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Estimation of barley yield under irrigation with wastewater using RBF and GFF models of artificial neural network

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ABSTRACT

In this study, barley yield has been estimated via radial basis function network (RBF) and feed-forward neural networks (GFF) models of artificial neural network (ANNs) in Torbat-Heydarieh of Iran. For this purpose, a dataset consists of 200 data at three levels of irrigation with well water, industrial wastewater (sugar factory wastewater), a combination of well water and wastewater in two levels (complete irrigation and irrigation with 75 % water stress) and soil characteristics of area were used as input parameters. To achieve this goal, based on the number of data and inputs, 200 barley field experiments data set were used, of which 80 % (160 data) was used for the training and 20 % (40 data) for the testing the network. The results showed that RBF model has high potential in estimating barley yield with Levenberg Marquardt training and 4 hidden layers. Also the values of statistical parameters R^2 and RMSE were 0.81 and the 33.12, respectively. In general, the results showed that ANNs model is able to better estimate the barley yield when irrigation water level parameter with well water is selected as input.

1. Introduction

Barley (Hordeum vulgare), a member of the grass family, is a major cereal grain grown in temperate climates globally. It was one of the first cultivated grains, particularly in Eurasia as early as 10,000 years ago (Rahmani et al. 2008; Akbarpour et al. 2013). In Iran, after wheat, barley is ranks second in cultivars, due to little water requirement and very good resistance to cold and salinity. Yousef genotype is a new cultivar of early barley, tolerant to late season with high water use efficiency is very suitable for cultivation in temperate regions of the Iran. Doing accurate farming methods and quantifying their impact depends on crop growth and yield. In recent decades, some researchers have tried to apply new methods such as geo-statistics technologies, hybrid models of neural networks and genetic algorithms and artificial neural networks, along with classical statistical methods such as multivariate regression to model and estimate crops yield. In the meantime, artificial neural network methods have grown exponentially due to their high accuracy and efficiency in modeling. In fact, artificial neural networks are a transcript of the brain structure and human neural network. In these networks, we are trying to come up with a structure that has the power of brain, learning, generalization and decision making. In these networks, we are trying to create structures that have the same power as learning, generalization, and decision making. The main idea behind these methods is based on the simulation of human brain function, which can have a very small scale of learning and generalization power (Gershenfeld .1999). Considering the special status of barley yield among the crops, modeling the barley yield and determining the factors affecting its growth is of great importance. Artificial neural network modeling is one of the modeling methods that have received much attention in recent years by researchers in different sciences. Researchers such as Merdun et al. (2006), Landeras et al. (2009) Piri et al. (2009) and Smith et al. (2009) used artificial neural networks to simulate and estimate parameters such as weekly evapotranspiration, daily evaporation, water retention capacity and water absorp drainage coefficient coefficient. Seiler et al. (2004) pointed to the high ability of artificial neural network method in estimating corn yield. Kaul et al. (2005) estimated corn and soybean yield using artificial neural networks and reported that ANN models consistently produced more accurate yield predictions than regression models. Norouzi et al. (2010) predicted dryland wheat yield in aride and semi-arid regions of Iran using artificial neural networks and concluded that sediment transport index was the most important topographic factor on the dryland wheat and the amount of protein in the seeds was affected by the total soil nitrogen content. Taghizadeh Mehrjerdi et al. (2016) correlated observed crop yields with auxiliary variables (DEM and Landsat images) using genetic programming (GP) in Gotvand area (Khuzestan Province). The results indicated GP (2) with auxiliary data selected through wrapper algorithm could also reasonably predict wheat crop yield (RMSE, coefficient of determination and Lin's concordance coefficient, 530.82, 0.86 and 0.79, respectively). Rahmani et al. (2008) estimated barley yield in eastern Azerbaijan using drought indices and climatic parameters by artificial neural network (ANN). The results showed that due to the high values of R^2 of the optimal model, the neural network method was highly efficient in predicting the barley yield. Bagheri et al. (2012) predicted the silage maize yield using artificial neural network in Varamin province. The results of artificial neural network analysis showed that when at least three parameters of irrigation, fertilizer and growing degree days (GDD) were introduced as the input of ANN, the model could predict the performance of silage maize with high accuracy. Esmaielzadeh-KordKheili (2012) estimated the rice yield using statistical methods, artificial neural networks and multiple regression methods in paddy lands of Lash-e-Nesha of Guilan province. Results showed that the

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new model of artificial neural networks were more efficient to predict the rice yield rather than the multiple regression (MR) model. Zareh-Abianeh (2012) evaluated artificial neural network and geostatistical methods in estimating the spatial distribution of irrigated and dry wheat yield in Khorasan Razavi. Results showed that among the methods of geostatistics, simple kriging with circular model with NRMSE=0.120 and ordinary kriging with exponential model with NRMSE=0.348 was suitable to forecast wheat yield. Adab et al. (2013) prepared the map of autumn rapeseed yield using perceptron neural network in Sabzevar city. The results showed no significant difference between the predicted and measured values at the significant level of 0.05. Akbarpour et al. (2013) evaluated the performance of artificial neural network models in estimating saffron yield based on climatic parameters. The results showed that the proposed neural network had a good accuracy in estimating saffron yield with values of R^2=0.95. Bariklo et al. (2017) predicted irrigated wheat yield by using hybrid algorithm methods of artificial neural networks and genetic algorithm. The results showed that the hybrid model can be a powerful tool for estimating wheat yield. Akbari et al. (2017) predicted discharge coefficient of triangular plan form weirs using the Radial Base Neural Networks (RBNN) and M5' methods. Results showed that the M5' model is capable of modeling the discharge coefficient more accuratelyAzimi et. (2018) Simulated the hydraulic break of Malpasset dam using the FLOW-3D software. Results showed that the numerical model were in good agreement with those predicted by the EDF model. According to the studies, the main advantage of the neural network methods is that not need to specify the initial structure unlike classical regression analysis and have non-linear nature and able to estimate complex systems better than classical linear statistical methods. Given that the modeling of barley yield has not investigated yet, and also limited studies have been conducted on barley yield modeling under irrigation with wastewater, in this study, using RBF and GFF models of artificial neural network to estimate barley yield.

2. Materials and methods
2.1. Case study

In order to use artificial neural network (ANN) method to estimate barley yield, Torbat-Heydarieh (Longitude 59º12'E and Latitude 34º17'N) region located in Khorasan-Razavi province, in northeast Iran was selected (figure 1). The experimental site has an arid climate and is 1333 m above sea level. The average annual rainfall and temperature at the site are 260 mm and 21 ºC, respectively (http://areo.ir/). The experiments included three levels of irrigation water ((well water, industrial wastewater (sugar factory wastewater), a combination of well water and wastewater in two levels (complete irrigation and irrigation with 75 % water stress)).

The industrial wastewater used in this experiment was from the sugar factory wastewater of Torbat-Heydarieh located near Mashhad city. The experiment was conducted at four replications. The first treatment was well water (T_1) and served as control. The second treatment was industrial wastewater (T_2), the third treatment was a combination of well water and wastewater in two levels (complete irrigation and irrigation with 75 % water stress) (T_3). The land used in the previous years was fallow. Based on soil experiments and the recommendation of Khorasan Razavi Agriculture Jihad Organization, 30 tons of animal manure, 180 kg of urea, 250 kg of phosphorus fertilizer and 50 kg of potassium sulfate (SOP) were recommended for one hectare of barley cultivar (Yousef genotypes). Wheat was planted on May, 10 irrigations were applied and 3 months after planting it was harvested. The amount of seed recommended by the Agricultural Jihad Organization for one hectare of barley is 250 kg. 100 grams of seeds were used for plots of this study that were 4 square meters (2*2). The amount of water requirement was calculated using the NETWAT software and according to meteorological data of Torbat Heydariyeh station and by FAO Penman-Monteith method with constant irrigation interval of 7 days. For water stress treatments, 75 % of water requirement was calculated and delivered to plots by volume meter with precision liter. Data were analyzed statistically the statistical software called SAS 9.2 and Excel 2013. Table 1, shows the soil physical and chemical properties of experimental field.

2.2. Modeling of barley yield using artificial neural network (ANN)

All optimization problems consist of two stages of modeling and planning including, the formation of objective function, constraints and limitations (first stage, modeling) and the determination of the optimal conditions to achieve the ideal solution (second stage, planning). Artificial neural network consists of a set of neurons with internal links with one another, which can provide output responses based on the input data and information. Neural networks are usually created in a layered and regular manner. The first layer, which the input data are entered, is the input layer. The middle layers of the hidden layers and the last layer, in which provides the output responses are the model, is the output layer (Menhaj. 2000).

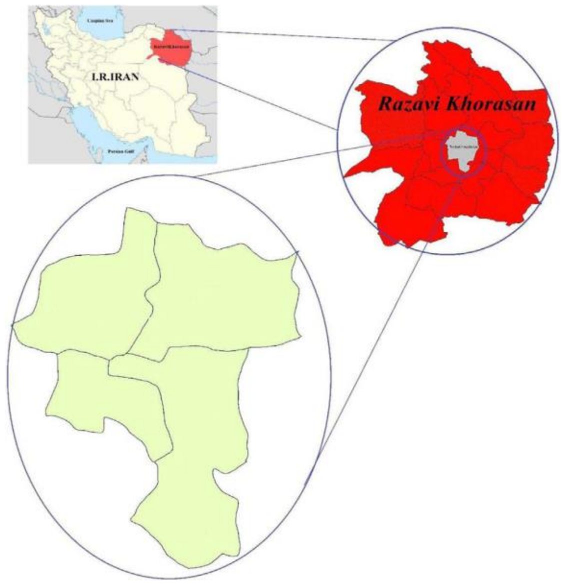

Fig. 1. The location of the study area.

Table 1. Selected soil physical and chemical properties at the experimental field.

Experiment type	Unit	Results of experiment
Potassium	mg/Kg	175
Phosphorus	mg/Kg	5.3
Nitrogen	%	0.011
Salinity	dS/m	6.3
Acidity	-	7.6
Lime	%	18.75
Organic material	%	0.081
Sand	%	58
Clay	%	9
Silt	%	33
Saturation percentage	%	27.9

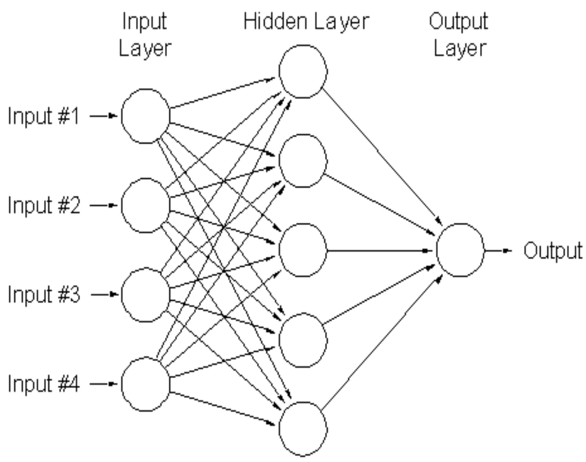

Fig. 2. A view of neural network method.

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3.2. GFF Model

3.2.1. Feed-forward neural networks

Feed-forward networks have the following characteristics:

1. perceptrons are arranged in layers, with the first layer taking in inputs and the last layer producing outputs. The middle layers have no connection with the external world, and hence are called hidden layers.
2. Each perceptron in one layer is connected to every perceptron on the next layer. Hence information is constantly "fed forward" from one layer to the next and this explains why these networks are called feed-forward networks.
3. There is no connection among perceptrons in the same layer (Fig. 3).

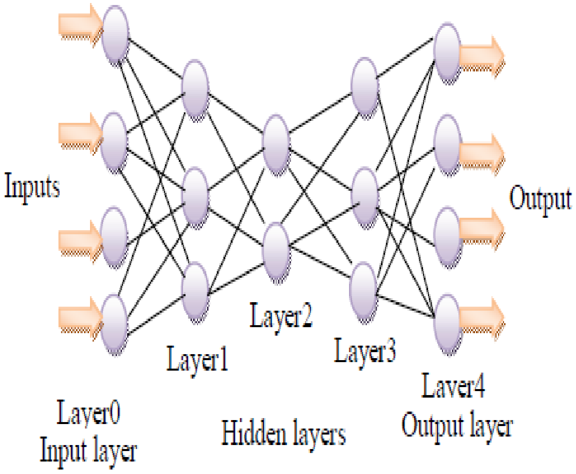

Fig. 3. Feed forward network.

4.2. RBF model

In the field of mathematical modeling, a radial basis function network is an artificial neural network that uses radial basis functions (RBF) as activation functions. The output of the network is a linear combination of radial basis functions of the inputs and neuron parameters. Radial basis function networks have many usages, including function approximation, time series prediction, classification, and system control. They were first formulated in a 1988 paper by Broom head and Lowe, both researchers at the Royal Signals and Radar establishment.

Radial basis function (RBF) networks typically have three layers: an input layer, a hidden layer with a non-linear RBF activation function and a linear output layer. The input can be modeled as a vector of real numbers. The output of the network is then a scalar function of the input vector, and is given by where is the number of neurons in the hidden layer, is the center vector for neuron, and is the weight of neuron functions in the linear output neuron. Functions that depend only on the distance from a center vector are radially symmetric about that vector, hence the name radial basis function. In the basic form all inputs are connected to each hidden neuron. The norm is typically taken to be the Euclidean distance (although the Mahalanobis distance appears to perform better in general) and the radial basis function is commonly taken to be Gaussian. The Gaussian basis functions are local to the center vector in the sense that i.e. changing parameters of one neuron has only a small effect for input values that are far away from the center of that neuron. Given certain mild conditions on the shape of the activation function, RBF networks are universal approximators on a compact subset of (Jafari. 2014). This means that an RBF network with enough hidden neurons can approximate any continuous function on a closed, bounded set with arbitrary precision. The parameters are determined in a manner that optimizes the fit between the data.

4.2.1. Training

RBF networks are typically trained from pair of inputs and target values:

$$x\,(t), y\,(t), t = 1, \dots, T \qquad (1)$$

The main structure of the RBF network consists of 3 layers, as in Fig. 4.

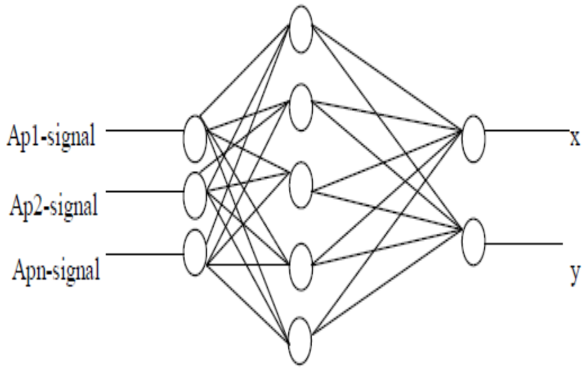

Fig. 4. Hidden layer (The weight associated with the cluster center and the output function are usually Gaussian).

4.2.2. Momentum algorithm

Momentum algorithms in neural networks and the applications for solving linear systems are discussed. In this algorithm, we can consider the weight change law so that the weight change in the repetition of n depends on the size of the weight change in pervious repetition (equation 2):

$$\Delta W_{ji}(n) = \eta\delta_i X_{ji} + \alpha\Delta W_{ji}(n-1) \qquad (2)$$

in which, the amount of momentum α, like as $0 \le \alpha \le 1$.

4.2.3. Sigmoid function

Sigmoid functions are often used in artificial neural networks to introduce nonlinearity in the model. A neural network element computes a linear combination of its input signals, and applies a sigmoid function to the result. Derivatives of the sigmoid function are usually employed in learning algorithms. The non-linear transfer function, usually in the form of a sigmoid, is defined as follows:

$$f\,(s) = (1 + \exp(-s))^{-1} \qquad (3)$$

y" output can be the result of the model or input of the next layer (in multilayer networks).

4.2.4. Levenberg–Marquardt algorithm (LM)

In mathematics and computing, the Levenberg–Marquardt algorithm (LMA or just LM), also known as the damped least-squares (DLS) method, is used to solve non-linear least squares problems. These minimization problems arise especially in least squares curve fitting. The LMA is used in many software applications for solving generic curve fitting problems. However, as with many fitting algorithms, the LMA finds only a local minimum, which is not necessarily the global minimum. The LMA interpolates between the Gauss–Newton algorithm (GNA) and the method of gradient descent. The LMA is more robust than the GNA, which means that in many cases it finds a solution even if it starts very far off the final minimum. For well-behaved functions and reasonable starting parameters, the LMA tends to be a bit slower than the GNA. LMA can also be viewed as Gauss–Newton using a trust region approach. The algorithm was first published in 1944 by Kenneth Levenberg (alborzi. 1998) while working at the Frankford Army Arsenal. It was rediscovered in 1963 by Donald Marquardt (Aljairry. 2010).

4.3. Datasets

In this study, to estimate the barley yield, soil characteristics at 0-40 cm depth were used. Then, soil properties (table 2) and three levels of irrigation with well water, sugar factory wastewater and a combination of well water and wastewater in two levels (complete irrigation and irrigation with 75 % water stress) as input parameters and barley yield was considered as the output of the models. In order to evaluate the capability of two models of ANN, a 2 years monthly statistical data (2014 to 2015 years) was carried out for analysis. The dataset used in this range consists of 200 unique data, which is used in calculations.

In many references, divide data into training and testing, the two methods are 80 to 20 and 70 to 30 percent. The choice of each of these methods depends on the number of data and inputs, which is in this study, to train and test the proposed models, 80 % (160 data) and 20% (40 data) of the dataset were used, respectively. This pair of data has been selected randomly from all possible historical couples by main training time continuity. The reason for random selection is to provide adequate training information for all events in the historical time series. Using the validation data, we can examine the effectiveness of trained model.

4.3.1. Model development

Communication weights and the constants between intermediate the input layer also the middle layer to the output for the optimal model selected with 6 neurons in the middle layer is shown in table 2 and 3. By using these coefficients and constants, by identifying data normalization and the transfer function used in network, one can simulate the neural network and use it to estimate barley yield with simple calculations.

Table 2. ANN model communication weights**.**

Hidden neurons	Connection weights					
1	**Well water**	**sugar factory Wastewater**	**Combination of well water and wastewater**	**Data**	**Complete irrigation**	**75% Water stress**
2	-3.06	-2.16	-4.60	-3.35	-2.52	-0.38
3	7.24	-1.37	0.00	0.035	0.27	-0.32
4	-0.06	1.20	0.36	0.00	-0.105	-1.15
5	-2.90	-0.015	0.25	0.2	0.93	0.83
6	3.06	5.7	-4.52	-0.085	-0.72	-0.49
	-2.91	-3.47	0.00	0.025	-0.76	-1.03

4.3.2. Evaluation criteria

In order to compare the models with each other and evaluate them, we need criteria that can judge the function of the models in the entire datasets compared with the experimental results. In this study, correlation coefficient (R^2), mean absolute average error (MAE) and root mean square error (RMSE), were used (Ghorbani et al. 2017):

$$R^2 = \frac{\sum_1^n (\text{calc}-\text{avg.obs})^2}{\sum_1^n (\text{obs}-\text{avg.obs})^2} \quad (4)$$

$$\text{RMSE} = \frac{\sqrt{Q_o - Q_M}}{N} \quad (5)$$

$$\text{MAE} = \frac{\sum |Q_o - Q_M|}{N} \quad (6)$$

where, obs is average measured data, n is number data, cal is estimated data and Q_o and Q_m are the measured and estimated parameters, respectively.

Table 3. Constants of the ANN model.

Bias						
Hidden neurons						**Output**
1	2	3	4	5	6	1
3.71	1.86	-0.350	-0.261	0.922	-1.546	-2.232

The input of data in raw form reduces the speed and accuracy of the model, so the inputs and outputs must be standardized between 0 and 1, hence the data are normalized as equation 7.

$$\begin{cases} Y_i = \frac{X_{oi}}{X_{omax}}, & X_{oi} \geq 0 \\ Y_i = \frac{X_{oi}}{|X_{omin}|}, & X_{oi} < 0 \end{cases} \quad (7)$$

in which, Y_i, X_{Oi}, Xo_{min} and Xo_{max} are standardized, observation values, minimum observational and the maximum observational values, respectively.

3. Results and discussion

The ANN function was selected to determine the best answer by using the statistical parameters of R^2, RMSE and MAE on both the training and testing data sets. After the trial and error, the optimal network from the input layer to the median and the middle reaches the output (Table 4).

3.1. Determining the best topology (number of training nodes and neurons, number of layers and appropriate function)

The purpose of determining the network topology is to determine the best number of nodes, the number of hidden layers, the training and testing functions and ultimately the type of network. For this purpose, regression coefficient and error analysis were used. In this section, the best chosen topology along with comparison graphs of measured and estimated values and the results of regression and error analysis for barley yield are presented in Table 4. The best topology in this case is linear sigmoid tangent function with 1000 repetitions. Fig. 4 clearly illustrates the above mentioned.

Table 4. Error analysis between measured and estimated values of barley yield.

Criteria	Value
MSE	6.982110
NMSE	1.587221
MAE	2.640323
Min Abs Error	3.951269
Max Abs Error	0.101874
R^2	0.948541

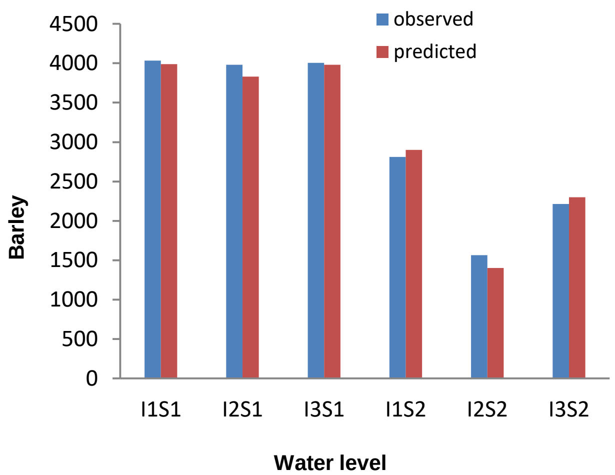

Fig. 4. Comparison of measured and estimated values of barley yield with the best ANN topology.

The results show the efficiency and accuracy of neural networks in estimating barley yield. The results of this study with a R^2=0.948 for estimating barley yield are consistent with the results of other researchers' studies, such as Seiler et al. (1998), Tiscareno-Lopez et al. (2003), Eitzinger et al. (2005) and Rahmani et al. (2008), where the optimal model performed by them had a R^2 less or equal to 0.9, and even improved the results of their studies.

3.2. Comparison of RBF and GFF models in estimating barley yield

The design of an ANN involves selecting the number of hidden layers and processor elements (neurons) for hidden layers, which is a trial and error process to obtain the best possible output.

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3.3. The results of training and testing of ANN model

In this study, soil characteristics, three levels of irrigation with well water, industrial wastewater and a combination of well water and wastewater in two levels (complete irrigation and irrigation with 75 % water stress) were investigated as Input variables different networks.

The output parameter in all networks was barley yield. The number of 1000 cycles and one hidden layer for estimating barley yield was considered as appropriate ones (table 5). The best results for each artificial neural networks model are presented in Table 6. Also, the correlation of measured yields and estimated values of barley yield by GFF and RBF models is shown in figures 7 and 8.

Table 5. Error analysis between measured and estimated values of barley yield.

Parameter	Best training function	Number of nods	Number of layers	R^2
Barley yield	Linear sigmoid tangent	1000	1	0.9317
Barley yield	Linear sigmoid tangent	5000	2	0.9309

Table 6. Comparison different models in predicting barley yield.

Type of model	Transfer function	Training algorithm	Network Training Stage		Network Testing Stage	
			RMSE	R^2	RMSE	R^2
RBF	SigmoidAxon	momentum	0.038	0.79	33.12	0.88
GFF	SigmoidAxon	momentum	0.041	0.76	39.71	0.78

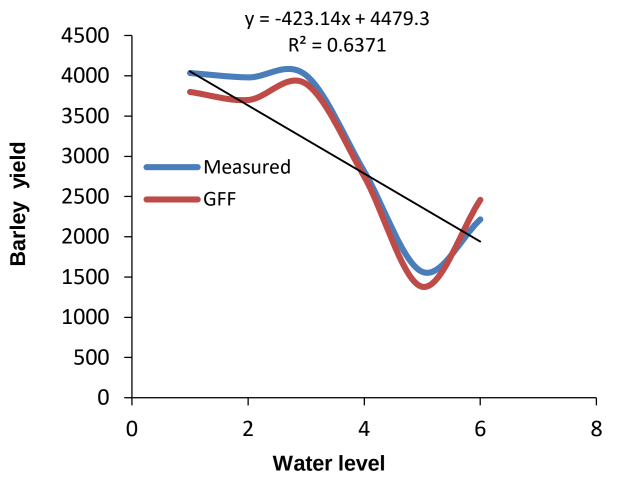

Fig. 5. The correlation of measured yields and estimated values of barley yield by GFF model.

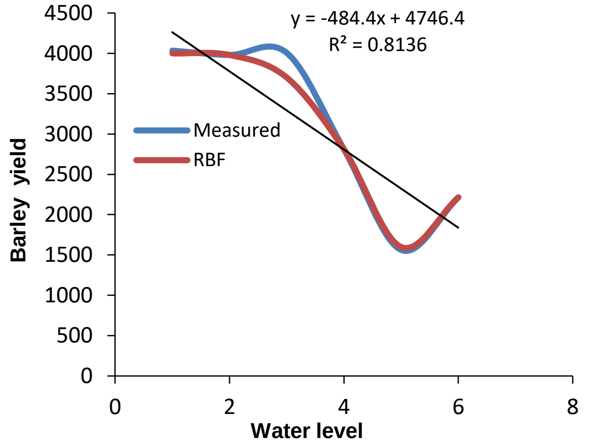

Fig. 6. The correlation of measured yields and estimated values of barley yield by RBF model.

According to the above diagrams, after comparing the results of RBF and GFF models, RBF model with different irrigation levels parameter as input was known as the best model. The obtained values of R^2 and RMSE for RBF model was 0.81 and 33.12, respectively.

3.4. Selecting the best model

Barley field experiments data was trained and tested by RBF and GFF models of artificial neural network with different training algorithms, neurons and with 1 and 2 hidden layer. After applying different patterns and training the network, the best pattern was chosen from selected patterns. Selecting criterion is the network that has the best training and provides satisfactory results. Of course, in choosing a network, we need to be careful about occurrence of the preprocessing phenomenon, because in tests where the error approaches zero, network generalization will be unacceptable. The results of this section are presented in Table 7. After applying the test set to the selected networks, the networks generalization was examined and finally the network that showed the best generalization in the test setup was considered as an optimal network to estimate barley yield.

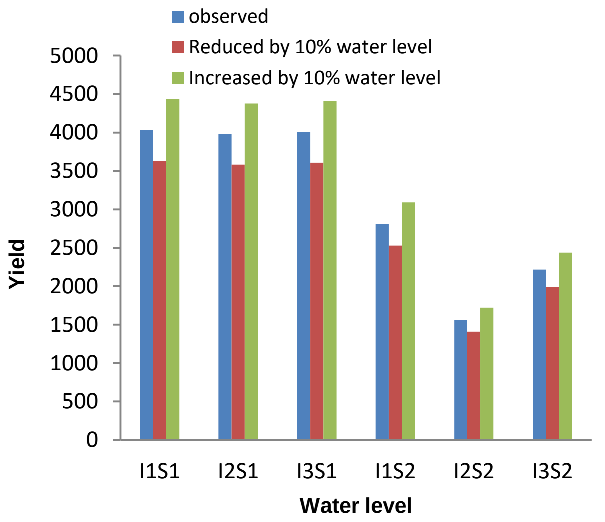

Fig. 7. The ratio of yield calculated by RBF model to irrigation water levels changes.

According to the results presented in table 7, the GFF model with Conjugate Gradient training and the RBF model with Levenberg-Marquardt training have optimal results in estimating barley yield with and 4 hidden layers. Also, given the values of R^2 and RMSE, the RBF model is known as the best model. According to the results of other researchers' studies, such as Kaul et al. (2005), Sadras and Calvino (2001) and Bagheri et al. (2012), available water parameter is one of the main factors in estimating the agricultural yields. Sensitivity analysis showed that irrigation water levels parameter plays an important role in estimating barley yield. In fact, the amount and type of irrigation has an effect on the development of leaves and the plant reproductive development and also affects plant yield through its effect on the balance of water supply and demand. The ratio of yield calculated by RBF model to irrigation at two levels of complete irrigation and 75 % water stress presented in Figs. 7 and 8.

Table 7. Selected test patterns from suggested patterns for estimating barley yield.

Network type	Network training type	The number of first-layer hidden neurons	The number of second-layer hidden neurons	R^2 of Test	MSE of verification	R^2 of verification
GFF	Momentum	4	-	0.874	0.0976	0.83
		8	10	0.873	0.0825	0.82
	Conjugate Gradient	8	-	0.915	0.056	0.88
		5	8	0.869	0.06	0.86
		9	10	0.9	0.059	0.87
	Levenberg Marquardt	2	-	0.965	0.057	0.87
		2	4	0.98	0.063	0.86
RBF	Momentum	5	-	0.9	0.0518	0.89
		6	-	0.898	0.0464	0.90
		8	-	0.896	0.0389	0.92
		4	4	0.895	0.071	0.83
	Conjugate Gradient	5	-	0.915	0.0415	0.91
		10	-	0.9	0.034	0.92
		5	8	0.926	0.0478	0.88
		6	5	0.91	0.0565	0.86
	Levenberg Marquardt	4	-	0.999	0.0437	0.92
		5	-	0.999	0.0337	0.95
		5	5	0.998	0.055	0.88
		7	9	1	0.0748	0.87

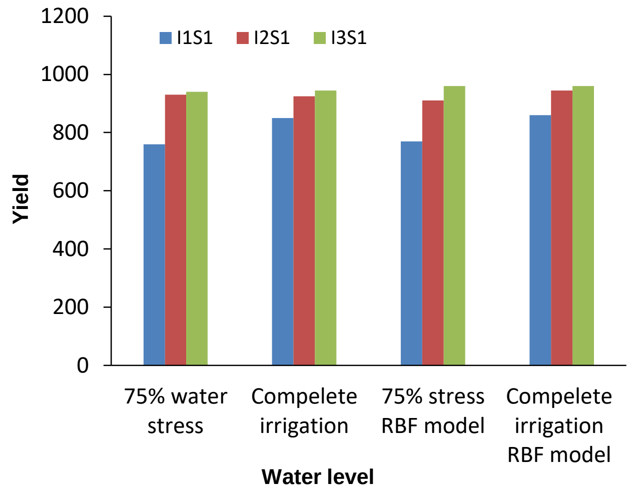

Fig. 8. The ratio of yield calculated by RBF model to irrigation at two levels of complete irrigation and 75 % water stress.

4. Conclusions

In this study, barley yield was estimated using ANNs method (comparison between RBF and GFF models). Test result of suggested models of this paper showed that in finding the purpose of the problem, the introduced models perform successfully and operate in high speed. 1000 cycles for the barley yield was chosen as the appropriate one using trial and error method. After running the models, the results showed that RBF model of artificial neural network has better performance compare with the GFF model in estimating barely yield. According to the obtained diagrams and after comparing the results of different models, the RBF model was known as the best model. This model contained one hidden layer. The obtained R^2 and RMSE for RBF model was 0.81 and 33.12, respectively. Also, the results show the superiority of the RBF model compared with the other proposed model (GFF model). The results indicate that RBF model provides very acceptable results for estimating barley yield. Due to the differences in geometric, type of product and physical or chemical characteristics of soil, in this study, such characteristics were not considered as inputs and only the barley yield in Torbat-Heydarieh region was investigated.

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