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ASSESSMENT OF ARTIFICIAL NEURAL NETWORK PERFORMANCE AND EXPONENTIAL REGRESSION IN PREDICTION OF EFFECTIVE RAINFALL

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ABSTRACT

According to the current water crisis and spend more than 94 percent of water in agriculture the mechanized irrigation systems, and revised the actual plant water estimation are needed it is facilitate to predict rainfall in the growing season. In the design of irrigation systems should be noted that the total rainfall occurred was not available for plant and part of the rainfall runoff and part of it penetrate to soil and only part of it that is called effective rainfall is able to disappear plant water stress and influence plant growing. In this study, the results of regression model exponentially and based on field observations were compared with artificial neural networks (ANN). Its result showed more accuracy of mathematical and natural patterns (ANN) than pure mathematical patterns (regression). The use of neural networks in prediction of effective rainfall leads to decrease the cost of irrigation systems and water consumption. It also leads to reduce from unprofessional comments and consequently the imposition of water stress on the plant and the product.

INTRODUCTION

The extent of planted land is 1.6 billion hectares in the world each year that consist of 270 million hectares (17%) irrigated land. This value is 0.5% of the entire surface of the Earth and 2% of land surface area Distribution of irrigated land in the world is not uniform. Also, Asia has the highest area of irrigated land in the world approximately 181 million hectares (67%). North America and Europe, with 13 and 11 percent respectively are in the second and third categories. Since the products of irrigated land play fundamental role in providing food of people worldwide, until a few years ago irrigated land are developed for more food production. But currently for the development of agriculture land in the world, there is not enough water, soil and funds. For this reason approximately from 60 years ago until now per capita of irrigated land was remained 0.045 acres per person in the world increase of irrigated farms has been proportional to the increase in population.

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This process cannot be continuing, because the per capita of water and suitable land for agriculture is declining strongly. For example, there was 0.6 hectares of suitable irrigated land for every person in the world in 1950. This declined to 0.25 acres per person in 2000 and after that is decreasing due to the increase in population (Basheer and Hajmeer, 2000 and Wu *et al*., 2010).We know that the efficiency of plant production in dry land is less than irrigated agriculture with low. Thus, irrigated agriculture is common in worldwide. In this type of agriculture is assumed that all irrigated plant plant water requirement is supplied and usually the amount of rainfall in the growing season was eliminated.

MATERIALS AND METHODS

Part of rainfall that can be used to plant was called effective rainfall. Plant the amount of effective rainfall (P_{eff}) is reduced from the amount of evapotranspiration (ET) to calculation of plant water requirement (R). Effective rainfall is a function of precipitation of rainfall and plant water requirement. Table 1, has been prepared on the basis of field observations that average monthly rainfall can be obtained for each month of growth with respect to the total water requirement and the

Table 1. The average monthly effective rainfall as a function of the amount of precipitation and evaporation – desired plant transpiration

P(mm)	12.5	25	37.5	50	62.5	75	87.5	100	112.5	125	137.5	150	162.5
ET_c (mm)	Effective monthly rainfall average in mm (D= 75mm)												
25	8	16	23										
50	8	17	24	32	39	46							
75	8	18	26	34	41	48	55	62	69				
100	9	18	27	36	44	51	58	66	63	80	87	93	100
125	9	20	29	38	46	54	62	70	77	84	92	99	106
150	10	21	30	40	48	57	65	73	80	89	97	104	112
175	10	22	32	42	51	60	69	78	86	94	102	110	118
200	11	23	34	44	54	64	73	82	91	99	108	116	124
225	12	24	36	47	57	67	77	87	96	105	114	123	132
250	12	26	38	50	60	70	81	92	101	111	120	130	139

average rainfall in that months. Statistics in this table are applied with assuming that normal depth of water drain (D) of the soil before irrigation is 75 mm (which is true in most cases). In situation that the normal discharge of water depth is not 75 mm, number of table should be multiplying to correction factor f (D) that is only a function of D (Table 1).

$$f(D)= 0.53+0.0116\ D- 8.94\times10^{-5}\ (D)^2+2.23\times10^{-7}\ (D)^3$$

After estimating the amount of effective rainfall, we can estimate the plant water requirement.

$$R=CWR=P_{eff}$$

In the above equations: R is irrigation requirement, CWR is plant water requirements, including leaching requirement and efficiency of irrigation and P_{eff} is effective rainfall. All parameters are in millimeters. According to previous year findings, linear and non-linear regression was used to assess the association between dependent and independent variables. So that with this method tier 1 curve (line), 2, 3, 4, logarithmic, exponential, and etc are passed from data desert collected and after that instead of referring to population, a relationship can be used that justifies the extensive statistical sensitivity to changing phenomenon, the phenomenon is creating variables. But at the present time and with digital computers and prosperity of the key concepts of artificial intelligence known as artificial neural network patterns, use the regression equation seems illogical (Abbot and Marohasy, 2012 and Mohsenifar *et al*., 2011). Because neural networks inspired by the behavior of neural stem cells able to find science behind the phenomenon by target population or complex field data to justify math or the physical and measure its sensitivity to changes in variables (Wu and Chau, 2011). Here before network simulation in MATLAB programming environment 1, refer to regression equation used and after the simulation attempted to compare the outputs of the neural network and regression and these compare with actual values obtained and show each error of them. After the statistical analysis, the best exponential regression equation was calculated that compare with other regression methods has less error. According to the relationship effective rainfall (P_{eff}) is an exponential function of rainfall in the month, including the variables (P_t) and evaporation - transpiration or plant water requirement in the same month (ET)

$$P_{eff}= f(D)\ [1.25\ (Pt)^{0.824}-2.93]\times 10^{(0.000955ET)}$$

Artificial neural network is a kind of intelligent system of neural cell-like organisms, and mimics of the human brain in learning, processing and memorize information. Some neural network structure is not quite similar to the brain. Artificial neural network is a mathematical structure that combines the nonlinear relationship between inputs and outputs of the system and with the fully parallel structure process data. During the learning phase, the network is trained and tested and calibrated will be used for application in the next step (Kim and Pachepsky, 2010 and Kumar *et al*., 2011). Some of the areas of neural networks can be attributed to the late nineteenth and early twentieth century, in that time basic research in physics, psychology and neoruphisyology done by scientists such as Ivan Pavlov. This primary research is generally based on the learning theory, vision and condition and did not mention the mathematical models of network performance (Najah, 2011). A new vision of artificial neural networks in the 40 decade of the twentieth century began with the work of Pitts and McCulloch. They show that the neural network function calculates the every arithmetic and logical function (McCulloch *et al*., 1943).

The first practical application of neural networks of perceptron network was by Frank Rosenblatt network in 1958. He built a network that is able to identify patterns (Rosenblatt, 1958). Bernard Widrow proposed adaline adaptive neural network learning with the new law, which was structurally similar to the perceptron network (Widrow and Lehr, 1990). Until 80 decade, researches on neural networks have been slowly due to unavailability of computers quickly to implementation, but increased with the development of miplantrocessor technology (Machado *et al*., 2011). Generally, it can be studied the progress of neural networks in three phases: in the first phase extensive research were performed on the relationship between neural neurons until 1969 a number of limiting factors characterized by Minsky and Papert (1969) and the second phase was started with discovery and propagation training algorithm generalization by Rumelhart and McClelland (1986). Before this phase, the training of the neural network was difficult in practical sizes and the third stage with a very detailed assessment of network constraints and generalization and its comparison was accompanied with other methods such as genetic algorithms and fuzzy theory and neural networks using proprietary hardware (Mustafa *et al*., 2011). In recent years, thousands of articles have been written on neural networks and this leads to further its application in various fields of science and engineering.

It should be noted that currently there is limited information about how the brain works and certainly in the future will be marvelous progress in this field (Asadi *et al*., 2013).

The overall structure of neural networks

Figure 1 shows a neuron cell or a normal neuron. In biological system, the seneurons are capable of memorizing, thinking and applying them to our past experiences. Each neuron is made of three parts, cell body, dendrites and axons. There is synapsis in connection area of two neuron dendrites. Through synapses message has been received from other neurons and combines. Neuron is the smallest unit of manufacturer of artificial neural network and in fact plays a role as neural cell of brain. So, the neural network is series of artificial neurons. These neurons have a structure similar to the structure of real neurons but are much simpler than biological neurons (Abbot and Marohasy, 2014). Artificial neurons assess input data instead of programmable and with regulation of time and repetition, provide appropriate outputs (Liu *et al*., 2012).

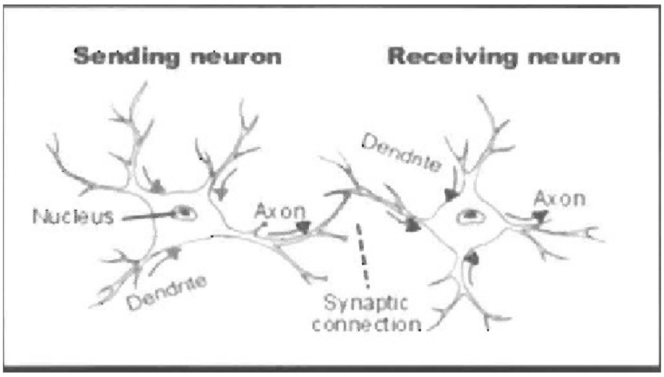

Figure 1. Neuron cell or a normal neuron

Figure 2 shows an overview of artificial neural networks. According to this figure, the network is made of an input layer, one or more intermediate layer and an output layer. Each layer is made of a number of neurons. Each neuron receives data from some input similar to dendrite in real neuron, and after the processing delivers data to its output that play similar to. Output of this neuron is used as input of next neuron (Chua *et al*., 2011). The number of neurons in the input layer and output are determined proportionally by function of network. About middle layer, the number of neurons is determined by the user using the trial and error method.

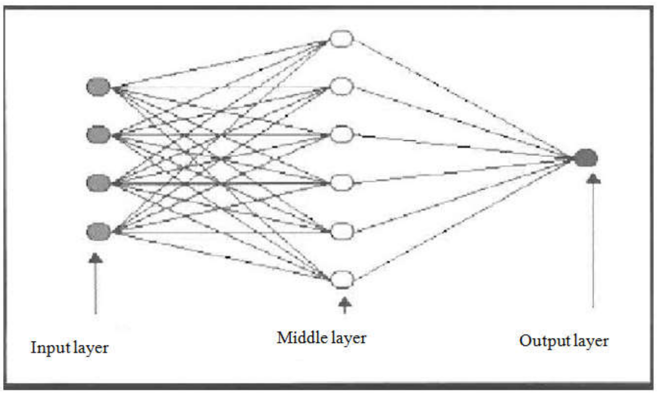

Figure 2. Overview of artificial neural networks

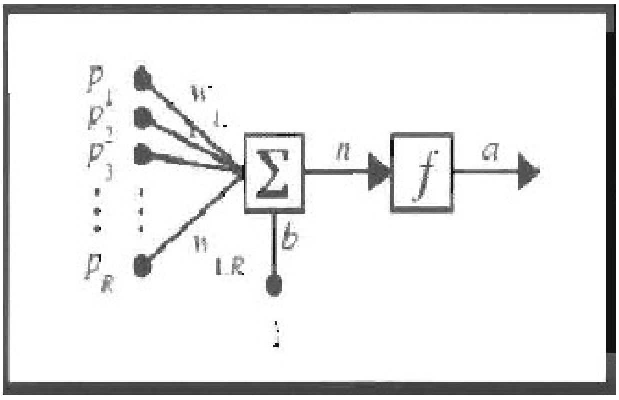

Figure 3. A progressive network with neurons in the middle layer

If the number of neurons is very low or high, the accuracy of the network decreases. Neurons in each layer by weight are connected to the next layer neurons. These weight and constant amount is called bias. That during training process regularly change network until they reach their best state (Nastos *et al*., 2014). Figure 3 shows a progressive network with neurons in the middle layer. Progressive network is a network for calculation of the input layer to the output layer, there is no turning back on the path. Network is made of input R that is connected to neurons by weights W in the middle layer. N output is calculated as follows:

n=Ó ($P_t \times W_t$) +b

The actuator functions are used to transfer the output of each layer to the next layer. The stimuli function as a non-linear amplifier is to neurons. This function can be sigmoid, linear, threshold, hyperbolic tangent or Gaussian function, which determined depending on network and learning algorithm uses (Richard and GopalRao, 2014).

RESULTS AND DISCUSSION

MATLAB software was used to simulate the neural network. Before the simulation, all the data i.e. values of evapotranspiration, precipitation and effective rain in were normalized Excel program and using the following equation (normalization is a type of standardized form of data):

$$X=\frac{Xi-Xmin}{Xmax-Xmin}$$

This method was used for the proper training of the network. 70% of the data was spent for training the network and as well as 50% was chosen for the test network. As can be seen between training and test data, there is a 20% overlap. selected function was sigmoid type and after than many trial and error a neural network structure with four layers obtained (two middle layer), that the input layer has two neurons (input variables are the rainfall and evapotranspiration), the intermediate layer has seventeen neurons and output layer has one neuron (effective rainfall is output variable).Chart of network and convergence process are shown in Figures 4, 5 and Figure 6 shows the error rate of computational neural networks and exponential regression. This graph shows the accuracy of the neural network in predicting of effective rain rate, because in a

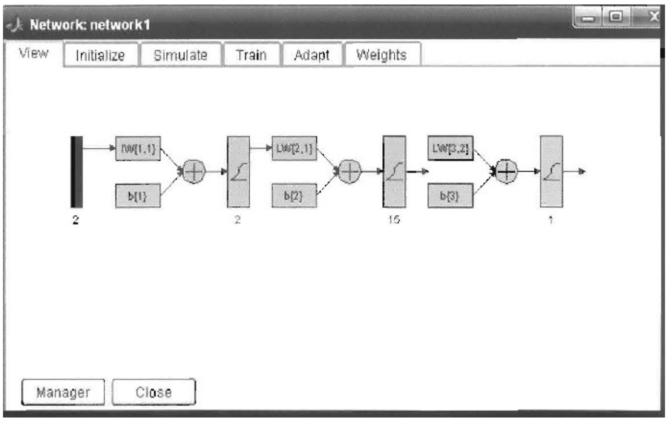

Figure 4. Chart of network and convergence process

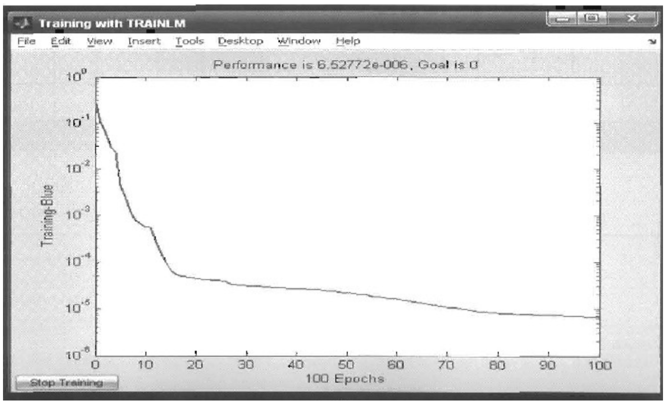

Figure 5. Chart of network and convergence process

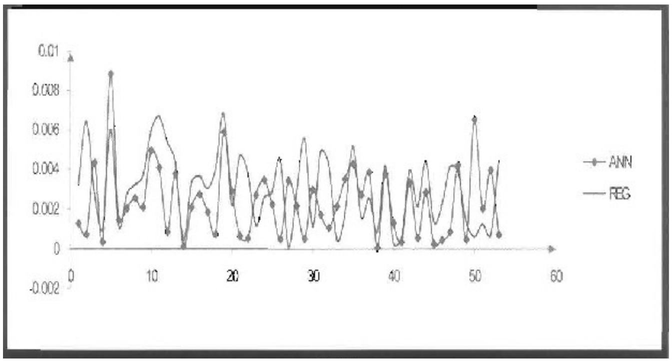

Figure 6. The error rate of computational neural networks and exponential regression

number of computational points has higher accuracy than the exponential regression equation and the cumulative error is less than it. So the neural networks based on mathematical theories and mathematical patterns are more successful compare with pure mathematical model as regression methods for prediction of events

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