ARTIFICIAL NEURAL NETWORKS APPROACH TO ESTIMATE WETTING PATTERN UNDER POINT SOURCE TRICKLE IRRIGATION

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ABSTRACT

Many attempts have been made to determine the wetting pattern under trickle irrigation using sophisticated mathematical and numerical models. These models required detailed information concerning soil physical properties that are too complicated for routine use. For this reason, an alternative methodology is proposed, which combines artificial neural networks (ANNs), laboratory and field experiments. The model's input parameters were saturated hydraulic conductivity, emitter application rate, volume of water applied and average change of moisture content. The model outputs were surface wetted radius and vertical advance of wetting front. A total of 280 and 100 vectors were used to train the ANNs model for surface wetted radius and vertical advance of wetting front estimations, respectively. To test the ANNs model, a total of 132 and 76 vectors were selected in case of surface wetted radius and vertical advance of wetting front estimations, respectively. Results of the test showed that the surface wetted radius and vertical advance of wetting front can be predicted with determination coefficients (R^2) of 0.80 and 0.81 for the surface wetted radius and vertical advance of wetting front, respectively. Additionally, the ANNs approach was found to produce equally or more accurate descriptions of wetting pattern for point source trickle irrigation as compared to other analytical and empirical models.

***Key words:** Artificial neural network, Surface wetted radius, Vertical advance of wetting front.*

INTRODUCTION

Trickle irrigation is based on the principle of low quantity of water application at frequently close intervals. Water is supplied to only those parts of the soil where water uptake by the root system is the most efficient. Water trickling from a point source enters the soil and moves downwards and sideways. This reduced evaporation and minimal weed growth which result in considerable savings in the amount of water applied to a given field. There has been much speculation on the shape of the wetted soil volume. Based on this, it is then possible to determine the number of emitters required per plant in order to wet a prescribed portion of the plants root zone. This is quite important in design, operation and management of a trickle irrigation system. There are many attempts to determine the wetting pattern under trickle irrigation using sophisticated mathematical and numerical models. These models required detailed information concerning soil physical properties which are too complicated, due to the highly nonlinear complexity of the flow system, for routine use (Brandet *et al.*, 1971; Taghavi *et al.*, 1984; Zazueta *et al.*, 1995; Vellidis *et al.*, 1990; Li *et al.*, 2003 and Li *et al.*, 2004). Artificial neural networks (ANNs) have proven to be effective tools for modeling nonlinear systems. ANNs methodology has been used in applications where the characteristics of the processes are difficult to describe using simple physical equations. There are a number of studies (Elizondo *et al.*, 1994 Schultz *et al.*, 1995; Francl and Panigrahi, 1997; and Arca *et al.*, 1998) in which some environmental phenomena are described by mathematical models based on ANNs systems, composed of many simple processing elements (neurons), store experimental knowledge provided in the form of examples, which enable them to compute complex and non-linear problems. ANNs, however, do not provide analytical information about the relationship between input and output. The current study was designed to utilize the input–output mapping capabilities of the ANNs to estimate the wetting pattern developed from a surface point source trickle irrigation based on data obtained from laboratory and field experiments.

MATERIALS AND METHODS

Artificial neural networks development

The multilayer networks using the feed-forward neural network backpropagation algorithm were used in this study. Four parameters were selected based on previous studies to represent the input layer in the neural network sets. These were saturated hydraulic conductivity (K_S), average moisture content ($\Delta\theta/2$), volume of water applied (V_w) and emitter application rate (q). These parameters have shown good correlation with the component of the wetting pattern (Schwartzman and Zur, 1986; Ben-Asher *et al.*, 1986 and Amin and Ekhmaj, 2006). The hidden layer started with a small number of neurons and increased progressively until the optimum structure was reached. Using optimum network architecture, the ANNs model was trained for given inputs and output sets. Due to the lack of the available data it was suggested to develop two ANNs models. The first model was designed to determine the surface wetted radius while the second was considered to determine the vertical advance of wetting front. Thus, there was only one output from each ANNs model which is surface wetted radius and vertical advance of the wetting front. The Levenberg-Marquardt (LM) training algorithm was used for the training purpose. Sigmoid transfer function is commonly used in multilayer networks that are trained using the backpropagation algorithm; the Log-sigmoid transfer function was used in the hidden layer while Hard-limit transfer function was used in the output layer.

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To build up and evaluate the ANNs model, independent datasets were acquired from available published data by Taghavi *et al.*, 1984; Risse and Chesness., 1989 Anglelakis *et al.*,1993; Yitayew *et al.*, 1998; Hammami *et al.*, 2002; Palomo et al., 2002; Li *et al.*, 2003; Li *et al.*, 2004; and Amin and Ekhmaj. 2006. The choice of theses data were based on their convenient data. The procedures of these experiments are available in their original papers. A total of 180, 100 and 132 records were used to train, validate and test the ANNs model for surface wetted radius determinations. To perform the ANNs model for the vertical advance of wetting front determinations the total numbers of the available data, .i.e. 208 data records were classified as, 70 for training phase, 62 for validating phase and 76 for testing phase. The results obtained from ANNs models were also compared thoroughly with some available analytical and empirical models (Schwartzman and Zur.1986, Ben-Asher *et al*,. 1986 and Amin and Ekhmaj 2006). All of data were processed and loaded into the neural modeling application Matlab© (2001) version 7.0 of Neural Network Toolbox (Graphical User Interface).

Statistical Criteria

The performance of ANNs models were evaluated by several statistical measures, such as root mean square error (RMSE), mean absolute error (MAE), correlation coefficient (r) , determination coefficient (R^2), and the linear regression equation with intercept equals zero. These statistical criteria can be calculated as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_i - O_i)^2} \quad (1)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|P_i - O_i\right| \quad (2)$$

$$R = \sqrt{\frac{cov(v_P, v_O)}{var(v_P)\,var(v_O)}} \quad (3)$$

where Pi is the predicted value from the ANNs model, Oi is the observed value and n is the number of records,. cov (v_P, v_O) is the covariance of predicted (vp) and observed (vo) data, respectively, and var (v_P, v_O) is the variance. R is in the range [–1, 1] (Hongli and Wiliam, 2004). The closer the value is to 1 or –1, the more positively or negatively correlated the two variables. The accuracy of the predictions in the correlation analysis is indicated by the determination (R^2). The RMSE, MAE statistics have as lower limit the value of zero, which is the optimum value for them (Naylor, 1970 and Hossein *et al.*, 2004). The general form of the linear regression equation with intercept equals zero is expressed as:

$$y = \alpha x \quad (4)$$

where y is the predicted value, α is the slope of the regression line, and x is the measured value.

RESULTS AND DISCUSSIONS

Because there are no standard rules to construct the network structure, the optimum network was defined using trail and error process. Multilayer networks using the backpropagation algorithm were used to construct the network. The input layer composed of 4 neurons and the output layer has only one neuron. The hidden layer was started with small number of neurons and increased progressively until the optimum structure was reached. Too few neurons led to underfitting and difficulty in mapping and too many neurons led to overfitting and increase the training time. The optimum model structure was accomplished through trial and error operations to determine the number of hidden layers and the number of neurons in each layer. It was found that a network of four neurons in the input layer, one hidden layer with 4 neurons and only one neuron in the output layer is the optimum network structure to simulate both the surface wetted radius and vertical advance of wetting front. In other words, the optimum structure is (4-4-1) as illustrated through Fig. (1).

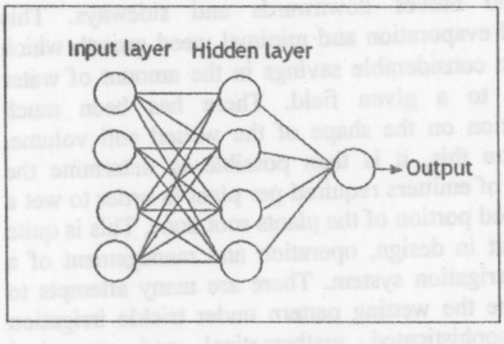


Fig. (1): typical architecture of a backpropagation neural networks

The results of comparison between observed surface wetted radius and vertical advance of wetting front with those predicted by the ANNs for all trials are plotted against a 1:1 line as shown in Fig. (2). In this figure, for a perfect model prediction all of the points would fall on the line across the graph signifying a slope of one (observed= predicted). It is clear that the observed–predicted data pairs lie very close to the 1:1 line, which represents an excellent agreement. The correlation coefficients (r) between observed and predicted values were 0.97 and 0.98 for surface wetted radius and vertical advance of wetting front, respectively. These results were accepted with high accuracy considering the complex mechanisms of water movement in soil under the complicated boundary and initial conditions from a surface point source.

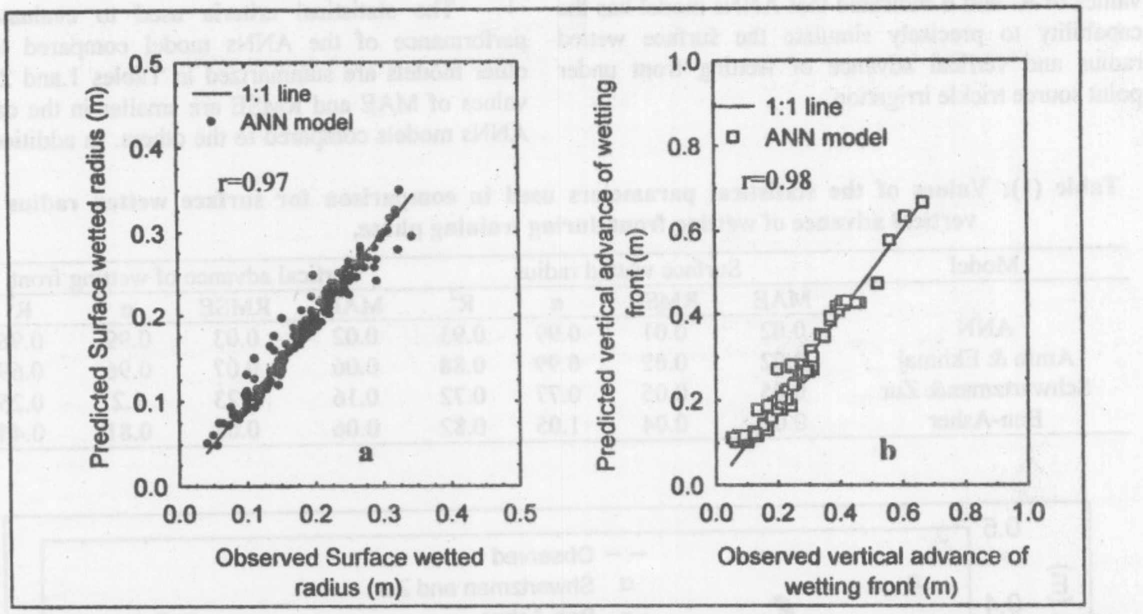


Fig. (2): The correlation between observed and predicted values of the training phase for (a) surface wetted radius and (b) vertical advance of wetting front.

The performance of the model was further evaluated using the independent data which did not included during training phase. If the results of comparisons between the observed and predicted data indicated high coincidence, it could then be reliably recommended in practice. Fig.(3) plot of model estimated for surface wetted radius (Fig.3a) and vertical advance of wetting front (Fig.3b), using the test data versus laboratory and field measurements shows a good fit, with r = 0.89 and r = 0.90 for surface wetted radius and vertical advance of wetting front, respectively.

The results obtained from ANNs models during training phase and test phase were also compared thoroughly with those obtained from available analytical and empirical models (Schwartzman and Zur, 1986; Ben-Asher *et al*., 1986 and Amin and Ekhmaj, 2006). Fig. 5 shows the comparisons between the surface wetted radius as obtained during the training phase (Fig.5a) and at test phase (Fig.5b) and those which predicted from Schwartzman and Zur 1986, Ben-Asher *et al*., 1986 and Amin and Ekhmaj 2006. These figures show that ANNs model captured precisely the observed data compared to the other models.

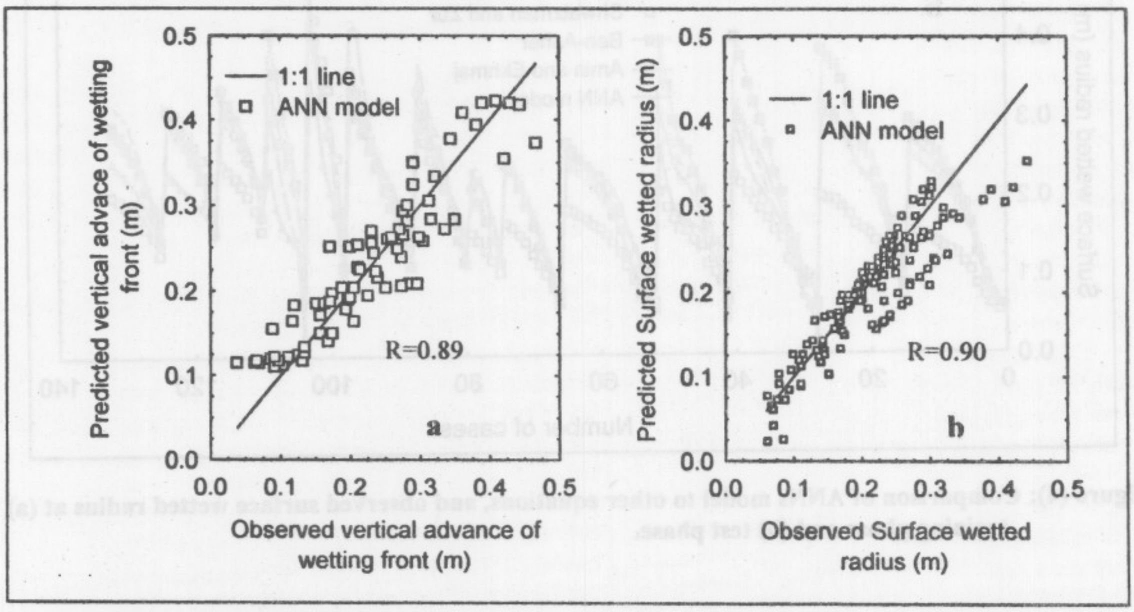


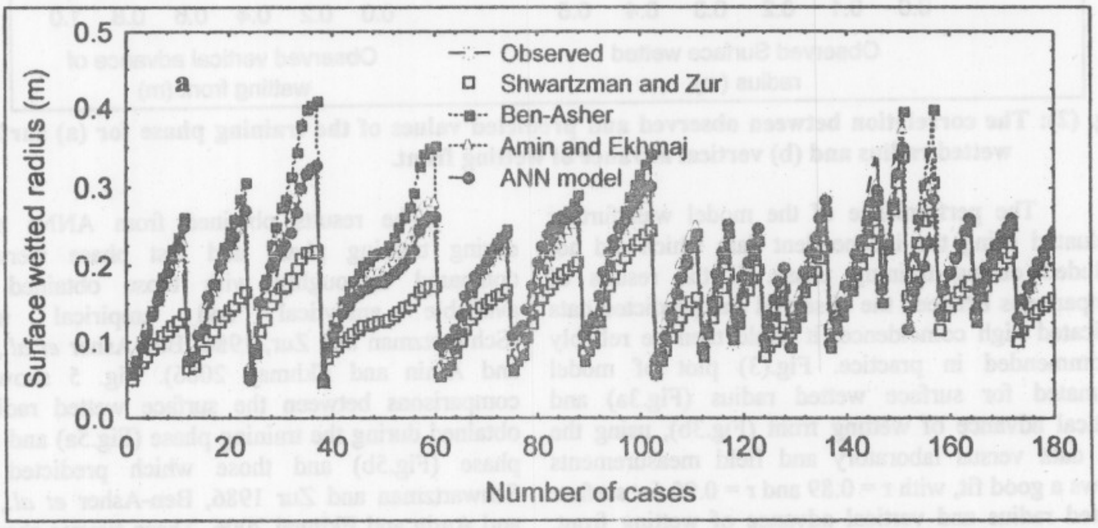
Figure (3): The correlation between observed predicted values of test phase for (a) surface wetted radius and (b) vertical advance of wetting front.

values of R^2 and α indicated that ANNs model has the capability to precisely simulate the surface wetted radius and vertical advance of wetting front under point source trickle irrigation.

The statistical criteria used to evaluate the performance of the ANNs model compared to the other models are summarized in Tables 1.and 2. The values of MAE and RMSE are smaller in the case of ANNs models compared to the others. In addition, the

Table (1): Values of the statistical parameters used in comparison for surface wetted radius and vertical advance of wetting front during training phase.

Model	Surface wetted radius				Vertical advance of wetting front			
	MAE	RMSE	α	R^2	MAE	RMSE	α	R^2
ANN	0.02	0.01	0.99	0.95	0.02	0.03	0.99	0.96
Amin & Ekhmaj	0.02	0.02	0.99	0.88	0.06	0.07	0.96	0.69
Schwartzman& Zur	0.05	0.05	0.77	0.72	0.16	0.23	1.2	0.25
Ben-Asher	0.02	0.04	1.05	0.82	0.06	0.08	0.81	0.44



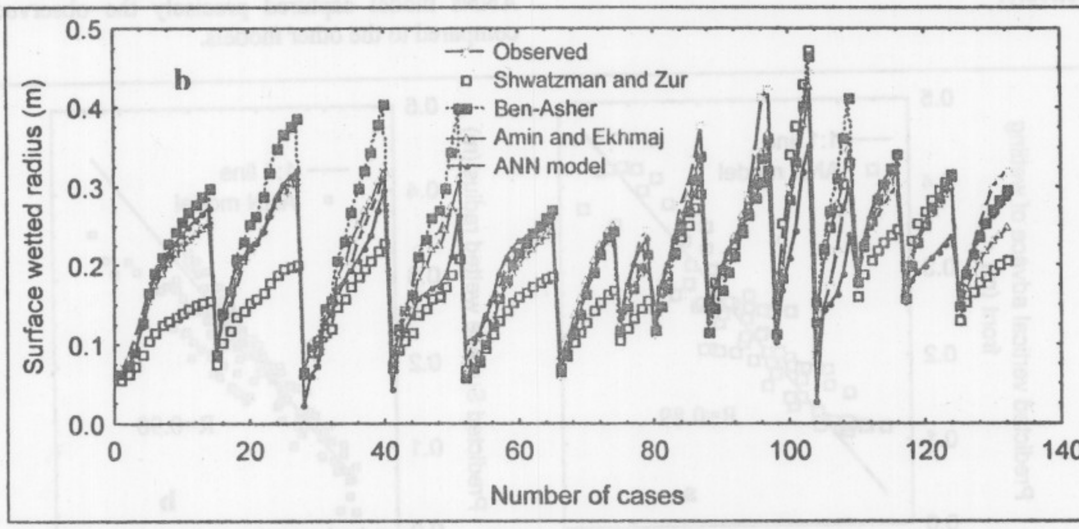


Figure (4): Comparison of ANNs model to other equations, and observed surface wetted radius at (a) training phase and (b) test phase.

Table (2): Values of the statistical parameters used in comparison for surface wetted radius and vertical advance of wetting front during test phase.

Model	Surface wetted radius				Vertical advance of wetting front			
	MAE	RMSE	α	R^2	MAE	RMSE	α	R^2
ANN	0.03	0.04	0.92	0.80	0.03	0.04	0.98	0.81
Amin and Ekhmaj	0.02	0.03	0.98	0.88	0.1	0.12	1.02	-0.09
Schwartzman and Zur	0.05	0.06	0.82	0.69	0.14	0.20	1.57	0.56
Ben-Asher	0.03	0.04	1.05	0.82	0.03	0.04	0.92	0.80

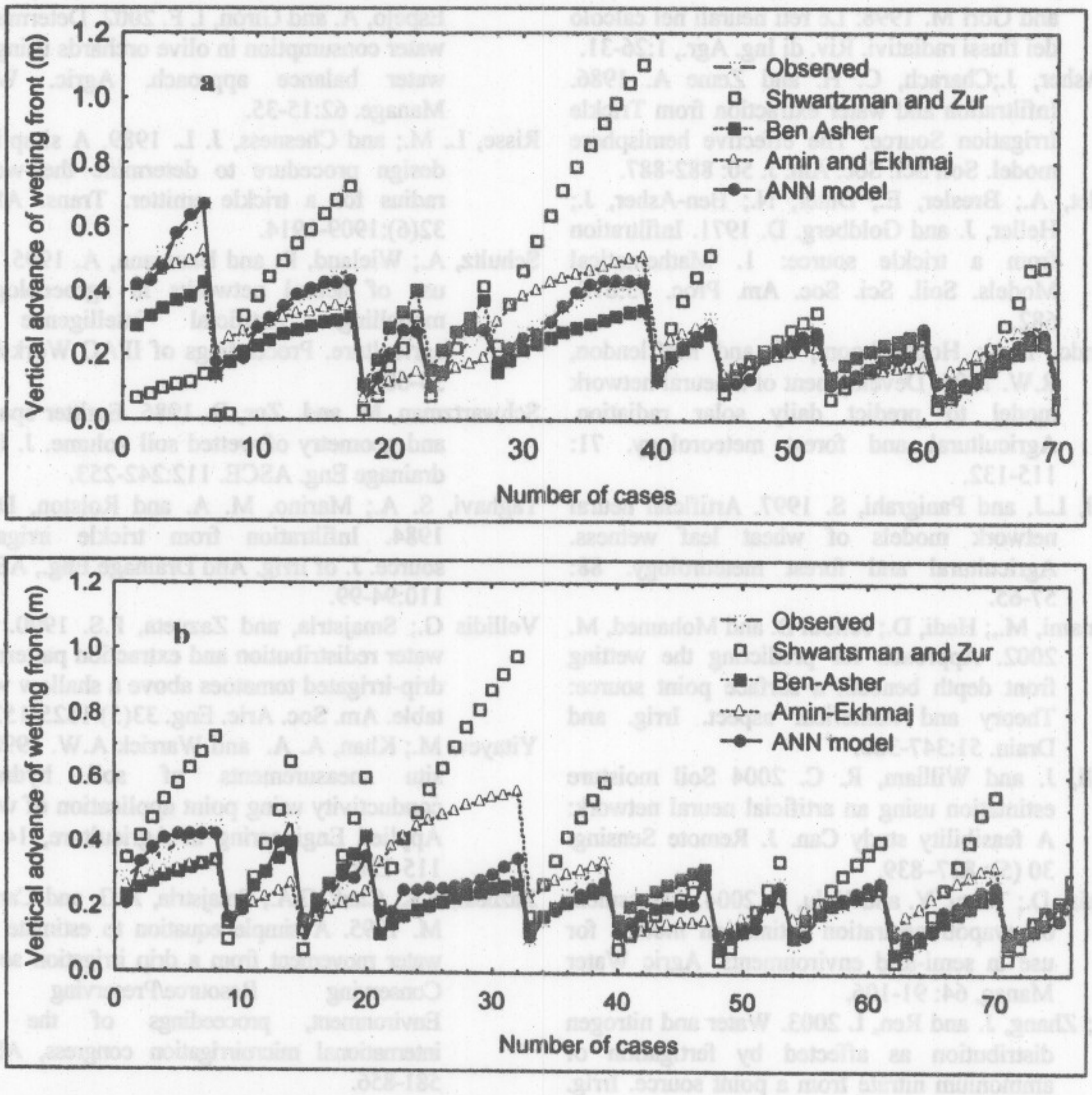


Figure (5) Comparison of ANNs model to other equations, and observed vertical advance of wetting front at (a) train phase and (b) test phase.

CONCLUSIONS

This study describes an efficient method using ANNs technique to determine the wetting pattern under point source trickle irrigation. The method was verified with high agreement for both training and testing data of surface wetted radius and vertical advance of wetting front. The ANNs approach was found to produce equally or more accurate descriptions of wetting pattern as compared to several analytical and empirical models which suggested and recommended to be used for point source trickle irrigation design.

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الملخص العربى

تقدير نمط الابتلال تحت ظروف الرى بالتنقيط باستخدام الشبكة العصبية الاصطناعية

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اجريت محاولات عديدة لتقدير نمط الابتلال تحت ظروف الرى بالتنقيط باستخدام نماذج رياضية معقدة تحتاج الى الكثير من المعلومات والتفاصيل المتعلقة بخواص الارض الطبيعية والتى تعتبر معقدة جدا بالنسبة للاستخدام اليومى. ولهذا السبب فقد اقترحت طريقة بديلة تتضمن التكامل بين شبكة العصبية الاصطناعية و التجارب المعملية والتجارب الحقلية. ومدخلات النموذج الرياضى المقترح هى معامل التوصيل الهيدروليكى المشبع ، معدل الاضافة ، حجم الماء المضاف ومعدل التغير فى المحتوى الرطوبى للتربة. اما المخرجات من النموذج الرياضى فهى قطر الابتلال السطحى والتقدم الراسى لجبهة الابتلال. وقد استخدم ٢٨٠ و ١٠٠ متجه لتدريب نموذج الشبكة العصبية الاصطناعية لتقدير لكل من قطر الابتلال السطحى والتقدم الراسى لجبهة الابتلال على التوالى. ولاختبار نموذج الشبكة العصبية الاصطناعية فقد تم اختيار ١٣٢ و٧٦ متجهه لكل من قطر الابتلال السطحى والتقدم الراسى لجبهة الابتلال على التوالى. واوضحت النتائج انه يمكن التنبؤ بقيم كل من قطر الابتلال السطحى والتقدم الراسى لجبهة الابتلال بمعامل تقدير ٠,٨ و ٠,٨١ لكل منهما على التوالى. بالاضافة الى ذلك، فقد وجد ان استخدام نموذج الشبكة العصبية الاصطناعية للتنبؤ بهذين الخاصيتين يكون اكثر كفاءة عند مقارنتـه بالعديد من النماذج التحليلية والاستنباطية التى تم اقتراحها للتنبؤ بنمط الابتلال اسفل المنقطات.