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神經網路應用於預測高粱產量

An Application of Artificial Neural Network to Predict Sorghum Yields

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摘 要

利用神經網路的學習能力來預測非線性的物理現象是統計學上的新理論，一個三層（輸入、隱藏、輸出）的神經網路模式被發展來預測高粱的產量。此模式開始於學習輸入（田間土壤水分）及輸出（高粱產量）資料間的關係，並求得其間的係數，學習完成後，僅需輸入資料，便可預測輸出值。嘉南農田水利會學甲試驗站的田間試驗資料被用來測試此模式，結果顯示此模式能準確的學習土壤水分及高粱產量間的關係。然而預測1992年高粱產量的絕對百分比則高至15.64&及低於4.98%。

關鍵詞：神經網路，後勤函數，平均差方。

ABSTRACT

A neural network model (NNM) was developed to model sorghum yields. The model consists of a three-layer learning network with input, hidden and output layers.The back-propagation method was used to conduct the training process to recognize the correspondence between inputs and outputs, where the inputs include weekly soil moisture and outputs are sorghum yields. After finishing the training process, the neural network model can be used to predict sorghum yields with only the input data and calibrated mode weights. The field experiment data, weekly soil moisture and related sorghum yields, with five treatments from 199 0 to 1991, were used for training.Weekly soil moisture data from 1992 were used to predict sorghum yields. The training process is shown to correctly represent the relationship between weekly soil moisture and yields. The absolute error percentage was as high as 15.64% and as low as 4.98%.

Keywords: Neural network, Logistic function, Mean square error.

Introduction

The use of Artificial Neural Networks (ANN) to predict the behavior of nonlinear systems has become an attractive alternative to traditional statistical approaches (Weigend et al. 1990). Many researchers (Das, 1992; Guan, 1991; Uhring, 1992;Cook, 1991; French, 1992; Ranjithan, 1993) have successfully applied ANN to solve problems in different fields.

Normally, irrigation engineers use the relative yield equation recommended by FAO lrrigation and Drainage Paper NO.33 (Doorenbos et al. 1979) to calculate actual crop yields as follows:

$$\frac{Y_a}{Y_P}=1-\sum_{j=1}^{NoStage}[K_{y\,i}\ (1-\frac{ET_a}{ET_P})\ ]$$

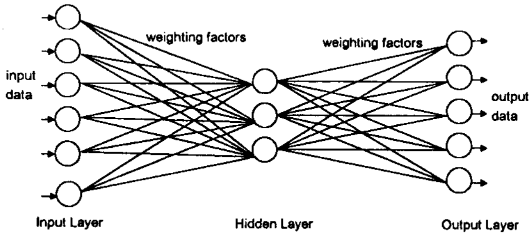
where Y_a is the actual crop yield; Y_p is the potential crop yield; $K_{y\,i}$ is the crop reduction coefficient in each stage; ET_a is the actual evapotranspiration; and ET_p is the potential evapotranspiration. A new approach is applying this equation is in using the patternmatching capability of ANN to decide the crop yields based on real field data. Crop yields is influenced by many factors such as soil moisture, weather, evapotranspiration, salinity, ground water tbale, etc. ; therefore, different types of field data will allow the training process to more precisely represent the real situation in the field. However, weekly soil moisture is the only input data in this study.

The objective of this paper is to demonstrate the ability of using a neural network to predict sorghum yields, and describes the process to establish the neural network model.

Neural Network Theory

The human brain is composed of networks of neurons. A typical neuron receives an order as input, then, the networks of neurous change the weighing factors many times from experience through training data to make the final decision, output. The finally weighing factors can represent the relationship between input and output, and can be used for purposes of prediction.

Backpropagation plays a key role in neural network and it is also the main method for training a neural networks in a number of commercial applications.The process of backpropagation is to find the optimal relationship between input and output by two procedures: mapping and learning (Smith, 1993). The mapping procedure processes inputs to outputs. On the other hand, the learning procedure flows from alternatives between forward and backward. Normally, the neural network includes three layers, input, hidden and output, and each layer includes several nodes, where layers are interconnected by a set of weighing factors.The structure of a typical neural network can be shown as follows:



The neural network model (NNM) used in this research is composed of the following steps: (1) input data; (2) randomly generated initial weighing factors;(3) forward; (4) backward, and (5) change weighing factors; and (6) yield prediction. The overall structure to develop the NNM model can be described as follows:

```
input DATA
Random Initial Weighing Factor
While (Mean Sequare Error <= Tolerance)
{
   For (n=1; n<=No. of Examples; n++)
   {
      Forward Subroutine
      Backward Subroutine
   }
   ChangeWeights Subroutine
}
Predict Yield Subroutine
```

The flow charts of program logic are shown in Appendix. Steps (1), (3), (4) and (5) are described by the following, respectively.

Step 1: The required data include (a) number of examples ; (b) number of input,hidden and output nodes; (c) input and output data for training; and (d) input data for predictiong yield. In this study, there were ten and five data sets for training and predicting, respectively. Each data set includes sixteen weekly soil moisture values and one seasonal yield. Therefore, the required data include(a) number of examples=10 and 5 for training and predicting, respectively; (b)input nodes=16 (soil moisture), hidden nodes=2 (default) and output nodes=1(yield); (c

) ten data sets with weekly soil moisture and seasonal yields of 1990 and 1991 for training; and (d) five data sets with weekly soil moisture from 1992.

Step 3: The logistic function is used to transfer data within the range from0 to 1 as follows (Smith 1993):

$$g(u)=\frac{1}{1+e^{-u}}$$

Assume a network with only one input and output node. Then, a node in the hidden layer can be visualized as: $u=a_0+a_1*x_1$ where a_0 can represent as bias weight and a_1 can represent as the weighing factor between input layer and hidden layer. Using the logistic function, the value of input to the hidden layer is $y=g(u)=1/(1+e^{-u})$. The value of the input to the output layer can be obtained as: $v=b_0+\Sigma b_j*y_j$. where j is the number of hidden nodes, b_0 is the bias weight of output layer,b_j is the weighing factors between hidden layer and output layer. Finally,the output of output layer can be calculated from logistic function as follows:$z=g(v)=1/(1+e^{-v})$.

Step 4: The mean square error is used for "training" the NNM model as follows(Smith, 1993):

$$E=\frac{\frac{1}{2}\sum_{n=1}^{N}\sum_{k=1}^{K}(Z_{kn}-t_{kn})^2}{NK}$$

where N is the number of examples in the data set, K is number of output nodes, t_{kn} is the k^{th} target output for the n^{th} example, and z_{kn} is the k^{th} actual output for the n^{th} example. The gradient descent method is the way used in this NNM. Smith (1993) stated that the key concept in back propagation is the sensitivity of the network's error to change in its weight. The derivative of the mean square error on a set of example is simply the sum of the derivatives an example in the set: ∂E/∂ (weight). Therefore, Smith (1993) concluded the partial derivatives of the squared error of an output node with respect to its weight (b_0 and b_j)are:

$\partial E/\partial b_j = P$ for a bias weight

py_j for a hidden weight

where j is the number of hidden nodes, and $p=(z-t)*z*(1-z)$, and $y_j = \partial v/\partial bj$, where z is the output of output layer , t is the target output, and v is the value of input to the output layer from step 3.

The derivative of the network's squared error with respect to the hidden node's weights (a_0 and a_i)are:

$\partial E/\partial a_i = q$ for a bias weight

qx_i for an input weight

where: i is the number of input nodes, and $q=(\Sigma p_k * b_k) * y * (1-y)$, $p_k=(z-t)*z*(1-z)$, and $b_k=\partial v_k/\partial y$, where k is the number of output nodes, y is the input to the hidden layer.

<u>Step 5:</u> The partial derivatives with respect to the output and hidden nodes(e.g. $\partial E/\partial b_j$,$\partial E/\partial a_i$) from step 4 are summed over all the unmber of examples. Then, the weighing factors are changed based on the accumulated derivatives. The process can be described as follows: New weight (W_m)=Previous weight (W_m)= Previous weigh (W_{m-1})+Change (C_m).

Application to Field Data

The field experiment data used in this study were held at the Hsuehchia Experiment Station of Chianan Irrigation Association from 1990 to 1992 by the Department of Agricultural Engineering, National Taiwan University, Taiwan. Shih (1993) stated that the experiments of sorghum have been done at three sites such as common field, drainage lysimeter, and auto-rain shelter lysimeter with five treatments (e.g. 0.2W, 0.4W, 0.6W, 0.8 W, 1.0W), where "W" is the normal water requirement. The input data (e.g. weekly soil moisture) and output data (e.g. seasonal yields) from 1990 to 1991 were used for training, and 1992 data was used for predicting. Therefore, ten example data sets (e.g. five treatments for 1990 and 1991,respectively) and five example data sets (e.g. five treatments for 1992) were used in this study. The type of neural network used required all input and output values to be between 0 and 1; therefore, it was necessary to normalize all input and output data by dividing them by their maximum observed values: soil moisture with 25 .6% and sorghum yield with 8762.9 kg/ha.

Results and Conclusions

With sixteen input nodes, two hidden nodes and one output node, the model performed 1003 iterations for

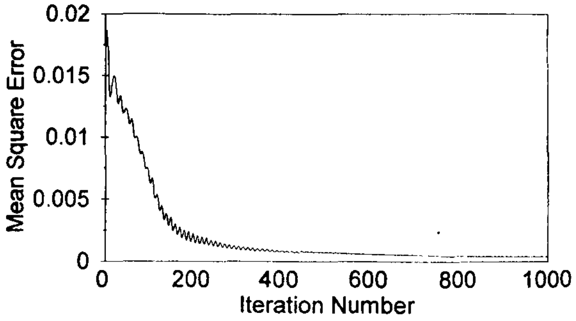


Figure 1: Mean square error vs. iteration number during the training process

a mean square error less than or equal to 0.0003.Figure 1 shows the mean square error with iteration number during the training procedure. Table 1 shows the results of calculation and target yield of 1990 and1991 during the training process, and Table 2 shows the predicted and actual yields of 1992 during the prediction process. From Table 1, it is clear that the training processes can strongly represent the relationship between input and output. On the other hand, Table 2 shows the absolute percentage error of up to 15.64%, and as low as 9.02% for five different treatments.

It is obvious that weekly soil moisture alone cannot fully represent sorghum yields; therefore, the absolute percentage error in Table 2 is as high as 15.64%,even though the results from Table 1 are very good. Certainly, more field data such as temperature, evapotranspiration, etc., should be included in the model to obtain better results in future studies. Instead of programming the entire model by oneself, commercial software packages such as NETS (Baffes 1989) and Neural Ware (Klimassauskas 19 91) are both good tools to use. The purpose of this paper is a demonstration of the possible use of neural networks to predict sorghum yields, even though the results are not as good as expected.

Acknowledgments

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Table 1: Calculated and target yields of 1990 and 1991 from the NNM training procedure.

Year	Yield	Calculated Yield (kg/ha)	Target Yield (kg/ha)
1990	1	5644.40	5713.41
	2	6178.41	6134.03
	3	5878.59	6030.63
	4	5674.30	5608.26
	5	5365.68	5268.26
1991	6	8309.84	8153.88
	7	8577.71	8626.20
	8	8510.16	8762.20
	9	8597.02	8661.25
	10	8585.42	8706.82

Table 2: Predicted and actual yields for 1992 from the NNM predicting procedure.

Year	Yield	Predicted Yield (kg/ha)	Actual Yield (kg/ha)	Absolute Percent Error (%)
1992	1	6265.08	6886.2	9.02
	2	7595.95	6568.9	15.64
	3	6634.14	6981.5	4.98
	4	7941.14	7401.6	7.29
	5	7188.20	6720.9	6.95

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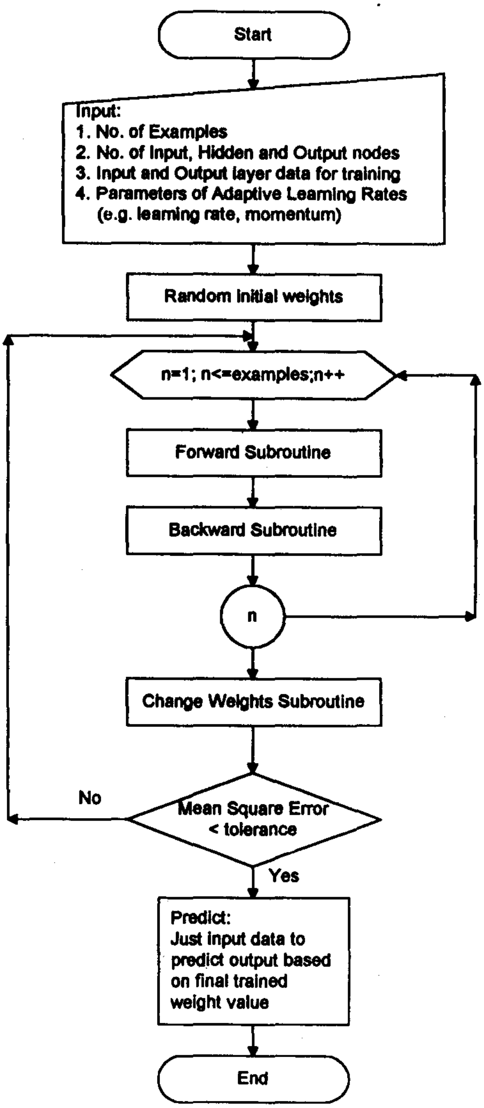
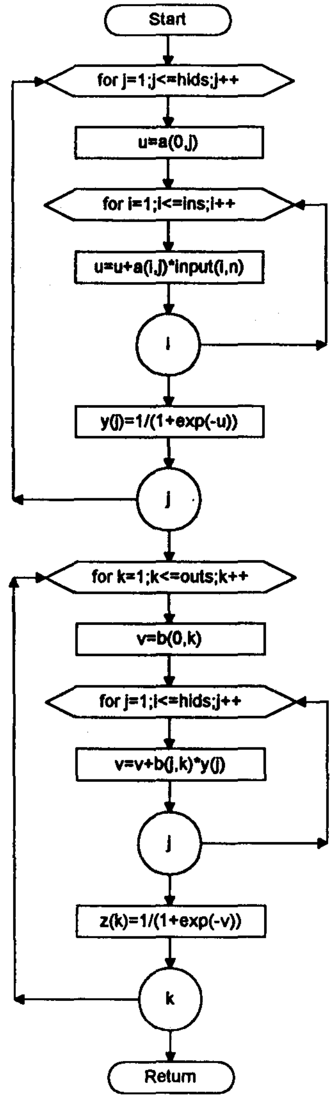
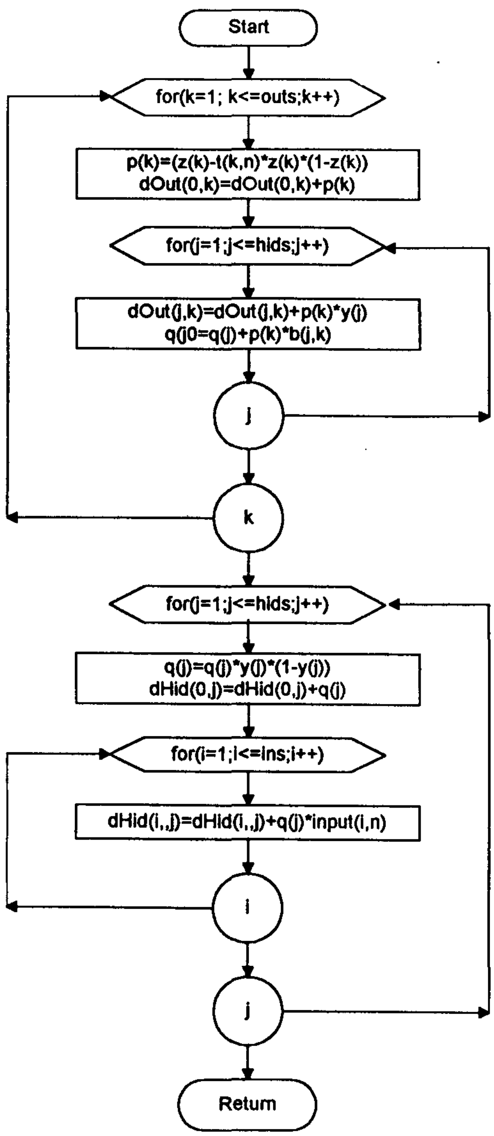
Appendix: Flow Charts of Program Logic



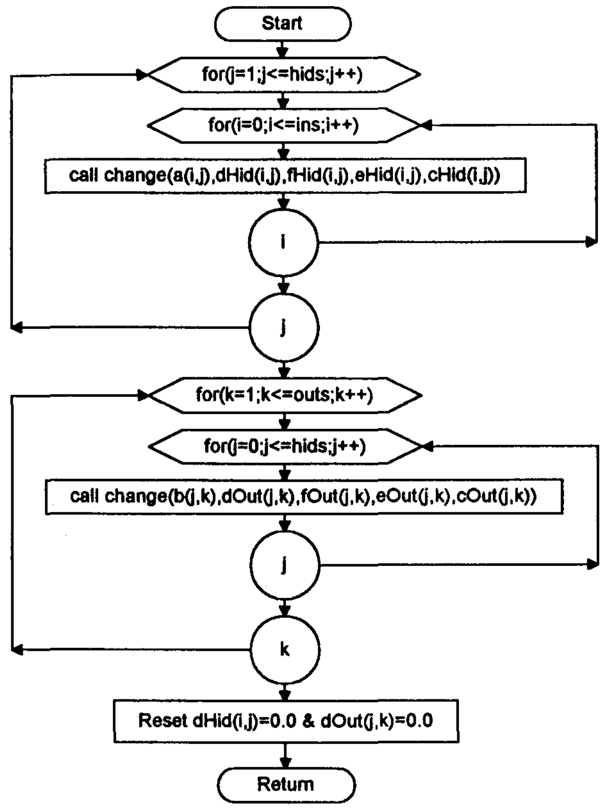
Backpropagation Method



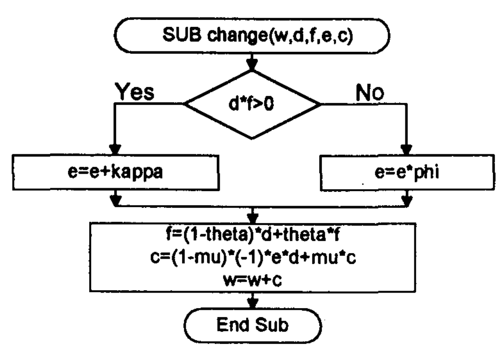
Backpropagation Method: Forward Subroutine



Backpropagation Method: Backward Subroutine



Backpropagation Method: Change Weight Subroutine



Backpropagation Method: Change Function

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