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Optimization of wheat grain yield by artificial neural network

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ABSTRACT: Wheat is more important than other grain crops. Maximum grain yield can be determined by several components that reflect positive or negative effects. The objective of this article is optimization of wheat grain yield by artificial neural network. Field experiment was carried out at the Department of Medicine Plant, Arak University, Iran. The results indicated that the remobilization of stored pre-anthesis assimilates to grain (R_1), crop height (R_2), 1,000-grains weight (R_3), grain number per ear (R_4), vegetative growth duration (R_5), grain-filling duration (R_6), grain-filling rate (R_7), tiller number (R_8), harvest index (R_9), and spike length (R_{10}), were effective. The R^2 for the training and test phases was 0.99 and 0.94, respectively, which reveals the capability of the ANN to predicting yield. The optimum values obtained were 15.1%, 107.2 cm, 38.5 g, 42.2, 108 d, 52 d, 1.16 mg seed^{-1} day^{-1}, 3.48 plant^{-1} and 12.5 cm for R_1 through R_{10}, respectively. The optimization increased the potential yield to 6200 kg ha^{-1}, which was higher than that observed for the cultivars (3200 to 5300 kg ha^{-1}). As a result of training the neural network, the accuracy of predicting yields is on average about 72%.

***Keywords*:** Wheat, Yield components; Artificial Neural Network

INTRODUCTION

Wheat is more important than other grain crops; because of it is a strategic food. Maximum grain yield can be determined by several components that reflect positive or negative effects. Conventionally, ordinary Y components, such as 1,000-grains weight, grain number per ear, spikelet number per spike, spike number per plant, number of primary branches per plant, number of siliquae per plant, and harvest index (Grafius, 1972; Prystupa, 2004; Ahmed, 2003).

Neural networks have been an explosion of interest over the last few years and are being successfully applied across an extraordinary range of problem domains, in areas as diverse as finance, medicine, engineering, geology, physics and biology. The excitement stems from the fact that these networks are attempts to model the capabilities of the human brain. From a statistical perspective neural networks are interesting because of their potential use in prediction and classification problems (Anderson, 2003). Artificial Neural Networks (ANN) is suitable for use in dealing with complex system, such as agricultural system, than that mathematical method (Hashimoto, 1997). ANN has the capability to recognize and learn the underlying relations between input and output without explicit physical consideration (Basheer and Harmeer, 2000). The benefits of using ANN are its massively parallel distributed structure and the ability to learn and then generalize the problem (Nugroho, 2003). In agricultural field, ANN has been applied to classify irrigation planning strategies (Raju, 2006); estimate subsurface wetting for drip irrigation (Hinnell, 2009) and Optimization of grain yield (Gholipour, 2013). In addition, ANNs are used in a wide variety of applications, including crop development modeling (Fortin, 2010; Huang, 2010; Zhang, 2009) and crop yield prediction (Green, 2007; Kaul, 2005; Park, 2005). The objective of this study examined the ability of an ANN model to optimize of wheat grain yield using ANN model. Then, the proposed ANN model was validated by comparing observed and estimated values of wheat grain yield.

MATERIALS AND METHODS

Field experiment was carried out at the Department of Medicine Plant, Arak University, Iran (2011/2012). In two year cultivated ten wheat (Triticum aestivum L.) cultivars (table 1). The experiment carried out by randomized complete block design in four replications. Each plot comprised five rows, which were 5 m long and had a 0.2 m inter-row spacing. The soil was loam silty with 0.2% organic carbon. Nitrogen fertilizer (Urea, 46%) was applied in 3 equal splits: at sowing, tillering and anthesis.

Table 1. The wheat cultivars used in the experiment

Cultivar	Entry
Omid	1
Roshan	2
Pishtaz	3
Back cross Roshan	4
Chamran	5
Mahdavi	6
Alvand	7
Biseton	8
Zarin	9
Navid	10

Ten plants were randomly used to measure Y components and certain traits (R; regressors). The regressors were the remobilization of stored pre-anthesis assimilates to grain (R_1), crop height (R_2), 1,000-grains weight (R_3), grain number per ear (R_4), vegetative growth duration (R_5; days from planting to heading), grain-filling duration (R_6), grain-filling rate (R_7), tiller number (R_8), harvest index (R_9), and spike length (R_{10}). Neural Network (ANN), also known as Neural Network (NN), is developed by getting inspiration from the working of human brain. ANN is nonlinear statistically data modeling technique to model the complex relation between input and output or to find pattern in the data. A single neuron can be represented mathematically as:

$$y = f\left(\sum_{i=j}^{n} w_i x_i + b\right) \qquad (1)$$

Where, x is Input, w is Weight and b is Bias to neuron. The output depends on the value of input, their weights, bias and the transfer function. In ANN, many neurons are connected with each other to make different combinations. Usually the neurons are connected in the form of separate layers. These layers are classified as Input layer, Output layer and Hidden layers. Input layer is the one where inputs are applied while output layer is the one from where the output can be derived. Hidden layers are the layers which are in between the input and output layers. ANN is commonly used in Feed forward architecture where flow of information in layers of neurons is from input to output. The other ANN architecture is Recurrent where information may flow in loops or in both directions. The dataset was shuffled and split into a training set (80% of total patterns) and a test set (20% of total patterns). These subsets were used to estimate the ANN model parameters and to check the generalization ability of the model, respectively. The following equation was used to normalize the dataset (Rohani, 2011):

$$X_n = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \times (r_{\max} - r_{\min}) + r_{\min} \qquad (4)$$

Where X is the original data, X_n the normalized input or output values, X_{max} and X_{min} are the maximum and minimum values of the concerned variable, respectively, and r_{max} and r_{min} correspond to the desired values of the transformed variable range. A range of 0.1 – 0.9 is appropriate for the transformation of the variable onto the sensitive range of the sigmoid transfer function. A Multilayer Perceptron (MLP) was used, which has maximum practical importance among various ANN models. Fig 1 shows an MLP with one hidden layer. Every node computes a weighted sum of its inputs and passes the sum through a soft nonlinearity.

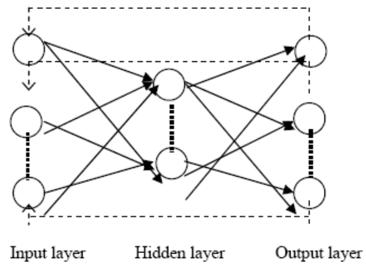

Figure 1. A neural network Schematic with one hidden layer (Vakil-Baghmisheh, 2002)

An interesting feature of ANN is training, where network is introduced to the inputs and/or outputs and run the algorithm to change the weights of the inputs of the neurons till the optimal solution is achieved. An efficient solution depends upon many factors such as learning type, learning algorithm, training data, number of hidden layers and number of neurons in each layer.

An efficient solution needs optimal combination of all these parameters. The usage of ANN remained limited till mid of 1980s. In 1986, Backpropagation Algorithm was introduced for learning which revolutionized the usage of ANN in solving the problems (Rumelhart, 1986; Gonzalez and Woods, 2002). The model with the smallest root mean-squared error (RMSE), total sum-squared error (TSSE), and mean absolute percentage error (MAPE) and the largest R^2 was considered to be the best. A computer code was developed in MATLAB software to implement the analysis .The optimization process is performed in cycles called generations.

RESULTS AND DISCUSSION

Results

The results indicate that R_1 to R_{10} had a significant positive effect and/or statistically considerable correlation with grain yield. Therefore, the input layer in the ANN analysis had 10 neurons representing the regressors and bias term (b=-1), while the output layer corresponded to Y (Fig. 2). The performance of the MLP tended to be improved by an increase in the number of hidden neurons .However, too many neurons in the hidden layer caused over fitting problems, which resulted in good network learning and data memorization, but an inability to generalize. However, the network could not learn, as only a small number of neurons in the hidden layer were used.

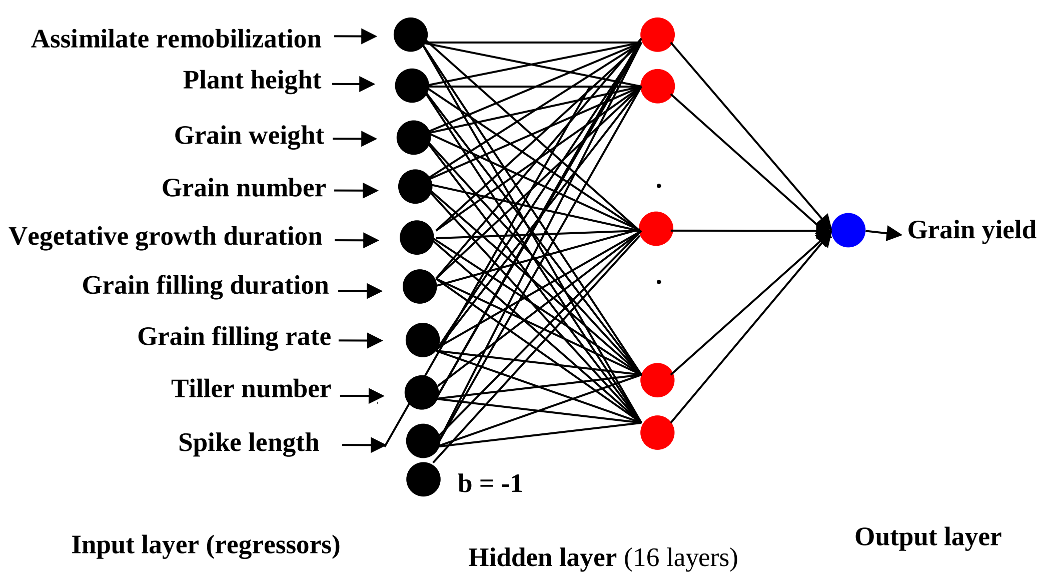

Figure 2. The layers Schematic of neural network for optimization of grain yield components to increase wheat grain yield

The performance of the ANN is shown in Tables 2 and 3. The low values of MAPE, RMSE, and TSSE proved the capability of the BDLRF algorithm for generating accurate estimates within the preset range by using the MLP neural network. Considering the mean value, standard deviation, variance, and other statistical variables, it can be deduced that the values and the distribution of the observed and predicted data are analogous .Accordingly, the neural network has learned the training set well; hence, the training phase is completed. The skewness, kurtosis, sum, minimum, maximum and the average values are similar; hence, it could be said that both series are similar for the observed and predicted wheat grain yield.

Table 2. Performances of ANN in prediction of grain yield

Phase	Performance criterion		
	MAPE (%)	RMSE	TSSE
Training	0.16	0.22	0.8
Test	0.18	0.26	2.2

Table 3. Some statistical properties of observed and predicted values of wheat grain yield in training and test phases

Value type	Mean	Variance	Standard deviation	Kurtosis	Skewness	sum
Training phase						
Observed	4131.2	301292	548	2.3	-0.12	206563
Predicted	4131.3	301291	548	2.3	-0.12	206562
Test phase						
Observed	3686.5	112666	335.6	2.6	-0.8	36865
Predicted	3696.6	113660	355.6	2.6	-0.8	36866

The result of experiment indicated that the optimal combination of the 9 parameters for maximum grain yield, the ANN grain yield model. The optimum values obtained were 15.1%, 107.2 cm, 38.5 g, 42.2, 108 d, 52 d, 1.16 mg seed^{-1} day^{-1}, 3.48 plant^{-1} and 12.5 cm for R_1 through R_{10}, respectively. The optimization increased the potential yield to 6200 kg ha^{-1}, which was higher than that observed for the cultivars (3200 to 5300 kg ha^{-1}). To achieve this, the output of the developed ANN was utilized in calculating the values of the fitness function. The convergence for the model reached a grain yield of 6200 kg ha^{-1}, which is the maximized grain yield. The optimum values of the regressors for this amount of grain yield are shown in Table 4.

Table 4. Optimal values of yield parameters for maximum grain yield as determined by ANN optimization process

Parameter	Optimum value
Assimilate remobilization	15.1%
Crop height	107.2 cm
1000 grains weight	38.5 g
Grain number per ear	42.2
Vegetative growth duration	108 d
Grain filling duration	52 d
Grain filling rate	1.16 mg seed^{-1} day^{-1}
Tiller number	3.48 plant^{-1}
Spike length	12.5 cm

Discussion

As shown in table 3, the predicted values were very close to the measured values. Therefore, it is concluded that the ANN model can be used as an appropriate tool to optimize of wheat grain yield. Erenturk et al. (2004) also concluded that a neural network represented the drying characteristics of Echinacea angustifolia better than regression models. Therefore, the ANN models can estimate the parameters with an acceptable accuracy, and consequently can be an appropriate substitute for regression methods in modeling rough rice drying. This result is in agreement with the universal approximation theorem, which states that a neural network with a single hidden layer and a sufficiently large number of neurons can well approximate any arbitrary continuous function (Haykin 1994). There are compensatory processes between the components of yield due to their close interrelationship. Therefore, increasing one component would be counterbalanced by a reduction in other component(s). This study aimed to optimize the important traits and yield components together using an ANN to minimize competition for photo-assimilates for increased yield. As Slafer, (1996) suggested, the remobilization of stored pre-anthesis assimilates to the growing grains appears to be an important trait in statistically increasing yield. A study by Bidinger, (1977) on one cultivar of barley and wheat revealed that approximately 12% of the yield of well-watered wheat comes from these remobilized assimilates. These compounds could buffer yield against unfavorable situations, including a rise in temperature, which occurs frequently during the grain-filling stage of wheat in many growing regions. In this situation, where the vapor pressure deficit tends to be high, the plants would suffer from water shortage even in well-watered conditions (Gholipoor and Sinclair, 2011).

Consequently, this artificial neural network can be used successfully for predicting wheat yield in Arak, with 72% accuracy. In the future it will be possible to increase the accuracy of predicting the yield by improving the selection of input parameters and perfecting the network. In particular, the use of additional data will permit obtaining more reliable results. This study demonstrated that an ANN is useful tools for simulating and optimizing grain yield. As shown in Fig. 1, the ANN is able to optimize regressors for more outputs, such as the yield for barley or for the oil content and quality of soybeans, which should be employed in future investigations.

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