Predicting the Productions of Napier-grass Based on Back-Propagation Neural Network

Chih-Yung Tsai*

Yih-Chearing Shiue**

Abstract

Predictions of the productions of Napier-grass （Penniseturn purprueum） not only help people understand the productivity of Napier-grass but also play an important role in maintaining a balance between supply and demand. Moreover, because Napier-grass is a perennial crop, many factors may cause a production surplus or a shortage in production. Therefore, predictions of the productions of Napier-grass can help farmers understand the current production and cost of this crop, and farmers can decide whether to stop planting this crop according to the information obtained in a manner mentioned.

The Back-Propagation neural network （BPN） is useful in prediction and classification. This study adopted the neural network to estimate the productions of Napier-grass and established model of production estimate according to weather factors and status factors. After the experimental results, the study found that the Back-Propagation neural network is a better tool for predicting productions.

Keywords: Back-Propagation Neural Network, Production Prediction, Napier-grass

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* Lecturer, Department of Information Management, Tzu-Hui Institute of Technology

** Professor, Department of Information Management, National Central University

倒傳遞類神經網路為基礎之狼尾草產量預測

蔡 智 勇*
薛 義 誠**

摘 要

狼尾草產量預測的主要功能，除了瞭解狼尾草的生產效能之外，對於產銷供需間是否獲得良好之契合，有其顯著的重要性。又因為狼尾草是屬於多年生作物，往往因各種因素造成生產過剩或者生產不足。因此，狼尾草的產量預測將能夠提供農民瞭解目前狼尾草的生產量、成本，更能提供是否停止生產的參考依據。

倒傳遞類神經網路對於預測、分類的應用問題，有不錯的效果。本研究試著採用類神經網路於狼尾草產量的預估上，並且以氣象因素與性狀因素，建立產量估算的模式。經由實驗結果，我們發現倒傳遞類神經用在產量預測上為較佳的預測工具。

關鍵詞：倒傳遞類神經網路、產量預測、狼尾草

* 慈惠醫護專校 資訊管理科講師

**國立中央大學 資訊管理系教授

I、Introduction

Napier-grass is an important grazing plant in Taiwan, accounting for about one-third of the land for cultivating grazing plants. The plantation is concentrated in Tainan, Pingtung and Hualien. Napier-grass is a permanent erect bunched tropical grazing plant of the grass family; the plant is tall and looks like slender sugar cane. It grows well in hot and raining regions, especially fast in spring and summer. Therefore, it is usually planted from March to September. Napier-grass makes up most of the grazing grass in Taiwan, and thus it is an important work to cultivate this plant and nourish its seeds （Lu, 2000；Xu, 1999）.

Predictions of the productions of Napier-grass can not only help farmers understand the productivity of Napier-grass but also play an important role in maintaining a balance between supply and demand. If there is no relevant planning before the plant is cultivated, it is very likely to experience excessive or insufficient productions, as a result of many factors, for Napier-grass is a permanent plant. Therefore, predictions of the productions of Napier-grass can help farmers understand the current production and cost of this crop, and farmers can decide whether to stop planting this crop according to the information obtained in this. Moreover, the information can provide a valuable reference for agricultural authorities in the government to formulate long-term planning.

For the present there is no overwhelming dominant model for predicting the productions of Napier-grass. Usually one can get a good predict method by giving “appropriate” linear combined weights to each predict model （Ma & El-Keib, 1994）. But there is no standard method to determine appropriate linear combined weights. Literature indicates that the neural network has significant effects when it used to predict and classify （Ye, 1991；Zhou, 1995；Fujita, 1994）.

Primarily because the neural network is inherited with modules of analysis, one can adjust the complexity of the modules to deal with the complicated historical record of the productions of Napier-grass, requiring no assumption. What is needed is to input the historical record of the productions of Napier-grass into the modules of the neural network. Therefore, this study would use the neural network that is not affected by parameters to predict the needs. The productions of Napier-grass predicted by using the neural work would be more accurate than those predicted by using traditional models of predict analysis.

II、Material

1、Data of Napier-grass

This study planned to compare and experiment with the strains of Napier-grass that were planted in the Pingtung region by Heng Tsun Station of Taiwan Livestock Research Institute （Lu, 2000；Xu, 1999）. Data on a total of eight strains were collected, each of which was assigned a number, 7201, 7214, 7259, 7262, 7301,7137, 8318 and A146 respectively. They were planted on July 3, 1987, and the last batch was harvested on July 14, 1994.The experimentation lasted for seven years. The crop was harvested five or six times every year, and the total number of harvests was 39. Each production was recorded in fresh weight and dried weight.

2、Data on Weather

The data on weather for this study included four items: accumulated temperature, relative humidity, actual exposure to sunlight, and precipitation. There were observation values from 1 through 39 on the weather data.

3、Data on Status

The data on status used in this study include five items: breed, the number of plants of the cultivation, the duration of growth, the age of plants cultivated, and the number of leaf of plants, and the values of observation of 39 cultivations were obtained.

III、Predict Model Estimated

This model used the related information obtained from the experimentations with the strains of Napier-grass that were cultivated in the Pingtung region by Heng Tsun Station of Taiwan Livestock Research Institute and as examples to predict the productions of fresh weight and dried weight with Napier-grass.

1、Selection and definition of input and output data

（1）Sample Variables

In the data used in experimenting with the strains of Napier-grass, the factors that affect productions can be divided into the weather factors and the status factors. Therefore, as far as the predict models were concerned, this study used these two main factors as the input variables, while the output variables included the predicted productions of Napier-grass in terms of fresh weight and dry weight.

（2）Ratio of Sampling Examples

This study obtained data primarily from Heng Tsun Station, and there were eight strains in the data. Of each strain, the status factors, fresh weights, and dried weights of 39 cultivations were recorded. There were four duplicate factors in the observation value of each cultivation. Three duplicate factors were randomly selected, according to the ratio of training to testing samples, from these four observation values as the training examples, and the remaining duplicate factor was used as the testing example.

（3）Sample Variables Pre-process

According to literature, the BPN can accept any values to input variables. If the variables range were dispersedness, the learning effecting and prediction accuracy were decreasing（Sietsma, 1987. Therefore, the variables range be able to normalization. It can adopt logarit）hm normalization. These are some variables need to preprocessing in Table 1.

Table 1 Summary of sample variable preprocessing

Variable	Variables range of before process	Preprocessing	Variables range of after process
Breed of Napier-grass	7301	Encoding	7301：0 0 0
	7137		7137：0 0 1
	7201		7201：0 1 0
	7259		7259：0 1 1
	7262		7262：1 0 0
	7214		7214：1 0 1
	8318		8318：1 1 0
	A146		A146：1 1 1
Accumulated Temperature	[428.3, 3296.2]	Log Function	[2.632, 3.518]
Relative Humidity	[602, 8908]	Log Function	[2.78, 3.9498]
Actual Exposure to Sunlight	[55.9, 598.1]	Log Function	[1.7474, 2.7777]
Precipitation.	[7.5, 1503.5]	Log Function	[0.875, 3.1771]

（4）Adjustment of Model Parameters

Avoid the situation that the changes of function are likely saturated in the very beginning of training（Neural Ware, 1996）. The numerical optimization formula:

$$Xnew=\frac{(Xold-X\min)}{(X\max-X\min)}(D\max-D\min)+D\min$$

Xmin the minimum value of static variable

Xmax:the maximum value of static variable

Dmin: the set minimum value

Dmax: the set maximum value

Therefore, this study projected all the values of input variables into the range of [0.2, 0.8], and transferred the output variables: they were projected into the range of [0.2, 0.8].

（5）Network Framework

By using the formula: the number of processed units in hidden layers = （the number of processed units of input * the number of processed units of output） / 2, the study estimated the number of processed units in hidden layers to be 11.

For the present, there is no theory that can help decide the number of hidden layers and processing units. In order to find the optimal network, several configurations were tried in which the number of hidden layer varied from ten to twelve. According to experiment result, this research chose two hidden layers having ten neurons.

Table 2 Convergence of Training in Different Network Configuration

Hidden Layer	Processes Units	Mean Square Error	Correlation Fresh Weight	Correlation Dry Weight
1	10	0.01168	0.74367	0.63528
1	11	0.00983	0.81691	0.67341
1	12	0.01077	0.81529	0.66876
2	**10**	**0.00938**	**0.82930**	**0.71233**
2	11	0.01163	0.77344	0.62625
2	12	0.01168	0.74367	0.63528

（6）Transfer Function

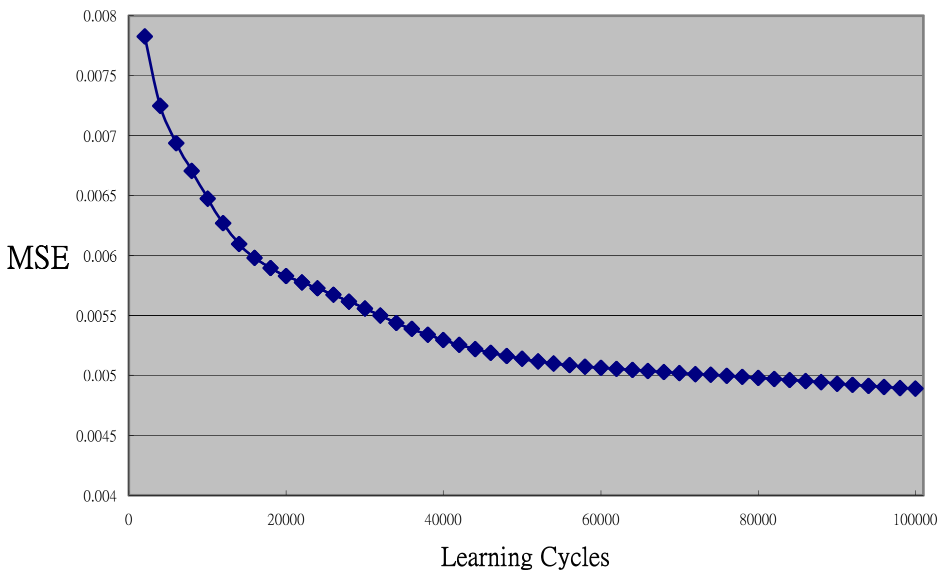
The widely used non-linear transformation function in back propagation network is Sigmoid Function （Sietsma & Dow, 1987）. The Sigmoid Function: when X value approximates a positive infinitely large number, the function value approximates 0. A transfer function of the sigmoid type was used in all cases.

2、Training and Testing of the Neural Network

This study adopted the Back-Propagation Neural network （BPN）. In training, an Mean Square Error （MSE） was recorded for every 1000 cycles. A decrease of the MSE indicates that the neural network is contracting; it is learning and figuring out linear / nonlinear classification models, which will eventually be recorded in every weight （Setiono,1997；Taukimoto, 2000）. Ossified learning readily occurs when the neural network is used in training, which is caused by excessive learning. Too much demand on accuracy of network training can usually make it impossible to identify external testing samples and to classify, leading to low accuracy of predictions （Anderson & Mayrhauser & Tom, 1996）. This study used the trial error method to figure out the optimal numbers of training to achieve the optimal profitability of network predictions.

From a alternative diagram of convergence for 100,000 training loops in training examples, MSE for training examples has converged to approach considerably about 40,000 training loops with the value about 0.0053; with 60,000 training loops, MSE for training examples has converged below 0.005. Retraining can’t greatly reduce MSE for training examples. Under consideration of learning time and error quality, this model selects 60,000 training loops so as to achieve more ideal convergence.

Figure 1　An Alternative Diagram of Convergence （100,000 times）



3、Test Result

When a network model is established completely and completed the training course, 321 test examples for the connection with network will be input to observe Mean Square Error and Correlation for 321 test examples so as to test an estimated ability of network. Therefore, the test results in this model will be discussed respectively as follow:

（1）Mean Square Error （MSE）

The mean square error is 0.00228 in the test results.

（2）Distribution Diagram

Figures 2 and 3 show points in a diagram are distribute on a diagonal whatever the fresh weight or dry weight. The fresh weight correlation is 0.83 and the dry weight correlation is 0.71.

Figure 2　A Distrubution Diagram of Test Result for Fresh Weight

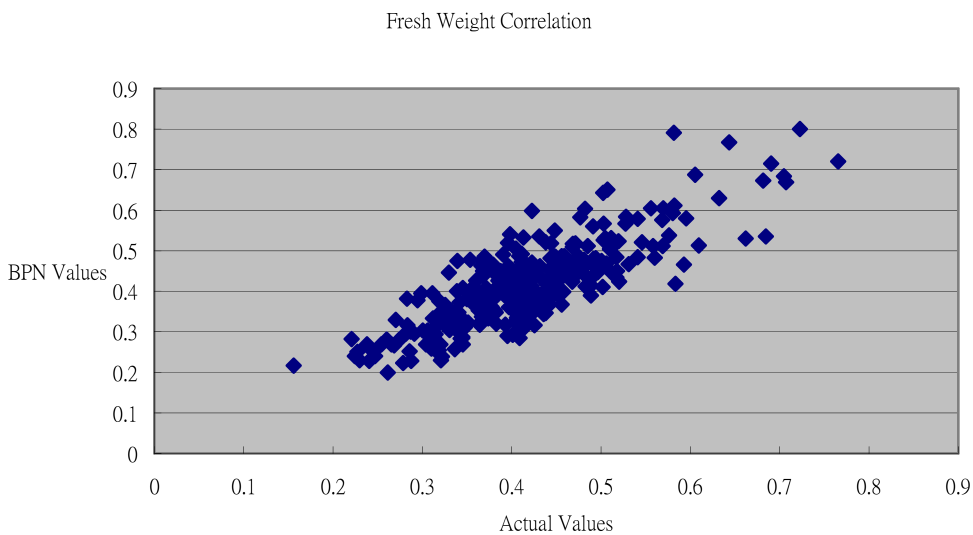
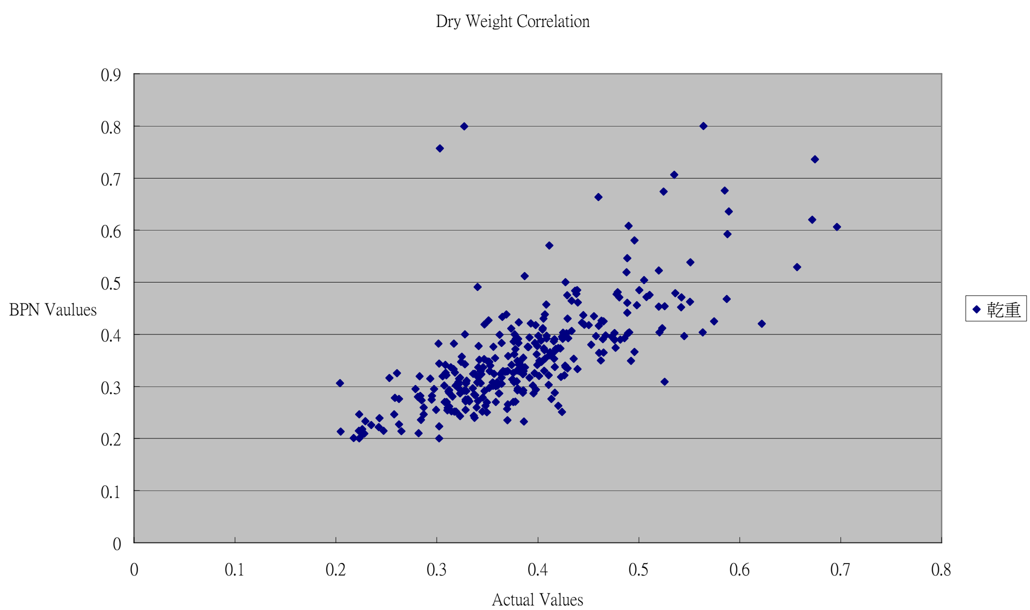


Figure 3　A Distribution Diagram of Test Result for Dry Weight



3、Model Measure

There are two criteria to measure the merit of a predict model for the need of the productions of Napier-grass:（1）accuracy, and（2）consistency（Tridas & Sunder, 1992）.Accuracy refers to the approximation of a prediction of the need for estimated productions to that of a prediction of the need for actual productions. Mean Magnitude of Relative（MRE）and PRED（L） are the indices of measurement. The measurement of consistency is done with CORR.

（1）Mean Magnitude of Relative （MRE）

$$\overline{MRE} = \frac{1}{n} \times \sum_{i=1}^{n} MRE_i \qquad MRE = \left| \frac{(E - \hat{E})}{E} \right|$$

E：actual cases　　$\hat{E}$ ：estimated cases

（2）Prediction at level L （PRED （L））

L represents the acceptable level of error, commonly set at 0.25, indicating the proportion of the cases of which the MRE is below L in all cases. It is represented as:

$$PRED(L) = \frac{K}{N}$$

K: the number of cases of which the MRE<L, N: cases in total.

（3）Correlation（CORR）

Uniformity is used to measure the correlation extent of estimated faults and actual faults, where Correlation is a weighted index. Correlation domain is [-1, 1], whose value more approaching 1 means estimated faults and actual faults are more uniform to present positive correlation.

The level of a model for MRE is less than 0.25 and PRED（0.25） is greater than 0.75 are acceptability（Conte et al, 1986）. We make use of these three weighted indices: MRE, PRED （L） and Correlation to weigh the applicability of this model and compare the results of other model.

312 test examples testing result as shown in Tables 3. The fresh weigh for MRE is 0.1111 and PRED（0.25）is 0.9071 and the correlation is 0.8293. The dry weight for MRE is 0.1609 and PRED （0.25） is 0.7917 and the correlation is 0.7123. These results showed that Back-Propagation network were suitable for predict the productions of Napier-grass.

Table 3　The result of model measure

	MRE	PRED（0.25）	Correlation
Fresh weight	0.1111	90.71%	0.8293
Dry weight	0.1609	79.17%	0.7123

4、Contrast to other models

Lu （2000） predict of the productions of Napier-grass using linear multiple regression. Lu using Napier-grass of samples examples the same as this research. Therefore, compared predicted results with Lu’s model. Table 4 summarizes the prediction results for BPN and Lu’s model. The BPN model prediction result of the productions of Napier-grass greater than Lu’s model.

Table 4　Comparison of Predicted Results

Breed of Napier-grass			Lu	BPN
7301	Fresh weight	MRE	0.8289	0.1179
		PRED（0.25）	0.3333	0.8205
		Correlation	0.2053	0.8464
	Dry weight	MRE	0.6851	0.1771
		PRED（0.25）	0.359	0.6923
		Correlation	0.2797	0.7701

Breed of Napier-grass			Lu	BPN
A146	Fresh weight	MRE	0.3689	0.1182
		PRED（0.25）	0.3846	0.8974
		Correlation	0.3955	0.7308
	Dry weight	MRE	0.5417	0.1622
		PRED（0.25）	0.359	0.8205
		Correlation	0.43	0.6858
7262	Fresh weight	MRE	0.3046	0.0901
		PRED（0.25）	0.5385	0.9744
		Correlation	0.4524	0.8862
	Dry weight	MRE	0.5	0.1566
		PRED（0.25）	0.3846	0.8718
		Correlation	0.2395	0.6227

IV、Conclusion

Many factors may cause a production surplus or a shortage in production due to Napier-grass is a perennial crop. Therefore, predictions of the productions of Napier-grass not only help farmers understand the current production and cost of this crop, but also decide whether to stop planting this crop according to the information obtained in a manner mentioned.

To conform to the principle of swiftness and accuracy, this research predictions of the productions of Napier-grass by taking advantage of the real-time analysis function of Back-Propagation neural network. This research also experimented and compared Lu’s model regression analysis in order to confirm that

Back-Propagation neural network is a good tool in predictions of the productions of Napier-grass.

The experimental results show that the BPN model is suitable to predict the productions of Napier-grass. In terms of prediction of Napier-grass, the BPN model is more accurate than Lu's model. Therefore, when applied to predict the productions of Napier-grass, Back-Propagation neural network will produce considerable benefits.

Next, predict the fresh weight greater than the dry weight in productions of Napier-grass whatever BPN model or Lu's model. The main reason may be that either the weather factors or the status factor can't represent all the factors that affect the dry weight in production of Napier-grass. There may be some potent factors yet to be discovered.

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