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# APPLICATION OF NEURAL NETWORKS FOR ESTIMATING EVAPOTRANSPIRATION

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## ABSTRACT

Estimation of daily and seasonal evapotranspiration is essential for water resource planning, irrigation feasibility study, and real-time irrigation water management. This paper is to evaluate the applicability of neural networks to the estimation of evapotranspiration. A neural network was developed to forecast daily evapotranspiration of the rice crop. It is a three-layer network with input, hidden, and output layers. Back-propagation algorithm with delta learning rule was used to train the neural network. Training neural network was conducted using daily actual evapotranspiration of rice crop and daily climatic data such as mean temperature, sunshine hours, solar radiation, relative humidity, and pan evaporation. During the training, neural network parameters were calibrated. The trained network was applied to a set of field data not used in the traing. The created response of the neural network was in good agreement with desired values. Evaluating the neural network performance indicates that neural network may be applied to the estimation of evapotranspiration of the rice crop.

Key Word : Neural network, Evapotranspiration, Back-propagation, Delta learning rule

## INTRODUCTION

A knowledge of evapotranspiration(ET) which is one of the important elements of the hydrologic cycle is prerequisite to planning and operating water resource systems. Involved are problems of water supply and water management for irrigation, power, and municipal and industrial uses. ET data are essential for estimating water requirements for irrigation, and are useful for estimating municipal and industrial water needs, and water yields from mountain watersheds (Jensen, 1973). In agriculture we have wide understanding of needs for ET data in planning and real-time decision making for crop production.

Estimating ET is based on physical principals controlling evaporation and the conservation of mass and energy, and use daily weather data. A number of methods have been developed to estimate ET. A classification of the estimating methods was reported by Jensen (1973) ; combination methods, radiation methods, evaporation methods, temperature methods, humidity methods, and multiple correlation methods. Some of the methods are relatively simple and require little data. Other methods are comprehensive and require large amount of data. Many variables of the estimating methods are interconnected in a very complicated way. The complexity makes it attractive to apply neural network approaches to problems which are difficult to describe mathematically.

Artificial intelligence and rule-based computers are limited in their ability to accommodate inaccuracies or fuzzy informations. Neural network has showed its potential in many areas, for example, forecasting, pattern recognition and classification, image understanding, sensor processing, robotic controls, and optimization (Klimasauskas et al, 1989; Kosko, 1992; Kung, 1993; Nelson and Illingworth, 1991). Additional reasons for th current interest in neural network applications are improvements in hardware and software.

The objective of this paper is to evaluate the applicability of neural networks to the estimation of ET of the rice crop. Specific objectives are to develop a neural network using multilayer back-propagation algorithm with delta learning rule to predict daily ET using daily climatic data and to present the results of its applications to an experimental area.

## WHAT IS NEURAL NETWORK ?

The human brain is a kind of computing device which has powerful functions like thinking, remembering, and problem solving. This attracted many attempts using computers to model the functionality of the brain and produced artificial neural network.

The following description of neural network was made by Klimasauakas et al. (1989). " The neuron is the fundamental cellular unit of the nervous system and, in paritcular, the brain. Each neuron is a simple microprocessing unit which receives and combines signals from many other neurons through input process called dendrites. Signals from the dendrites are communicated to the neuron body through synapses. ...... In an artificial neural network, the unit analogous to the biological neuron is referred to as a processing element. A processing element has many input paths and combines, usually by a simple summation, the values of these input paths. The result is an internal activity level for the processing elememt. The combined input is then modified by a transfer function. This transfer function can be a threshold function which only passes information if the combined activity level reaches a certain level, or it can be a continuous function of the combined input. The output value of the transfer function is generally passed directly to the output path of the processing element."

Processing elements are usually organized into groups called layers. A neural network consists of input, hiden, and output layers. An example of a simple neural network is shown in Fig.1. Each layer is fully connected to the succeeding layer.

## BACK PROPAGATION ALGORITHM

The training algorithm used in this study is back propagation. The back propagation algorithm has recently emerged as one of the most efficient learning procedures for multi-layer networks of neuron-like units, due to its incredible simplicity.

A processing element(PE) in back propagation algorithm transfer its input data in the following manner.

$$H_j^n = f\left(\sum_i (W_{ji}^n \cdot H_i^{n-1})\right) \quad \cdots\cdots\cdots\cdots\cdots\cdots \quad (1)$$

where $H_j^n$ is output of $j^{th}$ PE in layer $n$, $W_{ji}^n$ is interconnection weight between $j^{th}$ PE in layer $n$ and $i^{th}$ PE in layer $n-1$, and $f$ is transfer function. The transfer functions of the back propagation algorithm can be any differentiable function, but traditionally is the sigmoid function defined as

$$f(x) = \frac{1}{(1+e^{-xG})} \quad \cdots\cdots\cdots\cdots\cdots\cdots \quad (2)$$

where $x$ is the input data and $G$ is the gain which is used to adjust the slope of the transfer function. The value of the gain lies between zero to one.

The algorithm is to compute the error between the computed neural network output and desired output. Then, the interconnection weights in a backward sweep through the network are adjusted based on the magnitude of the error. Learning continues until either a desired level of accuracy is achieved or some maximum number of iterations is completed. The learning rule is the delta rule called least mean square method. The delta rule minimizes the square of the errors between computed and desired output. A measure of the error is given by

$$E = \frac{1}{2}\sum_n (D_n - O_n)^2 \quad \cdots\cdots\cdots\cdots\cdots\cdots \quad (3)$$

where, $D_n$ is desired output and $O_n$ is the computed output produced by the network. This error, transformed by the derivative of the transfer function, is back-propagated to prior layers where it is accumulated. And the error becomes the error term for that prior layer. The process of back-propagating errors continues until the first layer is reached. The weight update equations are as follows :

$$\begin{aligned} W_{ji}' &= W_{ji} + C1 * E * x_{ji} + C2 * Mji \\ M_{ji} &= W_{ji}' - W_{ji} \end{aligned} \quad \cdots\cdots\cdots\cdots\cdots \quad (4)$$

where $W_{ji}'$ is the interconnection weight after updated by the learning rule, $C1$ is the learning rate, and $C2$ is the momentum term used to smooth out the weight changes. The detailed description on this algorithm are available in the references (Cun, 1988; Khanna, 1990; Rumlhart and McClelland, 1986; Rumelhart et al., 1986).

## HYDROLOGICAL DATA

Hydrological data were collected in Suweon region to evaluate the applicability of neural networks to the estimation of daily ET. Daily climatic data such as mean temperature, sunshine hours, solar radiation, relative humidity, and pan evaporation were used as input variables of the neural networks. Actual daily ET of rice crop measured by the Irrigation & Drainage Lab. of the Seoul National University were used. The data used in this study for the period from 1983 to 1984 irrigation seasons. The daily ET data were measured once a day by a lysimeter method using Marriotte system (Chung, 1983-1984). The rice cultivar used in the study was mid matured Sangpung.

## NEURAL NETWORK TRAINING

The neural network training is to expose a network to a set of example stimuli to achieve a particular self-organization goal. For the training of the network the field data and daily climatic data of 1983 irrigation season were used.

Five climatic elements were used as input variables of the neural network to estimate daily ET. Consquently, the number of PEs in the input layer are five. The number of PEs in the output layer is one. Output variable is ET of the rice crop.

### Number of Hidden Layers

In order to identify the role of the number of hidden layers on neural network performances, five neural networks were developed. The neural network configurations are summarized as in Table 1. N-I and N-II are with one hidden layer, N-III and N-IV with two hidden layers, and N-V with three hidden layers. The networks were trained and recalled at different number of learning iterations. The computed outputs so called recalled results were compared with observed results. The ietration number ranged from 1000 to 20000. RMS(root mean square) errors were computed for each networks and the results are shown in Fig.2. As shown in the figure, at the iteration range from 1000 to 15000, neural network performance improved with increases in the number of iterations. The networks with one hidden layer showed better performance than the networks with two hidden layers did. The network with three hidden layers did not show satisfactory result.

**Number of Processing Elements**

The behaviors of the neural networks for different number of PEs in the hidden layer were evaluated. Number of PEs used in the exercise were 1, 3, 5, 7, and 9. Regression analysis and RMS error computing were executed to evaluate the network performances. Detailed results were shown in Fig.3. With the increase in the number of PEs in the hidden layer, the correlation coefficients for the neural networks slightly increased and RMS errors decreased. However, it is noted that the differences were not considerable. The neural network with 9 PEs showed the lowest RMS error and the highest correlation among all the neural networks.

Based on the trained results so far, the preliminarily proposed network is with five PEs in one input layer, nine PEs in one hidden layer, and one PE in one output layer and is shown in Fig.4.

The learning rate, the momentum term, and the gain are important parameters in the neural network. They control the behaviors of the neural natwork. Simplified sensitivity of the parameters was analized using the proposed network.

**Learning Rate**

The proposed network was applied with the different learning rates and the different learning iterations. The learning rate used were 0.9, 0.7, 0.5, 0.3, and 0.1. The same numbers of iterations were applied as used in the previous sections. The results are as shown in Fig.5. It is shown that the RMS errors decreased with the increase in the value of the learning rate. The network with the learning rate of 0.9 showed the better performance than the networks with other learning rates did.

**Momentum Term**

Four different values of the momentum term were applied to the proposed network; 0.8, 0.6, 0.4, and 0.2. The results in Fig.6 indicated that the proposed network with the momentum term of 0.6 showed the better performance than others did.

**Gain**

Fig.7 showed the behavior of the proposed network with the different values of the gain. The values of the gain used in the study ranged from 0.2 to one. The higher the value of the gain is, the better the performance of the network occurs.

Configuration and parameters of the proposed network are listed in Table 2.

## NEURAL NETWORK APPLICATION

In order to evaluate the applicability of the proposed neural network, daily ETs were simulated for 1984 irrigation season using the trained network based on the data of 1983. Simulated ET were compared to the observed values. RMS error between simulated and observed data was 1.016 mm/day. The results are shown in FIG.8. The simulated ETs for the period of 99 days after transplanting were in good agreement with the field data. This indicates that the neural network approach may be applied to the estimation of ET of the rice crop.

## CONCLUSIONS

For the evaluation of the applicability of the neural network approach to the estimation of daily ET of the rice crop, a neural network was developed and tested with the field data. The neural network was trained to calibrate the network parameters. The trained network was applied to simulate ET not used in training data and to verify the neural network. The results showed the simulated ETs were very close to the field observations. From the results of this study it is considered the neural network showed a preliminary potential in the field of forecasting. This study does not provide with a conclusive statement as to the ability of a neural network to ET estimating. More detailed study are required for better understanding and evaluating the behavior of neural networks.

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## TABLES AND FIGURES

Table 1. Summary of neural network configurations for the training

| Neural Network | Number of Processing Elements | | | | |
|---|---|---|---|---|---|
| | Input L. | Hidden L.-1 | Hidden L.-2 | Hidden L.-3 | Output L. |
| N-I | 5 | 5 | 0 | 0 | 1 |
| N-II | 5 | 9 | 0 | 0 | 1 |
| N-III | 5 | 5 | 5 | 0 | 1 |
| N-IV | 5 | 9 | 9 | 0 | 1 |
| N-V | 5 | 5 | 5 | 5 | 1 |

Table 2. Configuration and parameters of the proposed neural network

| Descriptions | Values |
|---|---|
| Number of hidden layers | one |
| Number of PEs in the hidden layer | nine |
| Learning rate | 0.9 |
| Momentum term | 0.6 |
| Gain | one |

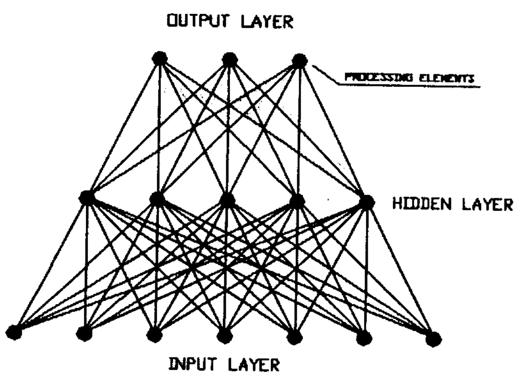


Fig. 1. Structure of a typical neural network

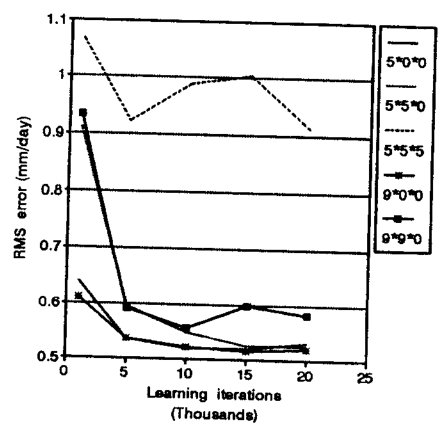


Fig. 2. Comparison of network performances for different number of hidden layers

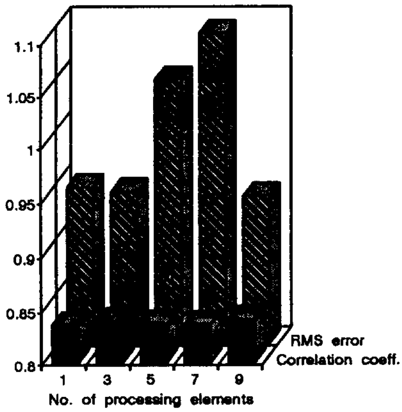


Fig. 3. Comparison of network performances for different number of processing elements

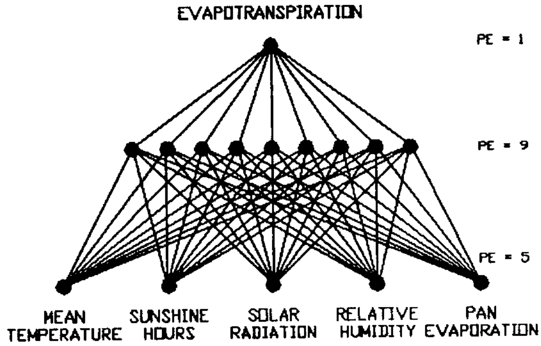


Fig. 4. A proposed neural network for estimating daily evapotranspiration

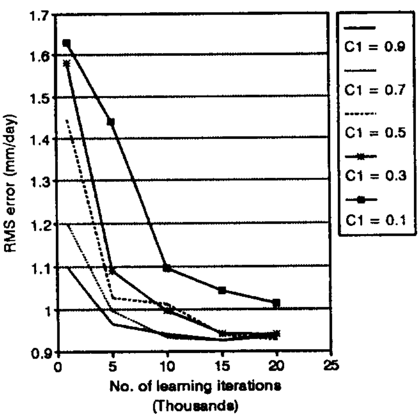


Fig. 5. Comparison of network performances for different learning rates

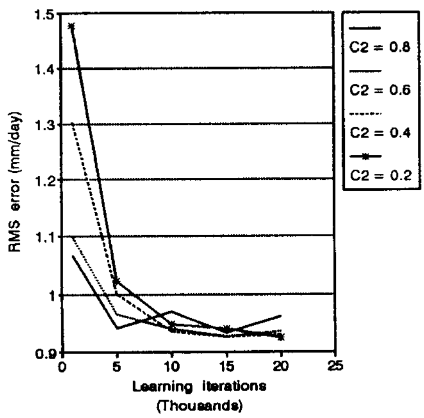


Fig. 6. Comparison of network performances for different momentum terms

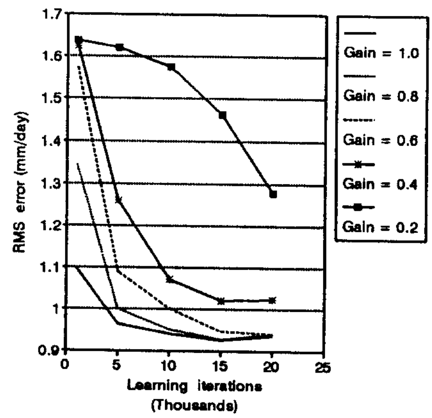


Fig. 7. Comparison of network performances for different gains

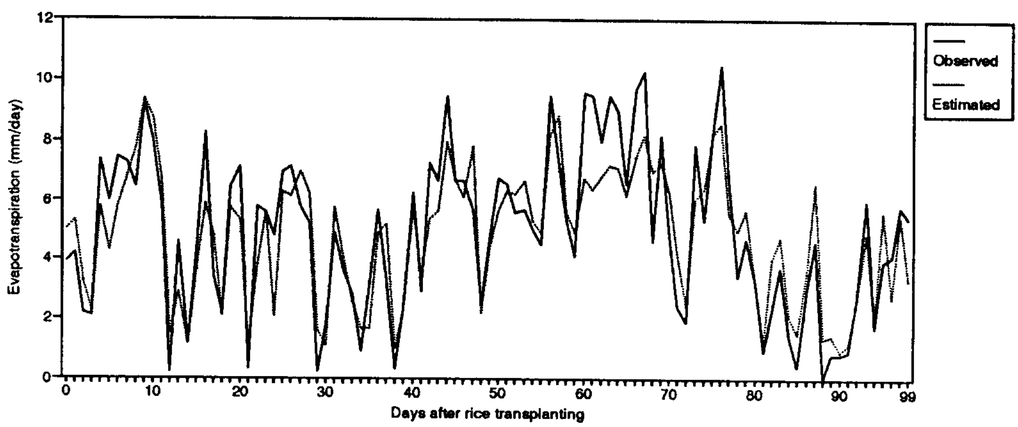


Fig. 8. Comparison of observed and estimated evapotranspirations for 1984