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Soil moisture and corn yield prediction using neural network

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Abstract

One of the most important factors that affect irrigation scheduling process is the continuous information about soil moisture content to decide when to apply water. The soil water content depends on so many factors such as crop age, maximum and minimum air temperatures, solar radiation, leaf area index, amount of irrigation water applied, evaporation from the soil, transpiration from plants, drainage, and initial soil moisture content. In this study, the artificial neural network models are used to predict soil moisture content and crop yield using data from literature. Two models were developed. The topology of the back-propagation models were 10 input nodes, 32 hidden nodes and one output node for both networks. The training process took 19010 iterations for soil moisture prediction with learning coefficient $\eta = 0.8$, momentum factor $\alpha = 0.86$ and the error term δ was 0.0002. For corn yield prediction network took 20000 iterations with learning coefficient $\eta = 0.8$, momentum factor $\alpha = 0.97$ and the error term δ was 0.0003. Both networks were tested and they gave good results. The correlation coefficients between the actual and predicted data for soil moisture content and for crop yield were 0.9963 and 0.9964 respectively. Meanwhile, the root mean square errors were 0.165% and 266.1 kg/ha for predicting soil moisture and corn yield respectively.

I - INTRODUCTION

Neural networks (NNs) can provide solutions for a variety of problems. Giarratano and Riley, 1989, and Eberhart and Dobbins, 1990, stated that the best candidate problems for NN analysis are those that are characterized by fuzzy, imprecise, and imperfect knowledge (data), and/or by lack of a clearly stated mathematical algorithms which provide sufficient accuracy and speed for the analysis of the data. It is, however, important that there is enough data to yield sufficient training and test sets to train and evaluate the performance of an NN effectively.

Altendorf et al. (1999) refined and validated a NN model capable of predicting soil water content using soil temperature as inputs. Their results confirm that the NN model has the potential to predict soil water content reasonably well, and certainly much better than linear regression model. Also McClendon et al.(1996) used the NN with the PNUTGRO crop growth simulation model to search for optimal irrigation decisions using Sequential Control Search approach (SCS). Their results indicated that neural network performed well in scheduling irrigation when incorporated as a subroutine in PNUTGRO model.

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Yang et al.(1996) used artificial neural network (ANN) model to predict midspan water table depth. The results indicated that ANN model can make predictions similar to DRAINMOD (a conventional water management model), faster and with fewer input data.

Ghazanfari et al.(1996) proposed and applied a multi-structure NN (MSNN) to classify four varieties of pistachio nuts. The MSNN classifier consisted of four parallel feed-forward NNs. Each network trained individually. The proposed MSNN classifier gave an overall accuracy of 95.9%, an average increase of 8.9% over the accuracy obtained by a multi-layer-feed forward neural network (MLNN) classifier. Elizondo et al.(1994) developed a NN model to predict flowering and physiological maturity for soybeans. The NN approach gave promising results when tested with field data. They planned to extend their evaluation by comparing their results with the crop simulation models.

The development of corn plants is a dynamic process from the day of emergence to the day of physiological maturity. It is influenced by several factors during the growth period. The major factors affecting the plant growth are: type of hybrid, climate, soil characteristics, available nutrients, available soil moisture, present condition of the crop, and damage due to insects and pests. One of the most influential controllable factors is available soil moisture, which can be managed by irrigation. Morgan et al., 1980, identified two phases of corn plant development; the vegetative phase, which begins at emergence and end just prior to silking, and the reproductive phase which begins prior to silking and end at physiological maturity. The reproductive phase begins approximately halfway between tasseling and silking, about 61 days after emergence (DAE) and ends at physiological maturity (126 DAE) This period is the most critical period of corn plant development in terms of grain yield. Moisture stress during this period will result in reduction of yield by as much as 50% (Classen et al., 1970). Although there are many factors that influence crop plant growth and yield, available moisture content and nutrients could be managed by irrigation and fertilization respectively. The effect of water stress is severe during the early stages of the reproductive period and is reduced at later stages. Therefore, the objective of this work was to develop NN models that predict soil moisture content and yield for corn during this period utilizing actual data from literature.

II – MATERIALS AND METHODS

2-1. Neural Network Description

Artificial neural networks (ANNs) are computational systems, either hardware or software, which mimic the computational abilities of biological systems by using large number of simple, interconnected artificial neurons (Rumelhart et al., 1986 and Maren, et al., 1990). Artificial neurons are simple emulation of biological neurons; they take in information from sensor(s) or other artificial neurons, perform very simple Boolean or arithmetic functions on this data, and pass the results on to other artificial neurons. NNs operate by having their many artificial neurons process data in this manner. The key of the functioning of an ANNs is the weights associated with each element (Giarratano and Riley, 1989). The input signals to the neuron are multiplied by the weights and summed to yield the total neuron input. The neuron output is often taken as a sigmoid function of the input. The three main characteristics which describe a NN, and which contribute to its functional abilities are: structure (a large number of very simple neuronlike processing elements, and a large number of connections between the elements which encode the knowledge of a network), dynamics (highly parallel, distributed control), and learning (internal representation is learned automatically) (Maren, et al., 1990, and Rich and Knight, 1991).

2-2. Backpropagation Algorithm

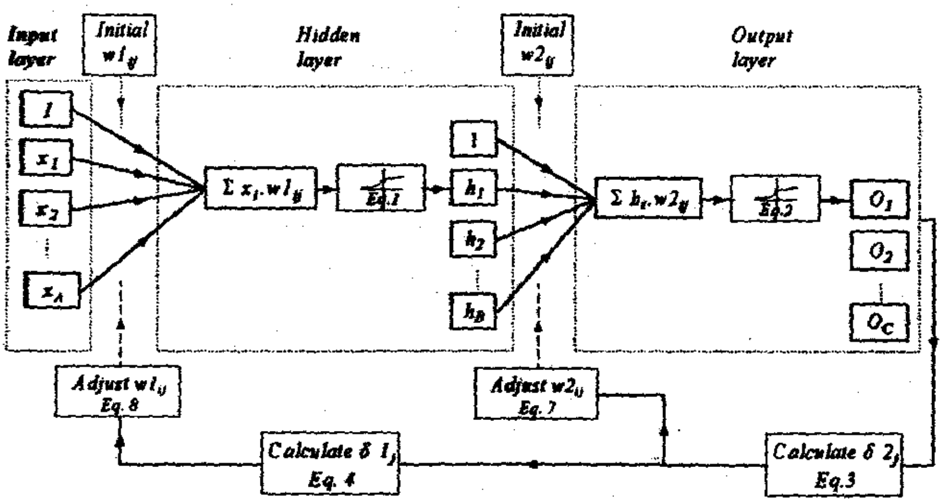
In general, the main purpose of using a NN is to compute a set of weights that maps inputs onto corresponding outputs, if a set of input–output vector pairs exists. This could be described as:

1 – Assume that A , B and C are the number of units in the input , hidden and output layers, respectively as shown in Fig. (1). The input and the hidden layers each have an extra unit used for thresholding; called the bias neurode, which is assumed to have an output of 1 at all times.

2- Initialize the weights in the network. Each weight should be set randomly to a number between –0.3 and 0.3. i.e;

$W1_{ij}$ = random (-0.3, 0.3) for all i = 0,……,A j = 1,………,B
$W2_{ij}$ = random (-0.3, 0.3) for all i = 0,……,B j = 1,………,C

3- Initialize the activation of the thresholding units where both x_o and h_o equal to 1.



xj activation level of the input layer. *w1ij* weights connecting the input layers to the hidden layer.
hj activation level of the hidden layer. *w2ij* weighs connecting the hidden layers to the output layer.
Oj activation level of the output layer.

Fig. (1) A multilayer neuron learning algorithm by backpropagation

4- For the input vector x_i and the target output vector y_i, assign activation levels to the input units.

5- Propagate the activations from the units in the input layer to the units in the hidden layer using the sigmoid activation function, shown in Fig. (2). The output of the sigmoid function is limited to values between 0 and 1. For a net input of zero to the neurode, the output is 0.5. For large negative net input values, the neurode output approaches 0; for large positive values, it approaches 1. This is explained by Eq. (1) as follows:

$$h_j = \frac{1}{1+e^{-\sum_{i=0}^{A} w1_{ij} x_i}} \quad for\ all\ j=1....,B \qquad (1)$$

6- Propagate the activations from the units in the hidden layer to the units in the output layer, as given by Eq. (2):

$$O_j = \frac{1}{1+e^{\sum_{i=0}^{B} w2_{ij} h_i}} \quad for\ all\ j=1......,C \qquad (2)$$

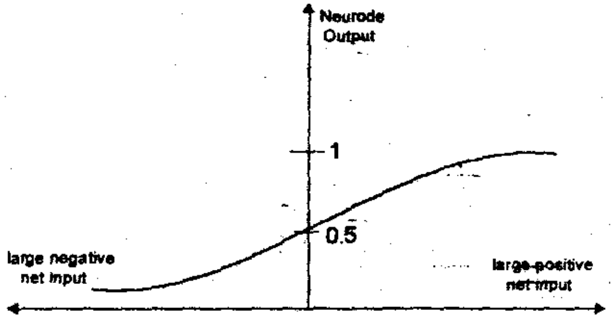


Fig. (2) Sigmoid transfer function used in back-propagation network.

7- Compute the errors of the units in the output layer ($\delta 2_j$), which are based on the network's actual output (O_j) and the target output (y_j) as:

$$\delta 2_j = O_j(1-O_j)(y_i - O_j) \quad for\ all\ j=1........,C \qquad (3)$$

The error over all neurodes was summed, giving a grand total for all neurodes and all patterns. Then the grand total was divided by the number of patterns, to give an average sum-squared error value. The goal of the training process is to minimize this average sum-squared error over all training patterns.

8- Compute the errors of the units in the hidden layer ($\delta 1_j$) as:

$$\delta 1_j = h_j(1-h_j)\sum_{i=1}^{C} \delta 2_i . w2_{ji} \quad for\ all\ j=1......,B \qquad (4)$$

9- Adjust the weights between the hidden layer and the output layer, as:

$$\Delta w2_{ij} = \eta . \delta 2_j . h_i \quad for\ all\ i=0,......,B,\ j=1,......,C \qquad (5)$$

Where:

η = learning rate between 0,1.

10- Adjust the weights between the input layer and the hidden layer, as:

$$\Delta w1_{ij} = \eta . \delta 1_j . x_i \quad for\ all \quad i = 0, \ldots, A, \; j = 1, \ldots, B \qquad (6)$$

11- Go to step 4 and repeat. When all input–output pairs have been presented to the network, one epoch has been completed. The speed of learning can be increased by modifying the weight modification steps 9 and 10 to include a momentum term α. The weight update formulas become:

$$\Delta w2_{ij}(t+1) = \eta . \delta 2_j . h_i + \alpha \Delta w2_{ij}(t) \qquad (7)$$

$$\Delta w1_{ij}(t+1) = \eta . \delta 1_j . x_i + \alpha \Delta w1_{ij}(t) \qquad (8)$$

Where h_i, x_i, $\delta 1_j$ and $\delta 2_j$ are measured at time $(t+1)$ and $\Delta w_{ij}(t)$ is the change the weight experienced during the pervious backward pass.

2-3. Model Development

In this study the source code of the NNTs written by Eberhart and Dobbins, 1990 was modified to be able to read and write data from files. The peripheral program for initializing the weights was also modified to be able to store the initial weights into files that will be recalled by the first program. Then, different values for the number of hidden neurodes (8, 10, 12, 16, 24, 32) along with different values of the learning coefficient η and the momentum factor α were used to develop and train the neural network models. The program was written in C^{++} language. Simple, three-layer back-propagation models (Fig.3) were developed in this study. The first NN model was used to predict soil moisture content during the reproductive phase of corn crop. The second model was used to predict the yield for corn crop during the same period. Both models consist of 10 nodes in the input layer, 32 nodes in the hidden layer and one node in the input layer.

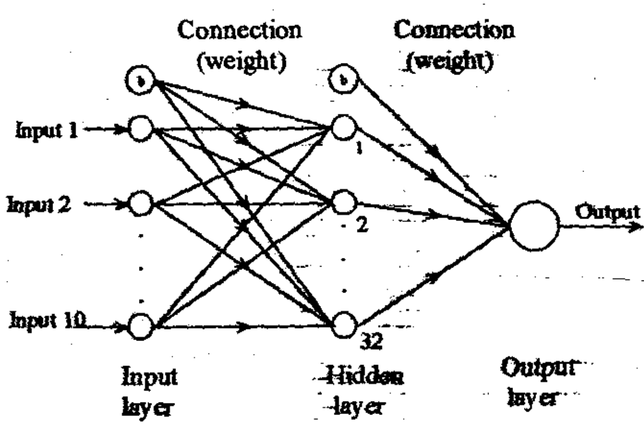


Fig. (3) Back-propagation network structure.

2-4. Network Input

The data collected by (Raju, 1984), at Manhattan, Kansas, were used to train and test the NNs. These data started from the day 61 after emergence till the day 126; end of physiological maturity. The NN inputs were; days since emergence (days), maximum temperature (°c), minimum temperature (°c), solar radiation (ly/day), leaf area index, irrigation water applied (mm/day), evaporation from the soil (mm/day), transpiration from the plants (mm/day), drainage (mm/day), and initial soil moisture content (%).

The combination of input and associated output comprises a pattern vector. The input part is listed first, then the output. All available patterns were divided into two categories or sets: training set and a test set. In this work, 36 patterns of the available data set (66 patterns) were used to train the network. Then the reminder 30 patterns were used to test the network.

2-5. Normalizing the data

Normalizing input patterns can actually provide a tool for preprocessing data in different ways. The data could be normalized by considering all of the inputs together, normalize each input channel separately, or normalize groups of channels in some way that makes sense. In this work, the second option was applied to normalize the input data by the following rule, as:

$$ND = ((D - D_{\min})/(D_{\max} - D_{\min})) * 0.75 \quad (9)$$

Where:

ND = normalized data,
D = data,
D_{min} = minimum reading for that data, and
D_{max} = maximum reading for that data.

The error term was chosen to be as small as 0.0002 for the first model (soil moisture content prediction) and as 0.0003 for the second model (crop yield prediction). For the soil moisture content prediction the network takes 19,010 iterations to be trained with $\eta = 0.8$, $\alpha = 0.86$ and the number of hidden neurodes is 32. For the crop yield prediction the network model takes 20,000 iterations to be trained with $\eta = 0.8$, $\alpha = 0.97$ and the number of hidden meurods is 32.

2-6. Testing the neural network models

The test/run operational mode just involves presenting an input set to the input neurodes and calculating the resulting output state in one forward pass. After the two models have been trained, they were tested using 30 patterns. These patterns were not exposed to the neural network before. The test/run mode involves presenting the testing set to the input neurodes and calculating the resulting output in one forward pass. The errors were 0.0002 and 0.00039 for testing both networks, respectively.

III- RESULTS AND DISCUSSION

To evaluate the performance of the network models, the results of training and testing the two models were plotted in Fig. 4, 5 and Fig. 6, 7 for the actual and the predicted data for soil water content and crop yield respectively. Visual inspection of the plots indicates that the neural network models follow the trend of the data very well especially with the soil moisture content prediction model. Statistics for all the test data sets are given in the following Table:

Item	Soil moisture	Expected yield
RMSE*	0.1645 %	266.1 kg/ha.
r^2	0.99629	0.996396
Slope	0.965215	0.953542
Intercept	0.404276	319.852

* Root mean square error

The RMSE is as low as 0.1645% for the soil moisture content and the r^2 values from the regression of the predicted versus measured were closer to 1.0 (0 .99629). While RMSE for the expected crop yield model is 266.1 kg/ha., and the r^2 value is also high and closer to 1.0 (0.99639). These results indicate that both models are good in expecting the actual values. The primary weakness of the second model is the over prediction of the crop yield at the early stage of the reproductive phase. However, the model predicts more accurately at later stages of the reproductive phase.

The overall performance of the NN models was very good. They could predict the soil moisture content and the crop yield accurately and much easier than the crop growth simulation modes. The results of the expected soil moisture content could be used for irrigation scheduling purposes. The results of the expected crop yield could be used for evaluating the expected revenue from the crop.

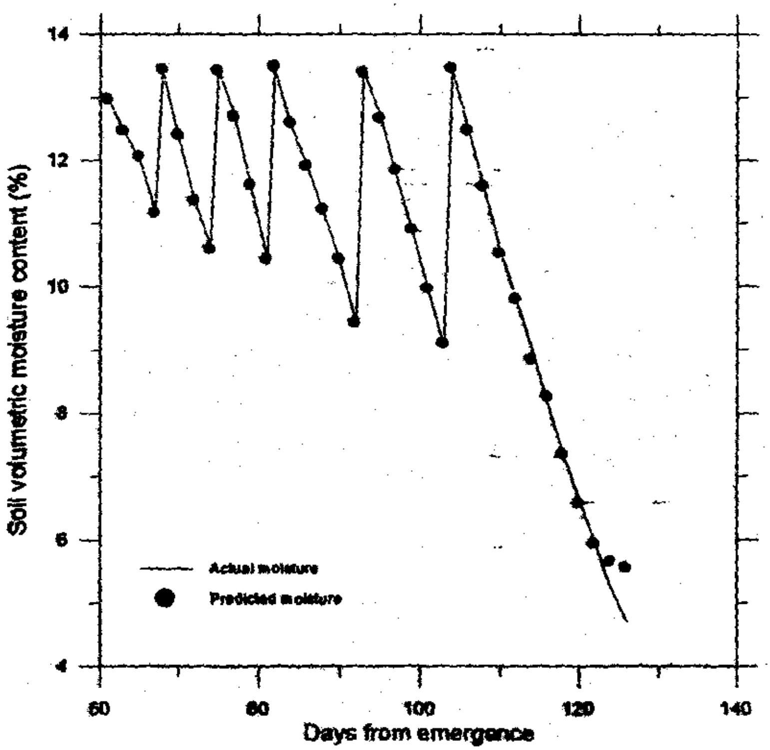


Fig. (4): Actual and predicted soil moisture content.

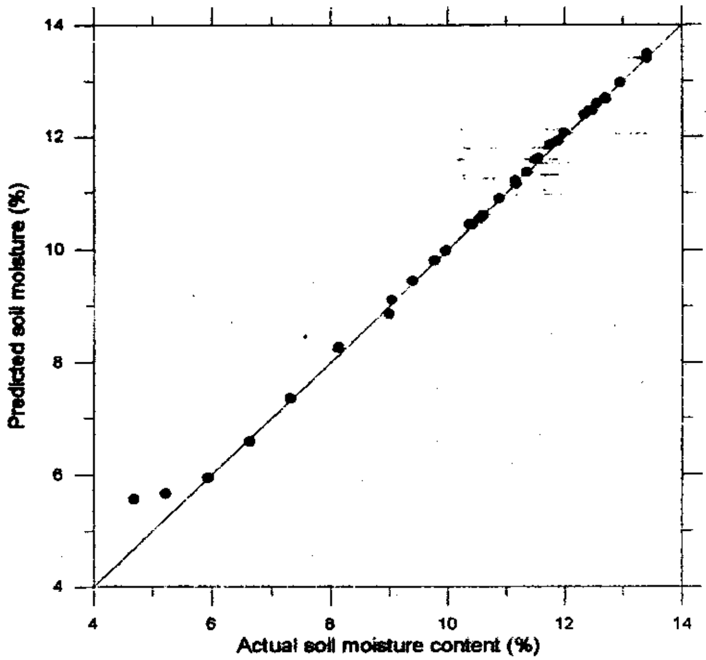


Fig.(5): Actual and predicted soil moisture content.

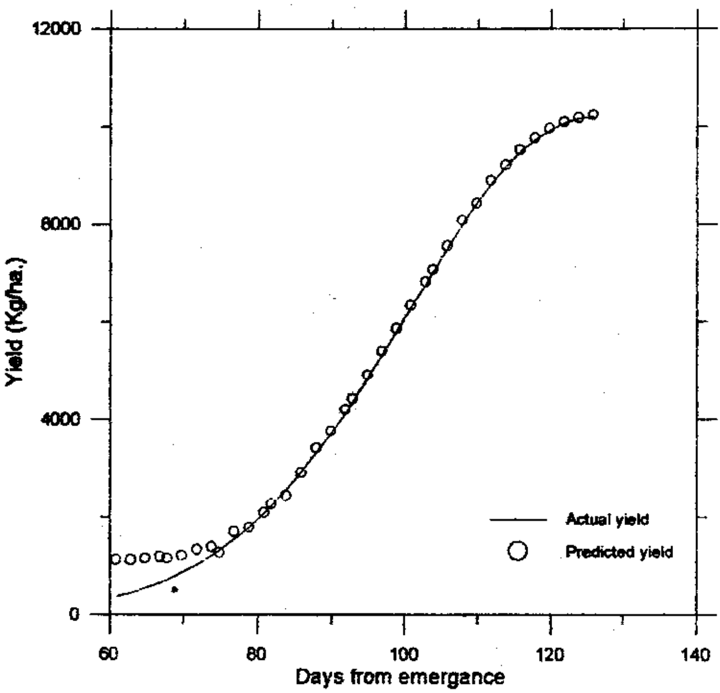


Fig. (6): Actual and predicted corn yield (Kg/ha.)

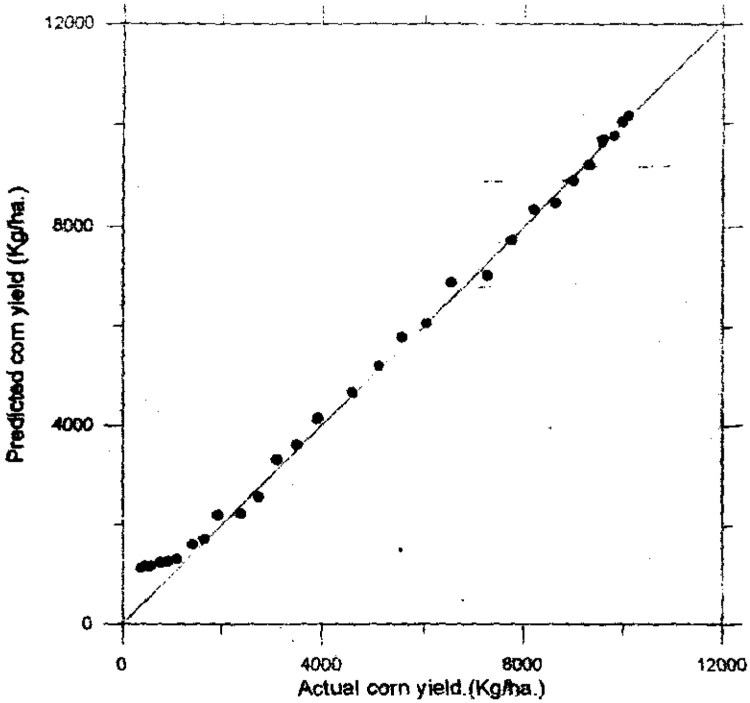


Fig. (7): Actual versus predicted corn yield.

IV – SUMMARY AND CONCLUSION

The overall objective of this research was to develop a system, which can predict soil moisture content and the crop yield for corn during the reproductive phase, accurately and inexpensively based on the available weather data. Use of a neural network was considered because once the network was trained, it is easier to use than crop growth simulation models.

Two separate networks were developed to predict soil moisture content and the crop yield for corn. The networks were trained using data from literature. A subset of the data was used as a training set. Once trained to a desired tolerance, the networks were tested using the reminder of the data. The overall performance of the neural network models was very good. The coefficient of determination (r^2) between the actual and the predicted values for soil moisture and crop yield were 0.9963, 0.9964 respectively. The primary weakness of the second model (crop yield) was a tendency to overpredict early values of crop yield.

Applying the back propagation neural network to predict soil moisture and yield for corn crop gives good results in both cases. The results could be used for irrigation scheduling according to the predicted soil moisture. Also, the predicted yield could be used to evaluate the net revenue from that crop.

References

المراجع العربية

العوضى، م. ن، القبانى ع.ج، قابيل م. ج , أبو كريمة ع. م . (٢٠٠٢): استخدام الشبكات العصبية والارتداد الخطى لتوقعات الطاقة اللازمة للحرث. المجلة المصرية للهندسة الزراعية. ١٩(٤):١١٥-١٢٥.

Altendorf, C.T., R.L. Elliott, E.W. Stevens, M.L. Stone. (1999). Development ahd Validation of a Neural Network Model For Soil Water Content Prediction With Comparison to Regression Techniques. Trans. ASAE, 42(3): 691-699.

Classen, M. M., and R. H. Shaw. (1970). "Water Deficit Effects on Corn – I Vegetative Components, Agronomy Journal, vol. 62, pp. 649-652.

Eberhart, Russell C., and Roy W. Dobbins (1990): Neural Network PCTools. Academic Press, Inc. : 35-49.

Elizondo, D.A., R.W. McClendon, and G. Hoogenboom. (1994). Neural Network Models for Predicting Flowering and Physiological Maturity of Soybean. Trans. ASAE, (37)3: 981-988.

Ghazanfari, A., J. Irudayaraj, and A. Kusalik. (1996). Grading Pistachio Nuts Using A Neural Network Approch. Trans. ASAE, 39(6): 2319-2324.

Giarratano, Joseph and Gary Riley. (1989). Expert Systems. Principles and Programming. PWS-KENT Publishing Co.: 48-55.

Maren, Alianna J.,Graig T. Harston, and Robert M. Pap. (1990). Handbook of Neural computing Applications. Academic Press. Inc. :1-13.

McClendon, R.W., G.Hoogenboom, I. Seginer. (1996). Optimal Control and Neural Network Applied To Peanut Irrigation Management. Trans. ASAE, 39(1):275-279.

Morgan, J. H., A. W. Biere, and E. T. Kanemasu. (1980). A Dynamic Model of Corn Yield Response to Water. Water Resources Research, 16 (1): 59-64.

Raju, Kosuri S. (1984). Dynamic Modeling of Crop Growth and Stochastic Optimization of Irrigation Scheduling. Ph.Dis. Kansas St. U.

Rich, Elaine and Kevin Knight. (1991). Artificial Intelligence. McGraw – Hill, Inc.: 487-529.

Rumelhart, D.E, J.L. McClelland, and the PDP Research Group. (1986). Parallel Distributed Processing. Vol. I : Found. Cambridge, Mass: MIT Press.

Yang, C. –C, S.O. Prasher, R.Lacroix., (1996). Applications of Artificial Neural Networks to Land Drainage Engineering. Trans. ASAE, 39(2):525-533.

الملخص العربي

التنبؤ بالمحتوى الرطوبى للتربة ومحصول الذرة باستخدام الشبكات العصبية

عزة عبد الفتاح حسن[1] جمال عطية شرف[2]

من أهم العوامل المؤثرة في عمليات جدولة الرى هى معرفة المحتوى الرطوبى للتربة باستمرار لمعرفة الميعاد المناسب لإضافة مياه الرى. والمحتوى الرطوبى للتربة يتوقف على عوامل عديدة منها عمر المحصول أو عدد الأيام من بداية الإنبات ، أقصى درجة حرارة، أقل درجة حرارة، كمية الإشعاع الشمسى، دليل مساحة الورقة، كمية مياه الرى المضافة وكمية البخر من التربة، كمية النتح من النبات، كمية مياه الصرف، المحتوى الرطوبى الأبتدائى للتربة. وبما أن الحصول على عينات يومية من التربة لتحديد المحتوى الرطوبى عملية مكلفة. لذا كان الاتجاه إلى التفكير فى استخدام نماذج الشبكات العصبية كأحد فروع علم الذكاء الاصطناعي في التدريب على التنبؤ بالمحتوى الرطوبى للتربة بعد تعريضها لعدد من البيانات المتحصل عليها من الأبحاث السابقة، واختبارها للتأكد من سلامة النتائج المتحصل عليها. وبالفعل تم الحصول على بيانات تخص جميع العوامل السابقة من اليوم ٦١ من بداية الإنبات (نهاية مرحلة النمو الخضرى) لمحصول الذرة وحتى اليوم ١٢٦ (ميعاد الحصاد). وتم تقسيم البيانات المتاحة إلى مجموعتين ٣٦ فى عملية التدريب و ٣٠ فى اختبار للشبكة. وكان التركيب البنيوى للشبكة (topology) عبارة عن ١٠ وحدات فى طبقة الإدخال و ٣٢ وحده فى الطبقة المختفية و وحدة واحدة فى طبقة الإخراج. وتم استخدام الدالة السيجمويد (sigmoid) كدالة تحويل. ولنموذج التنبؤ بالمحتوى الرطوبى للتربة كان معامل التدريب ٠,٨ ومعامل الدفع ٠,٨٦ وكانت نسبة الخطأ ٠,٠٠٠٢ . و تدربت الشبكة بعد ١٩٠١٠ دورة. وكان معامل الارتباط بين البيانات الأصلية للمحتوى الرطوبى للتربة والناتجة من نموذج الشبكات العصبية يساوى ٠,٩٩٦٣ . أما بالنسبة لنموذج الشبكات العصبية المستخدم فى التنبؤ بكمية المحصول كان الترتيب البنيوى للشبكة كما فى الحالة الأولى و كان معامل التدريب ٠,٨ ومعامل الدفع ٠,٩٧ وكانت نسبة الخطأ ٠,٠٠٠٣ وتدربت الشبكة بعد ٢٠٠٠٠ دورة وكان معامل الارتباط بين القيم الأصلية والقيم الناتجة من اختبار الشبكات العصبية يساوى ٠,٩٩٦٤ .

مما سبق يمكن القول أن استخدام نموذج الانتشار الخلفى للشبكات العصبية الاصطناعية يعتبر من التقنيات الواعدة والتى يمكن استخدامها فى مجال الزراعة بصفة عامة بدون تكلفة مرتفعة وبكفاءة عالية نظرا لطبيعة البيانات الزراعية.

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