. in hidden layer	9	8	12
Learning rate	0.1	0.1	0.1
MSE	0.0155	0.0193	0.0207

Table 5. Effect of the number of nodes on the network performance (Janggi)

	Case 1	Case 2	Case 3
Node no. in input layer	6	4	7
Node no. in hidden layer	12	9	12
Learning rate	0.02	0.02	0.15
MSE	0.0302	0.0321	0.0287

Table 6. Effect of the number of nodes on the network performance (Model tool)

	Case 1	Case 2	Case 3
Node no. in input layer	4	6	8
Node no. in hidden layer	9	12	12
Learning rate	0.1	0.05	0.05
MSE	0.0145	0.0134	0.0130



(a) Top view (b) Side view

Figure 1. View of model tool.

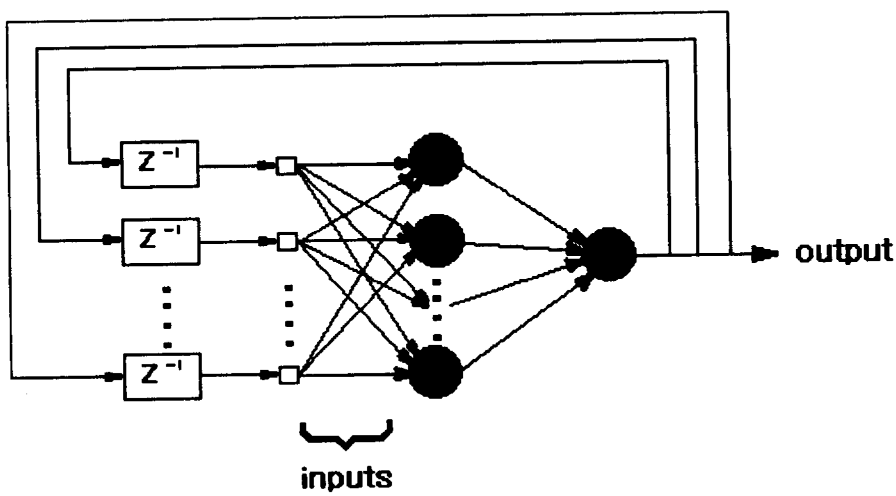


Figure 2. Construction of time lagged recurrent neural network.

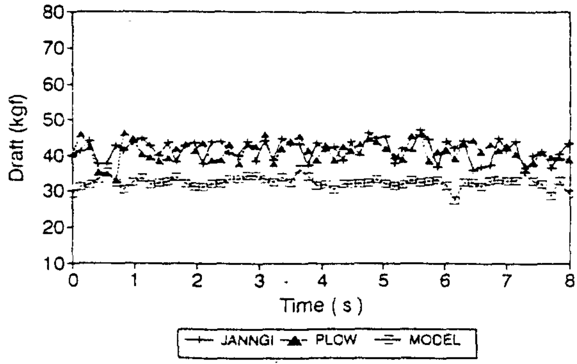


Figure 3. Changes of tillage tool drafts to time.

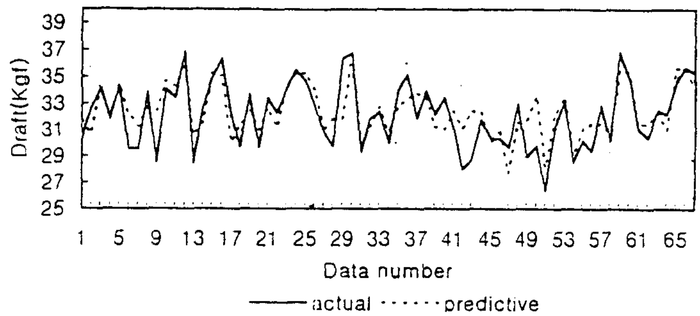


Figure 4. Draft prediction of the neural network (moldboard plow).

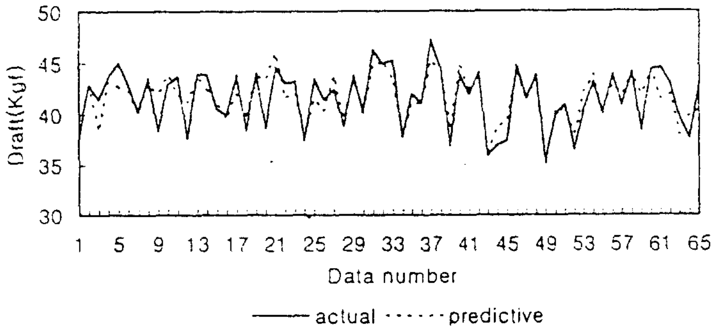


Figure 5. Draft prediction of the neural network (janggi).

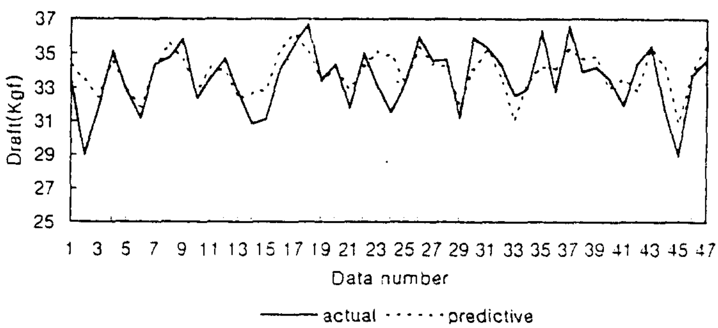


Figure 6. Draft prediction of the neural network (model tool).