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Detecting the principal components affecting soil infiltration using artificial neural networks

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Abstract

Considering the significance of the infiltration process in the design and management of surface irrigation and the artificial neural networks method capability in computational analysis of some processes, this research aimed to study the feasibility of using the artificial neural network method for detecting the main components affecting the infiltration of irrigation furrows. Infiltration experiments have been performed using a blocked furrow method. In applying artificial neural networks, the set of inputs including opportunity time, initial soil water content, flow depth, flow section area, wetted perimeter and wet bulk density, were considered and after mapping the data and selecting the appropriate hidden layer and using multilayer perceptron algorithms and principal component analysis for the training process, the cumulative infiltration values were satisfactorily estimated. The results indicated that the artificial neural network with the principal component analysis with a hidden layer and r = 0.97 and MSE = 0.006 in the validation phase is an appropriate method to analyze the infiltration of the furrows. Also, opportunity time and flow section area components, effectively influenced the cumulative infiltration of irrigation furrows.

Keywords: Infiltration, irrigation, multilayer perceptron, principal component analysis

Introduction

Infiltration is one of the important phenomena affected by physical and hydraulic parameters of soil, and recognizing this process as one of the components of the water cycle is essential for management, planning and increasing the efficiency of surface irrigation systems. Raghuwanshi and Wallender (1997) realized that irrigation design and planning and net income of irrigation are sensitive to infiltration changes, and these changes should be taken into consideration in the irrigation design of the furrows. Development of an efficient irrigation system in the first step requires the determination of the effective parameters on the infiltration (Hashemirad 2011). Koech *et al*. (2010) reported that furrow irrigation is one of the most extensively applied methods of surface irrigation by gravitational force. An experimental result in irrigation furrows indicated that the correlation of the infiltration rate with wetted perimeter was linear (Nestor, 2006). Also, Oyonarte *et al*. (2002) studied the infiltration changes in irrigation furrows, and their findings indicated that the main source of changes is the soil absorption properties. Panahi *et al*. (2012) and Mirzaie *et al*. (2012) investigated the infiltration values in irrigation furrows in separate studies. Another research by Holzapfel *et al*. (2004) aimed to investigate the infiltration parameters in furrow irrigation. In order to utilize the advantages and capabilities of new techniques and tools, these innovations need researchers to evaluate the old issues with new technologies. In this case, we can refer to artificial neural networks that have been used to solve many of the complex engineering problems. The utilization of this method in the field studies of temporal-spatial variation of soil characteristics, geology, as well as hydrology and salinity studies is expanding. Estimation of soil water characteristics was completed by physicochemical properties of soil by artificial neural networks (Mohammadi, 2002). In the context of water and soil issues in separate studies, Merdun *et al*. (2006) and Parasuraman *et al*. (2006) investigated the possibility of estimating the hydraulic conductivity of soil saturation by neural networks. In 2006, a multilayer perceptron artificial neural network was used for modeling the infiltration process and it was reported that neural network efficiency was satisfactory in this regard (Nestor, 2006). In 2010, Ekhmaj estimated the infiltration value using neural networks and multilayered regression (MLR) methods and considering low values of MAE and RMSE in neural

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network methods, presented it as a better estimation method. Ghorbani *et al*. (2009) and Parchami *et al*. (2010) confirmed the efficiency of artificial neural networks in estimating the amount of cumulative infiltration and estimating the parameters affecting water infiltration into the soil, respectively. The efficiency of artificial neural networks in evaluating organic and inorganic pollutants in soils, estimating soil drainage classes, and estimating soil moisture has been demonstrated by different researchers (Frate, 2003; Arif *et al*., 2012; Beucher *et al*., 2017; Bonelli *et al*., 2017). Sihag *et al*. (2020) applied neural network techniques for analyzing infiltration. A look at the history of the studies clearly indicates that despite research studies that have been done in the field of water infiltration into the soil, different aspects of infiltration have not been studied thoroughly. With regard to the importance of the infiltration process, the present study aimed at the feasibility of applying artificial neural network method to determine the principal components affecting infiltration in irrigation furrows. The research results can be used by researchers and design engineers of water and soil to study the accurate designing of furrow irrigation, reduce the costs of measurements in farms and achieve high efficiency.

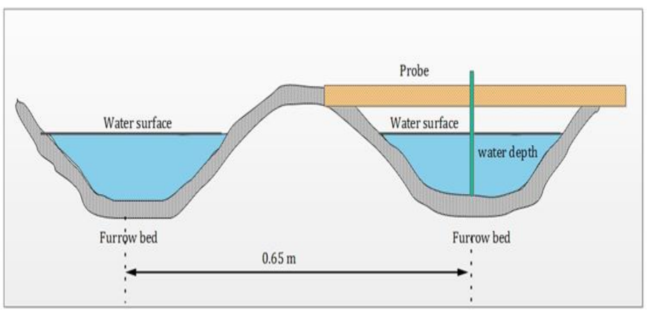

Figure 1: A set of blocked furrows for infiltration tests

Materials and Methods

Infiltration experiments

Experiments were conducted in East Azerbaijan province, Iran in the Agricultural Research Station of Tabriz University located at latitude 46º 17´ East and longitude 38º 5´ North and altitude of 1360 m. In order to conduct the experiment, we selected two separate sites, at 10 m intervals, including triple furrows as shown in Figure 1. The soil type of farm was sandy loam with 69.5% sand, 24.0% silt, 6.5% clay and with bulk density of 1.61 g cm^{-3}. The gravimetric field capacity was 12.2% with total available water of 10.7%. The infiltration was measured through blocked furrows method. The middle furrows were selected as the monitored furrows and the two lateral furrows as buffer furrows. The furrow cross-sections were taken using a profilometer, whereas flow section area and wetted perimeter were graphically determined from measured cross-sections. Initial soil water content was obtained by means of the gravimetric method, with drying by the burning alcohol technique in the field. Undistributed soil samples at initial water contents were also collected from the surface layer for wet bulk density measurements. The average duration of each infiltration experiment on the first and second sites was 157 and 264 min, respectively. The results of the experiments are presented in Figures 3 and 4. In order to analyze the cumulative infiltration data of irrigation furrows, the neural network method was used with multi-layer perceptron algorithms and PCA or principal component analysis.

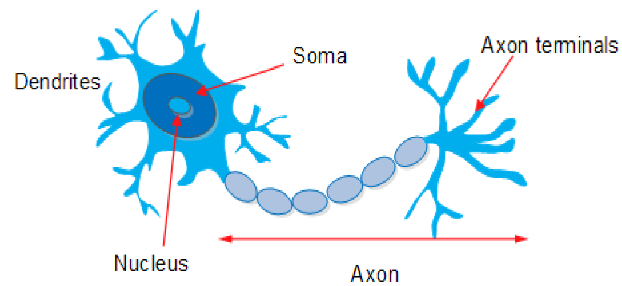

Figure 2: The structure of biological neuron

Artificial neural networks (ANNs)

The important part of the human brain is neuron. The neurons are divided into three categories, sensory neurons, interneurons and motor neurons. A neuron consists of a body, dendrites, and an axon. An artificial neural network is a simulation method inspired by the study of the brain system and the nervous network system of living organisms. Each simple artificial neuron, modeled from the biological neuron (Figure 2), calculates the sum of weighted inputs and compares the result with its threshold level and, if the sum is larger than the threshold, neuron becomes active, and otherwise, neuron becomes inactive. On the other hand, one of the assumptions for modeling the biologic neuron is that each of the neurons at the time of thus activity applies a stimulation function to the inputs. This function can be chosen linearly or nonlinearly. Each neural network consists of input, middle, or hidden and output layers, and is divided into different types, depending on the number and location of these network layers. In general, one of the most important characteristics of networks is its learning property. So that they can learn from the past and experience. The training of networks is done in two methods, supervised and unsupervised. Training methods include the Widrow Hoff method and the multilayer perceptron (Menhaj, 2009).

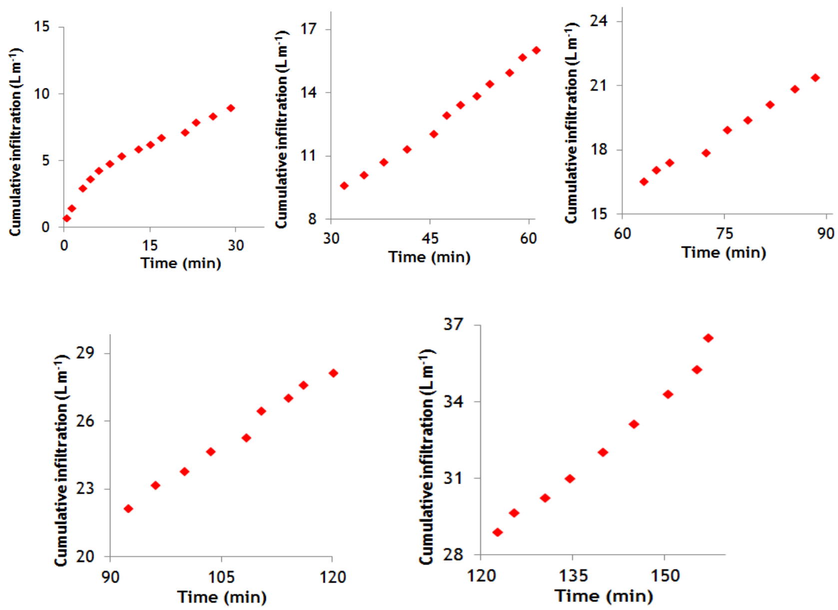

Figure 3: The cumulative infiltration at 30 minute intervals in the first measurement site

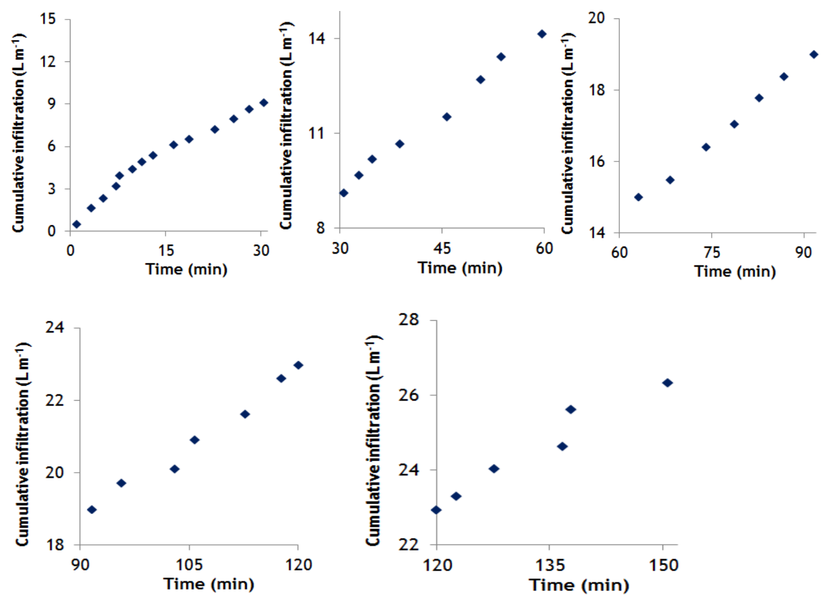

Figure 4: The cumulative infiltration at 30 minute intervals in the second measurement site

The utilization of neural network in detecting the principal components of infiltration

The multilayer perceptron consists of several regular layers, including the input layer, the hidden layer, and the output layer. The input layer units distribute the input values to the next layer and do not play a significant role in calculating. A multilayer perceptron acts in such a way that a pattern is presented to the network and its output is calculated. Comparing the actual and desired output, the weight coefficients of the network will be modified and corrected until a more accurate output is achieved (Menhaj 2009).

Another pattern is the principal components analysis, which is a data reduction method that reduces input data to several principal components.

To normalize the infiltration data, following relation was applied:

$$Zn = 0.1 + 0.80\,\frac{Zi - Z\min}{Z\max - Z\min} \qquad (1)$$

Table 1: Characteristics of selected models for infiltration analysis

No.	Hidden layers	Processing Elements	Step Size	Momentum	Correlation Coefficient
1	1	3	0.99	0.8	0.890
2	1	3	0.99	0.8	0.950
3	1	3	0.99	0.8	0.850
4	1	2	0.99	0.8	0.880
5	1	1	0.99	0.8	0.970
6	1	1	0.99	0.8	0.975

The type of training, multilayer perceptron and activation function, linear axon and number of inputs, were equal to six.

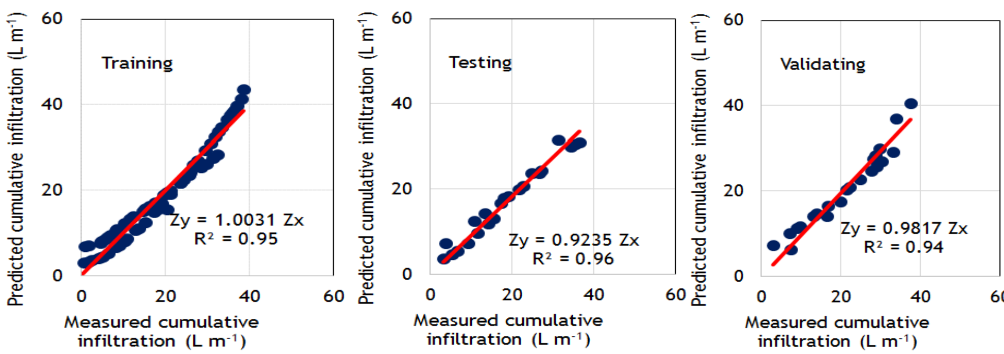

Figure 5: The measured and estimated cumulative infiltration with MLP for training, validation and test

where Zmin and Zmax are the lowest and highest infiltration values.

The statistical basis of the decision to choose the most appropriate artificial neural network model is the correlation coefficient (r) and mean squared error (MSE) defined as follows:

$$r = \left[1 - \frac{\sum (Z - \hat{Z})}{\sum Z^2 - \frac{\sum \hat{Z}^2}{n}}\right] \qquad (2)$$

$$MSE = \left[\frac{\sum (Z - \hat{Z})^2}{n}\right] \qquad (3)$$

Where r is the correlation coefficient, MSE is the mean squared error, Z is the measured cumulative infiltration, Ž is the estimated cumulative infiltration and n is the number of recorded data.

Results and Discussion

Initial results of experiments

The results of the infiltration measurement in the two measurement sites of the farms are shown in Figures 3 and 4. The cumulative infiltration at the end of the first thirty minutes in the first and second sites were 10.66 and 11.09, respectively, in the second thirty minutes, 17.2 and 17.84, respectively, in the third thirty minutes, 25 and 25.09 respectively, in the fourth thirty minutes, were 29.83 and 30.50, respectively and in the fifth thirty minute, 35.5 and 36.66 liters per meter. Generally, it can be said that for a given time, cumulative infiltration in the first site experiments, is more than the experiments of the second site. It may be due to the flow depth and flow section area in the furrow. The average initial soil water content in the first and second sites was 16.8 and 13.7 wt%, respectively. In these sites, the average bulk density was 1.48 and 1.55 g cm^{-3}. The flow depth at these sites was calculated to be 5 and 11 mm. The average flow section area in the first and second sites was 6.7 and 4.5 cm^3, respectively, and the wetted perimeter was equal to 8.8 and 9.0 cm.

The infiltration data analysis with artificial neural network

Six input sets, including opportunity time, initial soil water content, flow depth, flow section area, wetted perimeter and wet bulk density, and an output collection (cumulative infiltration), 110 samples were considered each to analyze the infiltration of irrigation furrow with artificial neural network. Then the data were randomized and 60% of the total data was allocated for training, 20% for cross validation and 20% for the test. The number of hidden layers was 1 and the number of elements was considered from 1 to 3. The linear axon function was used as the activation function with the momentum learning rule and with the step of 0.99 and coefficient of 0.8. The maximum number of epochs was 1000. The selection results among the best answers are summarized in Table 1. Among the different models, multilayer perceptron training with a hidden layer and one element (row 6) with a step and momentum coefficient of 0.99 and 0.8 for the output of 0.1 and 0.7 and with a correlation coefficient of 0.975 was chosen as the best method.

The estimated cumulative infiltration utilizing the neural network is presented with the multilayer perceptron training algorithm with the characteristics given in Figure 5. The correlation coefficient was 0.977, 0.985 and 0.970, for training, test and validation data, respectively. These figures indicated that the estimated cumulative infiltration value was more consistent with the measured values. Therefore, we can conclude that the utilization of artificial neural network in the analysis of infiltration of irrigation furrows has an appropriate efficiency .The network performance is evaluated with different indices. Among these indices, the correlation coefficient (r) and the mean squared error (MSE) are between the actual output and the estimated input. In Figure 6, the MSE index is presented in the training with multilayer perceptron algorithm for two stages of training and validation. In the multilayer perceptron training method, the mean value and minimum squared errors were 0.01 and 0.006, respectively, which were the same for both training and validation data. These values indicate the efficiency of artificial neural network in the infiltration data analysis using multilayer perceptron algorithm.

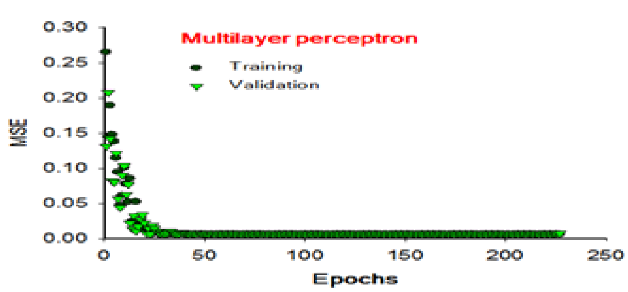

Figure 6: The mean squared errors in estimating cumulative infiltration for different epochs in MLP

The cumulative infiltration sensitivity to changes in its input set is presented in Figure 7. The most influential input in the cumulative infiltration value (output) is the opportunity time. In the multilayer perceptron training method, the effect of the wetted perimeter and the flow section area was approximately the same. We can also say that the effect of initial soil water content and flow depth were of the same and the bulk soil moisture density had a very slight effect on cumulative infiltration.

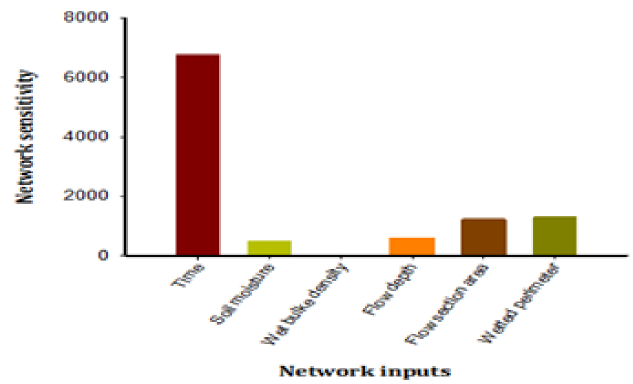

Figure 7: The network output sensitivity to the mean of its input changes in MLP

Table 2: The specification of the selected principal component analysis algorithm for infiltration analysis

No.	Hidden layers	Processing Elements	Principal Components	Correlation Coefficient
1	1	3	6	0.978
2	1	3	5	0.950
3	1	3	4	0.940
4	1	3	3	0.900
5	1	1	3	0.977
6	1	1	2	0.970
7	1	1	1	0.910

Considering the results of sensitivity analysis with multilayer perceptron training, the principal components analysis algorithm was used to detect the principal components affecting the infiltration and elimination of low inputs and, consequently, to reduce the cost of measuring the effective data on water infiltration and also to improve or enhance the network performance. The results of the selection are summarized in Table (2) among the best results using the neural network with the principal component analysis. In Table 2, it could be investigated that among different models, row 6 with hidden layer and an element with two principal components, including opportunity time and flow section area, with a correlation coefficient of 0.970, is selected as the best option. The criteria for selection were high correlation coefficient and simplicity of structure and low number of inputs. The estimated cumulative infiltration using the neural network is presented with the principal components analysis algorithm with the specifications selected in Figure 8. The correlation coefficients were 0.973, 0.982 and 0.975 for training, test and validation data, respectively. The comparative figures presented suggest the proper utilization of the principal component analysis algorithm in estimating the infiltration of irrigation furrows.

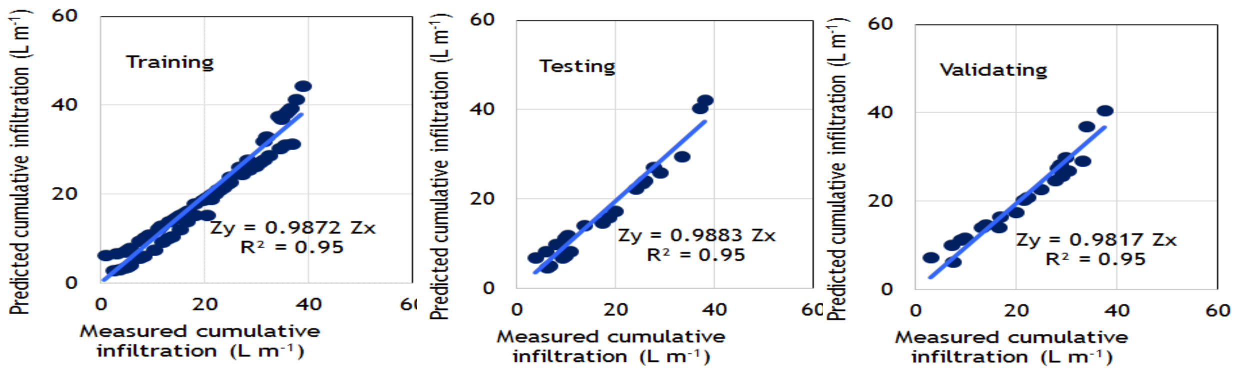

Figure 8: The measured and estimated cumulative infiltration with PCA for training, validation and test data

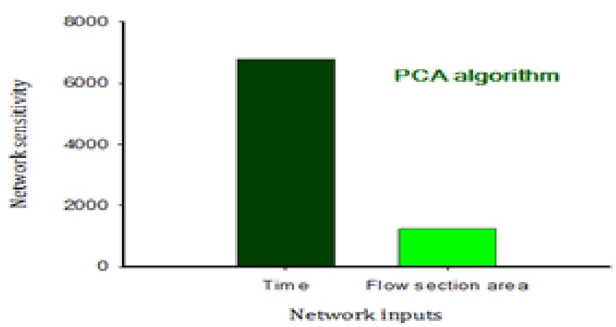

Figure 9: The network output sensitivity to the mean of its input changes in PCA

Table 3: The minimum and mean squared errors in principle components analysis with two components of opportunity time and cross flow section area

	Training	Cross validation
Epoch	322	34
MMSE	0.007	0.005
MSE	0.008	0.006

The cumulative infiltration sensitivity in the principle components analysis algorithm is shown in Figure 9. In this algorithm, the most influential input in the cumulative infiltration value was the opportunity time. The mean squared error between cumulative infiltration in the principle component analysis algorithm with two components of opportunity time and flow section area for training and validation data are presented in Table 3 and Figure 10. The minimum squared error value for training data was about 0.0075 and about 0.0055 for validation data. Also, the mean squared error for training data was about 0.008 and 0.006 for validation data (Figure 10 and Table 3).

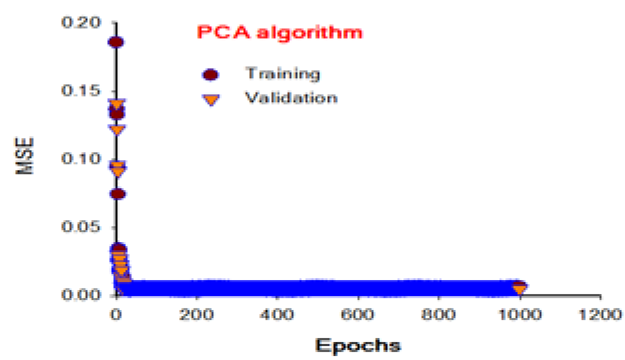

Figure 10: The mean squared errors in estimating cumulative infiltration for different epochs in PCA

We can say that in the absence of other factors that were measured, the sensitivity of cumulative infiltration to the mean changes of opportunity time was more than five times the sensitivity to the cross-sectional area. According to the opportunity time changes from 23.35 to 162.66 minutes, the cumulative infiltration changes were from 8.14 to 30.42 liters per meter. The flow section area changes were from 4.5 to 6.5 cm^2 and the changes in cumulative infiltration were from 17.14 to 21.42 liters per meter. Therefore, the present study indicated that using the artificial neural network method, the most important factors affecting cumulative infiltration are the opportunity time and flow section area. This finding is not consistent with Fangmir and Ramsey's report on the infiltration linear relation with the wetted perimeter, quoted by Mohammadi (2002), but is indirectly consistent, as Nasseri *et al* (2004) reported a positive correlation between the cross-sectional area and the wetted perimeter.

The utilization of artificial neural networks with principal components analysis model in this study indicated that the number of inputs that influence cumulative infiltration can be reduced to opportunity time and flow section area. Considering the fact that changes in cumulative infiltration of irrigation furrows by these two input variables can be analyzed and modeled with relatively high accuracy, reduction in the number of input data will reduce the measurement cost at the level of medium and large farms.

Conclusions

The results indicated that the utilization of artificial neural network is suitable for analyzing infiltration data of irrigation furrows. The principle components analysis algorithm was applied to detect the component affecting infiltration and excluding unrelated inputs and, consequently to reduce the cost of measuring the water infiltration data and also to improve or enhance the performance of the network. The use of a middle layer, an element with two principle components, including opportunity time and flow section area, were selected as a result of the high correlation coefficient and simplicity of structure and the low number of inputs as the best option. Considering that the opportunity time and cross flow section area components, efficiently affect the cumulative infiltration of the irrigation furrows, the infiltration equations of the irrigation furrows can be adjusted based on the spatial variability of the cross-sectional flow. Therefore, in order to adjust the infiltration equations of irrigation furrows in the conditions of this study, the necessity for applying other input variables such as bulk density, flow depth, wetted perimeter were not observed. The generalized possibility for various soil textures can be investigated in separate studies. Artificial neural network technique could be applied to detect components affecting furrow infiltration in surface irrigation.

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