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Full Length Research Paper

Predicting yield of wheat genotypes at different salinity by artificial neural network

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For examining efficiency of Artificial Neural Network (ANN) for prediction of yield in wheat, a factorial experiment was set out in a randomized complete block design (RCBD) with three replications in a glasshouse. The treatments were included of four saline solutions and 8 wheat genotypes. This paper shows the ability of artificial neural network (ANN) technology to be used for the prediction of yield and yield components of 8 wheat genotypes for different salinity levels. Based on analysis of variance, salinity had significant effect on all traits, as salinity levels increased, yield and 1000-grain weight and K+ concentrations decreased. The results showed that a very good performance of the ANN model was achieved. Some explanation of the predicted results is given. The ANN with training algorithm of back propagation was the best one for creating of nonlinear mapping between input and output parameters. The ANN model predicted the six yields and yield components with mean R^2 and T values of 0.977 and 0.97 respectively. Furthermore, the predictions of ANN model were compared with those obtained from six multi-linear regression (MLR) models. It was found that ANN model has better predictions than the MLR models for the experimental data.

Key words: Wheat, salinity stress, yield, artificial neural network.

INTRODUCTION

Mahajan and Tuteja (2005) reported that food productivity is decreasing due to the effect of various abiotic stresses; so minimizing these losses is a major area of concern for all nations to cope with increasing food requirements. Cold, salinity and drought are among the major stresses, which adversely affect plants growth and productivity; (Mahajan et al., 2005). Salinity is one of the major environmental factor limiting plant growth and productivity (Allakhverdiev et al., 2000). Bread wheat (*Triticum aestivum* L.) is a major food crop in most countries of the world which suffer saline soils, and therefore increasing salinity tolerance in bread wheat is necessary (Sadat and Harati, 2005). Kumar (2005) mentioned that during the onset and development of salt stress within a plant, all the major processes such as photosynthesis, protein synthesis, energy and lipid metabolism are affected. Maintenance of adequate levels of potassium (K+) is essential for plant survival in saline habitats. Under saline-sodic or sodic conditions, high levels of external sodium (Na+) not only interfere with K+ acquisition by the roots, but also may disrupt the integrity of root membranes and alter their selectivity. Bar-Tal et al. (1991) reported that increased salinity in the irrigation water significantly decreased yield. These investigators concluded that despite its beneficial effects on increasing K+/Na+ ratio within the plant, K+ fertilization did not reduce the deleterious effects of salinity.

Cellular injury also showed a significant positive correlation with Na+ and a negative correlation with K+ and grain yield. All salinity levels beyond 150 mM NaCl reduced grain yield differently, where this reduction in grain yield (GYR) was significant at 100 mM (23 and 26% of control, respectively) (Faroop and Azam, 2005). Study of Reddy et al. (2003) showed that abiotic stresses such as salinity affect rice yield components and grain quality. Among these components, 1000-grain weight (TGW) is thought to be quite constant due to a rigid hull whose size is genetically determined, but chilling and salinity stresses

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have been reported to strongly reduce TGW (Katerji et al., 2005). Francois et al. (1986) concluded that soil salinity reduced the ash content and improved the color and the protein content. The grain quality criteria of the sensitive variety were not affected by salinity. Literature does not mention relationships between salt tolerance and grain quality of Mediterranean durum wheat varieties. Breeding for adaptation to abiotic stress is extremely challenging due to the complexity of the target environments as well as that of the stress-adaptive mechanisms adopted by plants (Reynolds et al., 2005). The 1000-grain weight, ash content and beta- carotene content of durum wheat were improved, but the main parameters for the gluten index, declined considerably (Katerji et al., 2005).

The experiments described here were carried out to examine the potential for enhancing the degree of salinity tolerance in parent and their hybrids of wheat. The understanding and modeling of nonlinear relationship between salinity level with wheat seed yield, 1000-grain weight, grain/ear, K^+ concentrations, and K+/Na+ ratio in the first leaf below the flag leaf of different genotypes is an important object in farm management. Often times, finding an analytical expression of the relationship may not always be possible. However, more complex linear methods, including various forms of multiple linear regressions, have been widely considered in crop modeling. For instance, different researchers like: Oosterbaan (2003), Enclona et al. (2004), Eugene et al. (1996) Simane et al. (1993) and Dencic et al. (2000) used multiple linear regression model to predict wheat yield.

Crop growth is a multifactorial nonlinear process and different mathematical crop growth models have been developed for different purposes in agricultural management and economy (Khazaei et al., 2008c). The precise and prompt prediction of crop yield and yield components will be of great help in making scientific decisions and plans. Agronomic models to predict yield and crop growth are based on mechanistic or almost empirical approaches (Poluektov and Topaj, 2001). Mechanistic models use mathematical functions to represent biological processes (Whisler et al., 1986). In view of the fact that even the most deterministic models still rely heavily on empirical functional relationships to varying degrees (Jame and Cutforth, 1996), empirical crop growth models may play an important role as explanatory tools for identifying the hidden structure of crop growth processes. They may even offer a more reliable method of investigating crop response than poorly calibrated process models when the necessary data are available.

The main limitation of traditional regression-based empirical models is the lack of non-linear modeling ability, which is apparent in crop responses to agro-ecological conditions. Furthermore, one of the major limitations of empirical model building exercises is that they require a large amount of data to obtain reliable training results and to validate trained models (Schultz et al., 2000). This is a particularly an important issue in agronomic research considering the cost and time necessary for conducting farm trials. Furthermore, the representative problem that the statistical models can solve is one dependent variable versus several independent variables. Nevertheless, when researching the problem same as this one in this study, we study the relationship between several independent variables (assuming it includes two components: salinity level and genotype) and several dependent variables (yield, number of grain/ear, 1000-grain weight, K+ concentrations, and K+/Na+ ratio), and that this relation is obviously multiple-variables versus multiple-variables.

Given such complex relationships, one regression model is required for each output. This limitation increases the number of models which must be considered for each study. Furthermore, analytical models that explain a highly non-linear relationship with interactions among variables are often difficult to obtain. One of the most appropriate methods to eliminate these problems seems to be the soft computing techniques, such as artificial neural networks (ANN). ANN models are a powerful empirical modeling approach and yet relatively simple compared to mechanistic models. ANN can be used to develop empirically based agronomic models. ANN offers an alternative way to simulate complex and ill-defined problem. The use of ANNs has gained increasing popularity for applications where the dependency between dependent and independent variables is either unknown or very complex which are hard to describe by mathematical models. The ANN approach seems to work rather well with noisy data than its statistical counterparts (Khazaei et al., 2008). This ability is more important in modeling agricultural data.

The use of neural networks is motivated because of their accommodation of non-linearities, interactions, and multiple variables. Unlike statistical models which generally require assumptions about the parametric nature of the factors (which may or may not be true), ANNs do not require a priori assumption of the functional form of the model. ANN has the capability to develop functional relationships between input-output patterns obtained from any source and can be conveniently used to develop a generalized relationship from limited and sometimes inconsistent data. Agronomic ANN applications include prediction flowering time (Welch et al., 2003), soil–water retention estimations (Schaap and Bouten, 1996), yield estimation (Drummond et al., 1995; Khazaei et al., 2008c), crop development modeling (Elizondo et al., 1994), identifying of origin and subspecies of crop genotypes (Khazaei et al., 2008b), and classifying different varieties of agricultural crops (Mahmoudi et al., 2006). Starrett et al. (1997) reported that an ANN model performed better (R2 = 0.984) than a regression model (R2 = 0.780) when predicting applied-nitrogen leaking below the root zone of turf grass.

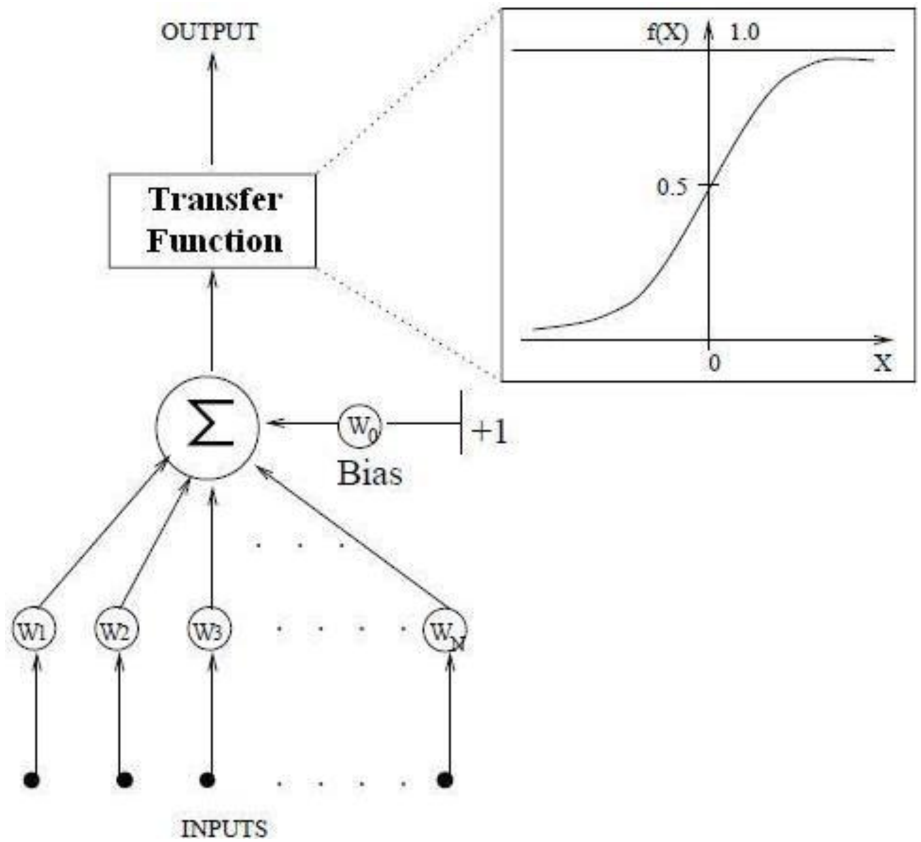

Figure 1. A typical neuron with sigmoidal function.

Pachepsky et al. (1996) reported ANNs estimated soil water content based on soil physical properties better than regression techniques. According to Batchelor et al. (1997), ANNs produced better results than traditional statistical methods when predicting soybean rust.

The goal of this study was to develop a simple yield and yield components prediction models for wheat with readily available data that could be easily applied by an end user such as a nutrient management specialist. The specific objectives of this study were to:

(1) Investigate if an ANN could effectively predict yield and yield components of 8 wheat genotypes for different salinity levels; and

(2) investigate the ANN model performance with variations of ANN parameters.

The fundamentals of the ANN technique, what ANNs are and how they work, is given in detail in various literature (Khazaei et al., 2008c; Marinia et al., 2004; Shearer et al., 1999). However, an ANN consists of a series of layers starting with an input layer, ending with an output layer and having a number of 'hidden' layers in between. Each layer consists of a series of linear or nonlinear neurons. Neuron is the smallest computation unit of data and is the basis of ANN models Figure 1. The number of input neurons is equal to independent (input) variables and number of output neurons is equal to number of dependent (output) variables. Hidden layers are required to introduce non-linearity in the problem and determine how well a problem can be learned. In order to train and validate an ANN model, it is usual to randomly divide the available data into training and test sets for training and testing the ANN model, respectively. Once a network is trained, the testing set is used to estimate the generalization performance of the model. If the level of prediction is not acceptable in the testing phase, training has to be repeated to optimize the ANN parameters such as number of hidden layers, neurons per hidden layer, activation function, initial weight range, learning rate, momentum, etc. so that better prediction is obtained during testing phase.

MATERIALS AND METHODS

Genetic materials

In this experiment we used four moderate salt-tolerant variety of bread wheat (*T. aestivum* L), Siette Ceros (CIMMYT, Mexico), Ho2(Libya), Lermaroja (CIMMYT, Mexico), Cajema (CIMMYT, Mexico) and three hybrids (Cajema x Sette Cerros, Cajema x Ho2, Cajema x Lermaroja) and a British salt sensitive variety (Axona) as control (Table 1). After making crosses and producing F1 and F2

Table 1. Name, origin and abbreviated name of genotypes.

Number of genotype	Group	Abbreviated name	Name	Origin
1		Caj × Set	Cajema × Sette Cerros	_
2	Hybrids	Caj × Ho	Cajema × Ho_2	_
3		Caj × Ler	Cajema × Lermaroja	_
4	Control	Ax	Axona	British salt sensitive
5		Set	Sette Cerros	CIMMYT, Mexico
6	Parents	Ho	Ho_2	Libya
7		Ler	Lermaroja	CIMMYT, Mexico
8		Caj	Cajema	CIMMYT, Mexico

Table 2. Nutrient solution for sand and water culture experiments based upon solution used by Hewitt (1966).

Salt	Concentration in stock solution (g l-1)	Add to 10 L deionised water to give solution full strength
CaNo3.4H2o	472.0	10
K2HPO4	58.0	30
MgSO47H2O	123.0	20
Fe EDTA	12.5	10
KCL	124.3	10
Trace elements		
MnSO4.4H2O	2.02	10
H3BO3	2.86	10
(NH4)6Mo7O24.4H2O	0.184	10
Zn SO4	0.44	10
Cu.SO4.5H2O	0.39	10

generations (Table 1), because of limited number of seeds generated in the F2 generations, all F2 families were grown on to provide F3 generation seed at the Ness Botanic Gardens in field conditions to provide suitable number of seeds.

Glasshouse experiment

The experiment was carried out in a glasshouse; day temperature 22±2°C and night temperature 16±2°C with natural daylight supplement by 400 watt mercury vapor lamps to give 16 h day length. Plastic pots of 18 cm diameter and 19 cm depth were filled with 4.40 kg washed river sand (oven-dried weight). The sand was thoroughly washed with tap water for one week, followed by three washings with full strength nutrient solution (Table 2) (Hewitt, 1966). Four salt concentrations were used: 0 (control), 150, 200 and 250 mM NaCl. All salt treatments were applied in the full strength solution. Six-day-old seedlings of each genotype were grown separately and equidistantly from each other in each pot at a rate of five seedlings per pot. Salt treatments were commenced 18 days after the start of the experiment, and the salt concentration was increased stepwise in aliquots of 25 mM every other day until the appropriate treatment concentration was reached. Twice per week, 200 ml of deionized water was added to each pot to maintain sand moisture and to prevent additional salt accumulations into the pots. Electrical conductivity of the leachates was tested weekly. The first leaf below the flag leaf from each plant was removed 30 days after the beginning of the salt treatment, rinsed in deionized water, dried between tissue papers, and oven dried at 60°C for 72 h. The dried leaves were chopped into 1 to 2 mm pieces, and used for the subsequent chemical analysis. The data obtained from the experiments were used for training and testing the neural network model.

Measurements

Sodium (Na+) and Potassium (K+): 10-15 mg leaf samples were placed in small glass bottles, and 1 ml concentrated nitric acid was added to each tube. Digestion was carried out on a hot plate at 80°C. After digestion the volumes of the samples were made up to 10 ml with deionized water. Na+ was measured at 598 nm and K+ at 766.5 nm wavelengths, using a flame emission spectrophotometer (Perkin Elmer Model 1373) a blank of 1 ml of concentrated nitric acid was used to adjust Na^+ and K^+ concentration in the samples. For measuring chloride\ (Cl-): 20 mg of leaf sample from each plant, and 10 ml deionized water were placed in small glass bottles and heated on a hot plate at 70°C for 3 h. Cl- content of the extracted samples was determined using a Mercuric thiocyamate reagent (Sigma Chemical Co.), and reading the color which developed at 460 nm. A blank of 1.5 ml of chloride reagent and 1.5 ml distilled-deionized water was used to adjust Cl-

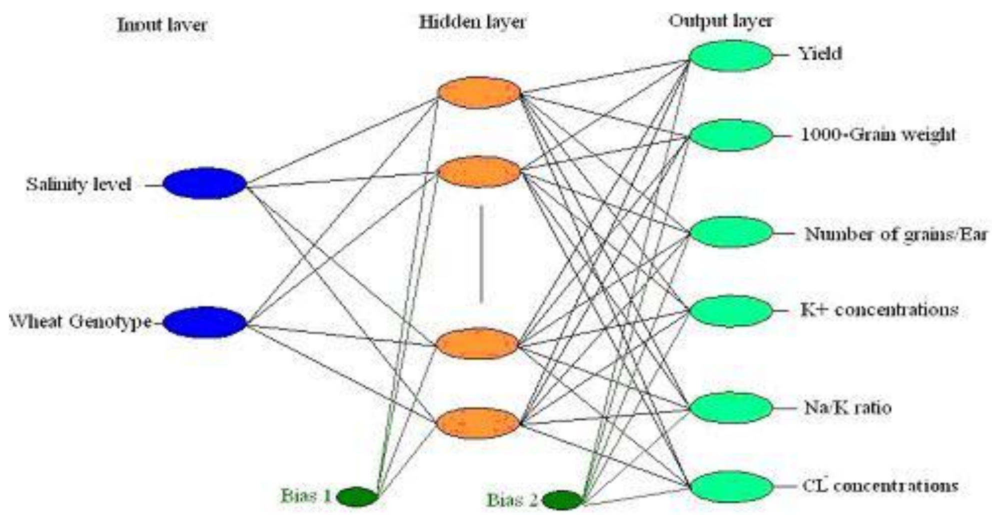

Figure 2. The neural network model for prediction of the yield and yield components of wheat.

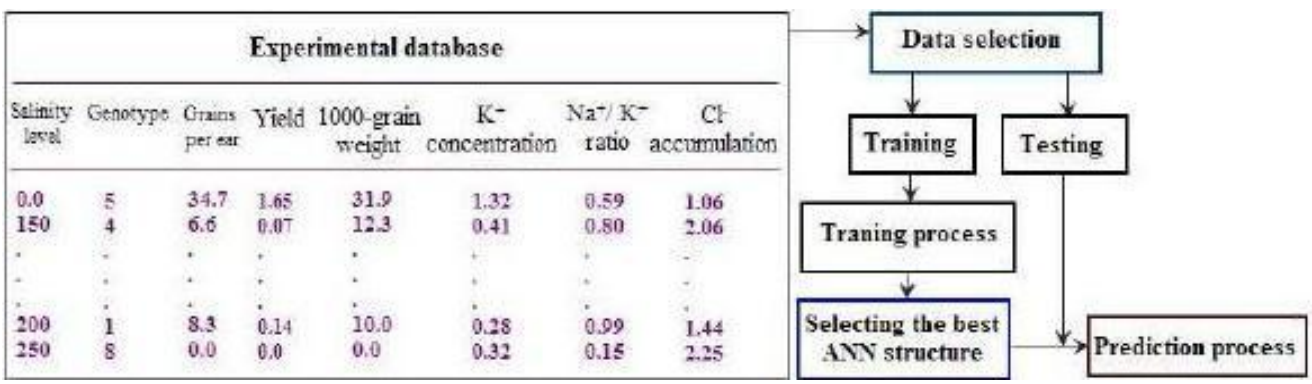

Figure 3. System configuration of ANN system for prediction of yield and yield components of wheat genotypes at different salinity.

concentrations in the samples.

Statistical analysis

Data were subjected to analysis of variance (ANOVA) by the PROC MIXED of SAS (SAS Institute, 1990) as a factorial experiment. The entries were arranged in a randomized complete block design with 3 replication. Within the model, both genotypes and salinity level were considered fixed effects and blocks considered as random effect. Comparison of means was also performed with Duncan's multiple range test (DMRT).

Neural networks model development

The general process to build an ANN model included creating data sets for training and testing, training networks with varied parameters, analyzing network results, and testing the models (Broner and Comstock, 1997). In this study, a feed-forward multi-layered perceptron (MLP) ANN trained by back propagation (BP) algorithm was selected to model the correlation between salinity levels and wheat genotypes with number of grains per ear, yield, 1000-grain weight, K^+ concentrations, Cl accumulation, and Na/K ratio in the first leaf below the flag leaf for 8 genotypes of wheat. The salinity levels and wheat genotype were inputs of the neural network. A feed-forward back-propagating ANN structure with one/two hidden(s) layer as illustrated in Figure 2 was used to develop yield and yield components prediction models. Different neural networks were made and the optimum values of network parameters were obtained by trial and error. In this study, there were a total of 32 patterns each with 8 components (Figure 3).

Two of the components were the input variables (X1 and X2 for salinity level and genotype respectively), whereas the last six components were the outputs(Y1-Y6 for grains per ear, yield, 1000-grain weight, K^+ concentration, Na^+/K^+ ratio, Cl- accumulation respectively) (Figure 3). These 32 patterns were randomly divided into training and testing groups. Twenty one data (67% of the experimental data) were used for the training and the remaining, 11 patterns, were used for testing the networks. Three steps were used to select an optimal ANN model. The first step was to work with various ANN structures, including 3- and 4-layer with different number of neurons in each hidden layer. In order to determine the optimal number of hidden neurons in hidden layers, training was used for 2-k-s-6 architectures. Where k and s were the numbers of neurons in the first and second hidden layers, respectively.

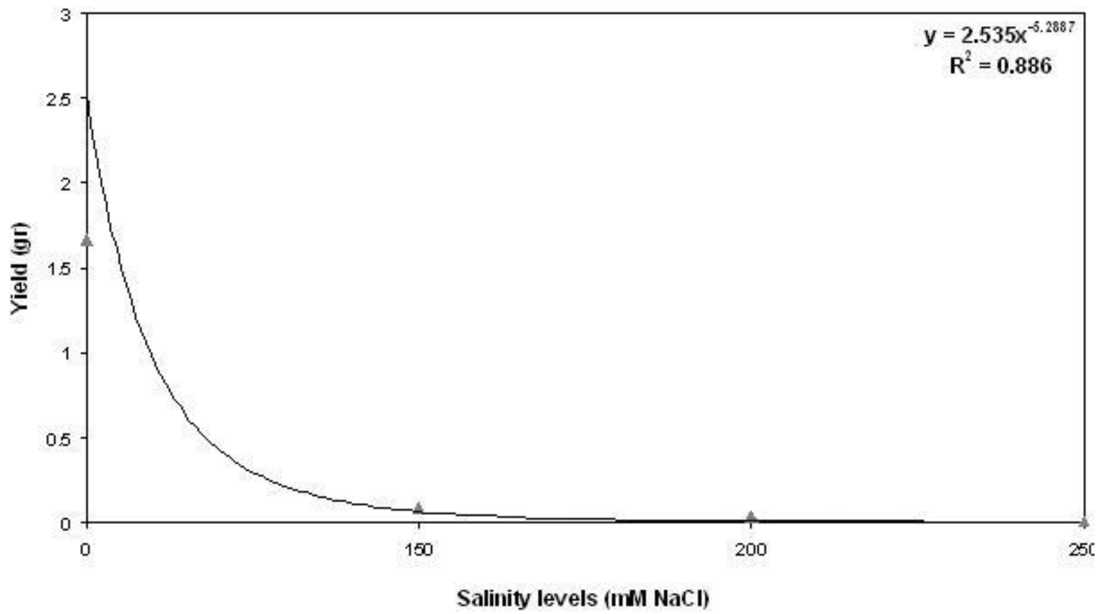

Figure 4. The effect Salinity Levels on yield of wheat genotypes.

The numbers of neurons in the hidden layers were varied from 4 to 38, by an increment of 2 in each step. The best three models were selected on the basis of the lowest root mean square error on train and test sets of data. Once a given ANN was trained using the appropriate training dataset, its performance was then evaluated using the testing dataset.

The optimum values of network parameters were obtained on the basis of the lowest error on train and test sets of data, by trial and error. The second step was to work with these three selected models to find optimum activation function. The third step was to find optimum learning rate and momentum values. The evaluating method for selecting optimal ANN was based on the minimization of deviations between predicted and observed values. The training and prediction abilities of the ANN models were compared using the root mean square error (RMSE), correlation coefficient, R^2, and T statistics (Khazaei et al., 2008a). T value measures the scattering around the line (1:1). When T is close to 1.0, a good fitting is prevailed (Khazaei et al., 2008a). The accuracy of the trained and tested ANNs was also evaluated by calculating the relative error (Khazaei et al., 2008a). In order to achieve fast convergence to minimal RMSE, the input and output data were normalized with respect to the corresponding maximum and minimum values. As a result of normalization, all variables acquire same significance (importance) during the learning process. It must be pointed out that the same normalization process should be used for both training and prediction data sets to ensure that all the data items lie over the same range.

In the present study, a transformation was performed as follows (Khazaei et al., 2008c):

$$X_T = 0.05 + 0.9\cdot[(X_I - X_{MIN})/(X_{MAX} - X_{MIN})] \qquad (5)$$

Where Xt is the transformation of the data point Xi; X min the overall minimum in training and prediction data sets; and X max the overall maximum in training and prediction data sets.

The value of Xt lies between 0.05 and 0.95, corresponding to Xt = X min and Xt = X max, respectively. The Matlab software, version 7, was the software package used in this study. The ANN modeling was accomplished by using the Neural Network Toolbox TM of the MATLAB computer- aided design software (The MathWorks Inc., Natick, MA).

RESULTS

Yield

Analysis of variance (ANOVA) showed that salinity levels had significant effect ($p<0.01$) on yield (Figure 4).

1000-grain weight

ANOVA Results showed that salinity levels, genotype and interaction of salinity levels x genotype had significant effect ($p<0.01$) on 1000-grain weight. Among genotypes, Ho (average 13.13 gr) and Caj*Set (average of 13.15 gr) had the most 1000-grain weight (Table 3). Data showed that high salinity levels due to decline 1000-grain weight (Figure 5). In control condition, among genotypes, Ler with average 39.84 gr had the maximum 1000-grain weight. In 150 mM salinity, Ax (average 12.30 gr) had the most 1000-grain weight among genotypes. In 200 mM salinity, Ho (average 10.66 gr) had the highest 1000- grain weight. Genotypes in 250 mM had no significant differences (Table 4).

Number of grain per ear

Results

Table 3. Mean comparison of genotype effects on yield, number of grain per ear, K^+ concentrations, Na^+/K^+ ratio and 1000-grain weight.

Wheat genotypes	Yield (g)	1000-grain weight (g)	Number of grain per ear	K+ concentrations (mgr 100-1gr biomass)	Na+/ K+ ratio	Cl- accumulation (mgr 100-1gr biomass)
Caj × Set	0.52[a]	13.15[a]	10.16[abc]	0.53[bcd]	2.79[b]	1.73[abc]
Caj × Ho	0.38[a]	8.98[ab]	10.41[ab]	0.44[d]	4.83[a]	2.39[a]
Caj × Ler	0.43[a]	9.41[ab]	11.66[ab]	0.55[abc]	3.20[ab]	2.22[ab]
Ax	0.45[a]	11.96[ab]	7.66[bc]	0.65[a]	3.64[ab]	2.01[abc]
Set	0.43[a]	10.96[ab]	11.33[ab]	0.61[ab]	3.12[ab]	2.07[ab]
Ho	0.42[a]	13.13[a]	13.33[a]	0.61[ab]	2.89[b]	1.70[abc]
Ler	0.40[a]	6.34[c]	7.08[c]	0.49[cd]	3.49[ab]	1.67b[c]
Caj	0.53[a]	9.38[bc]	9.66[abc]	0.55[abc]	1.78[c]	1.34[c]

Means followed by similar letter in each column are not significantly different at 5% probability level using DMRT.

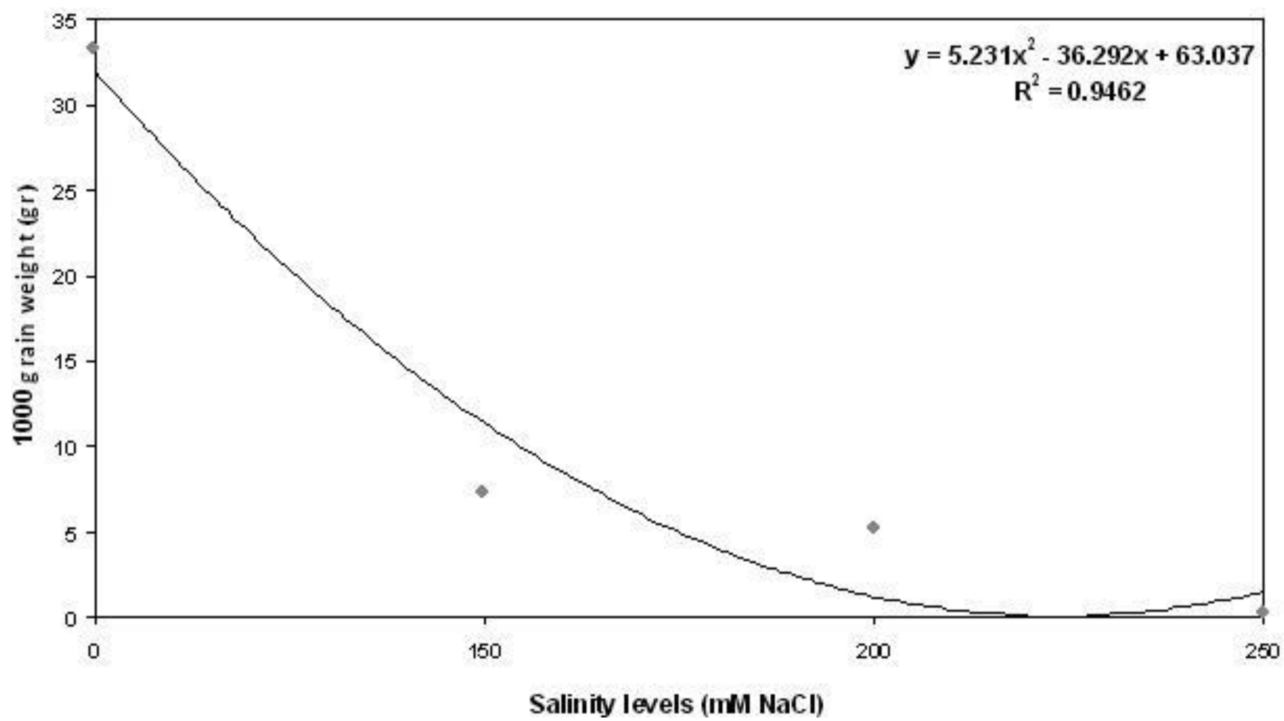

Figure 5. The effect of salinity levels on 1000-grain weight of wheat genotypes.

Table 4. The interaction between Salinity levels × Wheat genotypes on 1000-grain weight and K^+ concentrations in the first leaf below the flag of wheat genotypes.

Salinity levels (Mm)	Wheat genotypes	K^+ concentrations (mgr 100^{-1}gr biomass)	1000-grain weight (gr)
0	Caj × Set	1.275^{ab}	34.452^{a}
	Caj × Ho	1.273^{ab}	33.588^{ab}
	Caj × Ler	1.070^{ab}	28.266^{ab}
	Ax	1.232^{ab}	35.548^{a}
	Set	1.322^{a}	31.998^{ab}
	Ho	1.317^{a}	32.067^{ab}
	Ler	0.947^{b}	39.840^{a}
	Caj	1.337^{a}	30.691^{ab}
150	Caj × Set	0.272^{d}	7.900^{cd}
	Caj × Ho	0.356^{cd}	8.855^{cd}
	Caj × Ler	0.359^{cd}	5.180^{cde}
	Ax	0.405^{cd}	12.305^{bc}
	Set	0.430^{cd}	6.227^{cd}
	Ho	0.406^{cd}	9.810^{c}
	Ler	0.337^{cd}	3.033^{def}
	Caj	0.558^{cd}	6.103^{cde}
200	Caj × Set	0.281^{d}	10.020^{cd}
	Caj × Ho	0.347^{cd}	10.600^{cd}
	Caj × Ler	0.388^{cd}	4.205^{cde}
	Ax	0.605^{c}	0^{g}
	Set	0.346^{cd}	5.617^{cde}
	Ho	0.405^{cd}	10.667^{c}
	Ler	0.360^{cd}	0.000^{g}
	Caj	0.425^{cd}	0.737^{fg}
250	Caj × Set	0.286^{d}	0^{g}
	Caj × Ho	0.357^{cd}	1.867^{efg}
	Caj × Ler	0.397^{cd}	0^{g}
	Ax	0.347^{cd}	0^{g}
	Set	0.339^{cd}	0^{g}
	Ho	0.307^{d}	0^{g}
	Ler	0.311^{d}	0^{g}
	Caj	0.322^{cd}	0^{g}

Means followed by similar letter in each column are not significantly different at 5% probability level using DMRT.

($p<0.05$) had significant effect on Number of grain per ear. With an increase of salinity levels the number of grains decreased (Figure 6).

K+ concentrations

The salinity levels, genotype and interaction of salinity levels x genotypes had a significant effect ($p<0.01$) on K+ concentrations. Trend of K+ concentrations in the first leaf below the flag showed that increased salinity cause a decrease in K+ concentrations (Figure 7). Among genotypes, Ax (0.65 mg 100-1 gr biomass) had the maximum K^+ concentrations (Table 3). In control condition, Caj genotype (1.337 mgr 100-1gr biomass) had the highest K^+ concentrations. In 150 mM applied NaCl, among genotypes Caj (with 0.558 mgr 100-1gr biomass) had the highest K^+ concentrations. In 200 mM NaCl, Ax with 0.605 mgr 100-1gr biomass had the highest K^+ concentrations. In 250 mM applied NaCl, among genotypes Caj x Ler (with 0.397 mgr 100-1gr biomass) had the highest K+ concentrations (Table 4).

Na+/ K+ ratio

Analysis of variance showed that salinity levels and

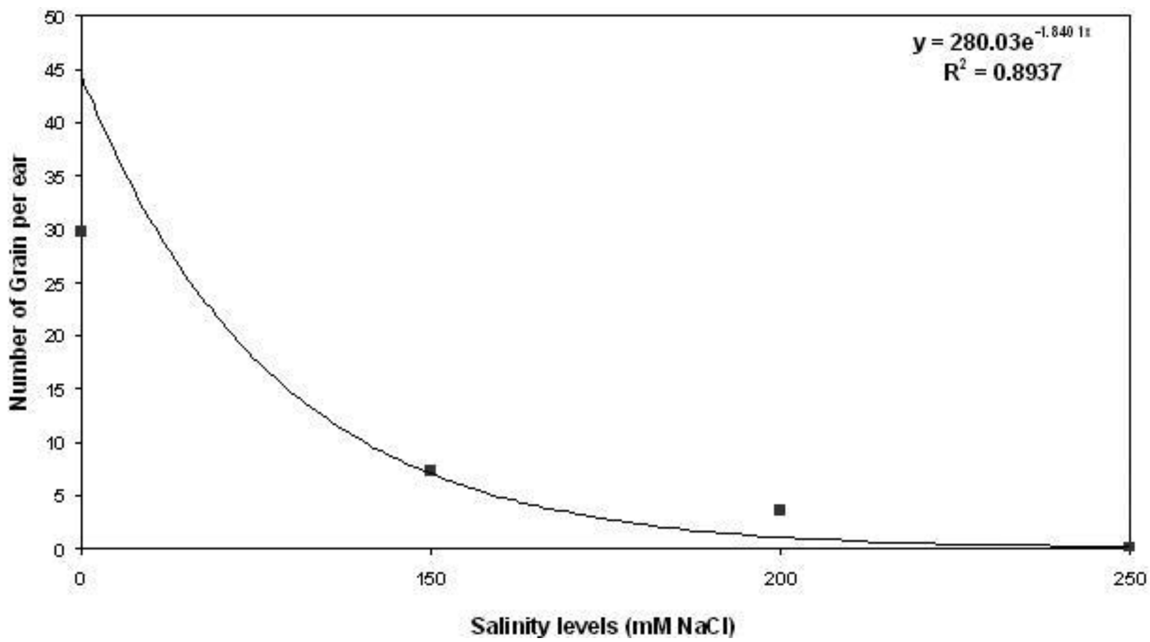

Figure 6. The effect salinity levels on number of grain per ear of wheat genotypes.

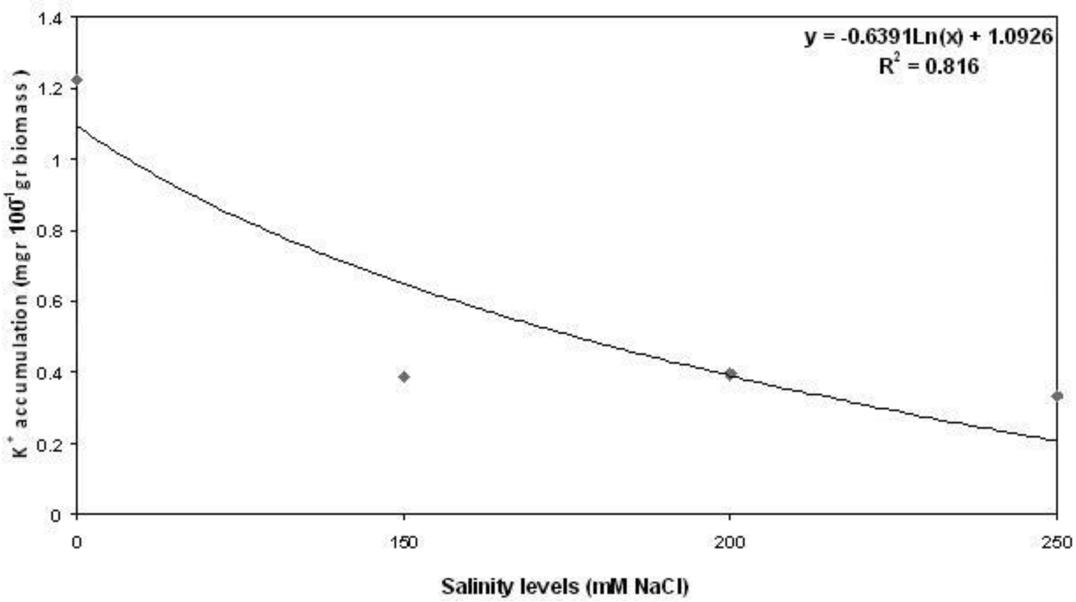

Figure 7. The effect of salinity levels on K+ concentrations in the first leaf below the flag of wheat genotype.

genotypes ($p<0.01$) had significant effect on Na^+/K^+ ratio.

Cl- accumulation

Salinity levels ($p<0.01$) and genotype ($p<0.05$) had significant effect on Cl- accumulation. Among genotypes, Caj x Ho with means 2.39 mgr 100-1gr biomass had the maximum Cl- accumulation (Table 3). With increase of salinity levels Cl- accumulation increased in a linear manner (Figure 9).

Artificial neural network modeling

Results showed that back propagation artificial neural

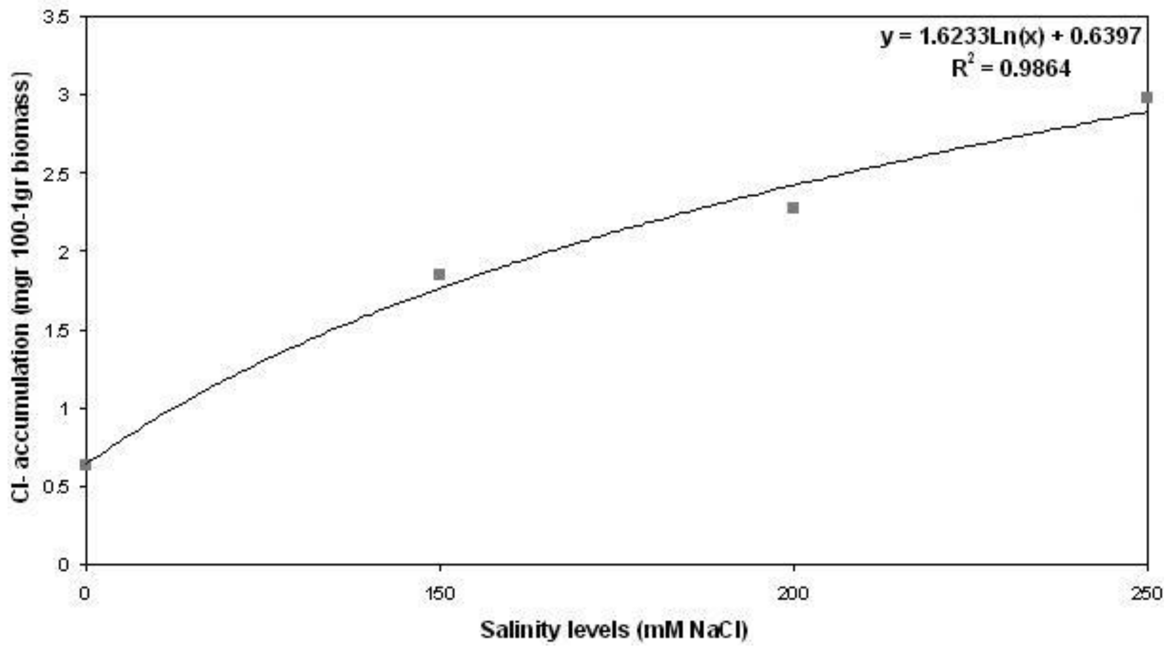

Figure 9. The effect salinity levels on Cl- accumulation in the first leaf below the flag leaf of wheat genotypes.

Table 5. The best structure and optimum values of the ANN used to predict the wheat seed yields and yield components.

MLP structure	Optimum		Transfer function	RMSE training	RMSE testing	T	Epoch ×1000
	Learning rate	Momentum					
2-28-6	0.7	0.2	Tanh in hidden layer and sigmoid in output layer	0.031	0.047	0.97	15

networks had a good ability for creating of nonlinear mapping between salinity level and wheat yield, number of grain per ear, 1000-grain weight, CL^- concentrations, K^+ concentrations, and Na^+/K^+ ratio in the first leaf below the flag leaf for 8 wheat genotypes. Among the various ANN structures, model of good performance was produced by the 2-28-6 structure with hyperbolic tangent transfer function in the hidden layer and Sigmoid in the output. We decided to employ the single hidden layer ANN structure, as it was capable of handling nonlinear relationships between the input and output variables. Table 5 shows the ANN parameters giving the best fits for the training data set. As it is seen, the model with 28 hidden neurons produced the best model performance in terms of training RMSE, testing RMSE, and testing T value. For the final ANN model, the RMSE between predicted and measured data for the six outputs were lower than 0.047 (Table 5). Ideally, RMSE values close to zero indicate there are no differences between the predicted and measured values. Meanwhile, it is also evident that the T values are close to 1.0, which indicates that the fitting was as desired (Khazaei et al., 2008c).

Figure 11 shows the training and prediction RMSE error are represented as a function of number of epochs for the final selected ANN structure. As can be seen, the training of the model was successfully accomplished. The training RMSE proceeded toward the minimum at epochs near to 15 x 103. The performance of the final selected ANN model for prediction of wheat yield and yield components are displayed in Figure 12. Each picture show 11 predicted data (test set data) versus the same set of measured data, for the final network trained with 15 x 103 epochs. It can be seen that there was excellent agreement between the experimental data and the predictions. For all the six outputs, the linear adjustment between observed and estimated values gave almost a slope practically equal 1. The mean values of RMSE, T value, and R^2 of the ANN model to predict each of the six dependent variables of wheat yield and yield components are displayed in Table 6. The mean resulting correlation coefficient and T values were 0.977 and 0.97, respectively for the regression between observed and estimated values (Figure 12), indicating that the ANN provided satisfactory results over the whole set of values for the six dependent variables. Differences between observed and predicted means were statistically non

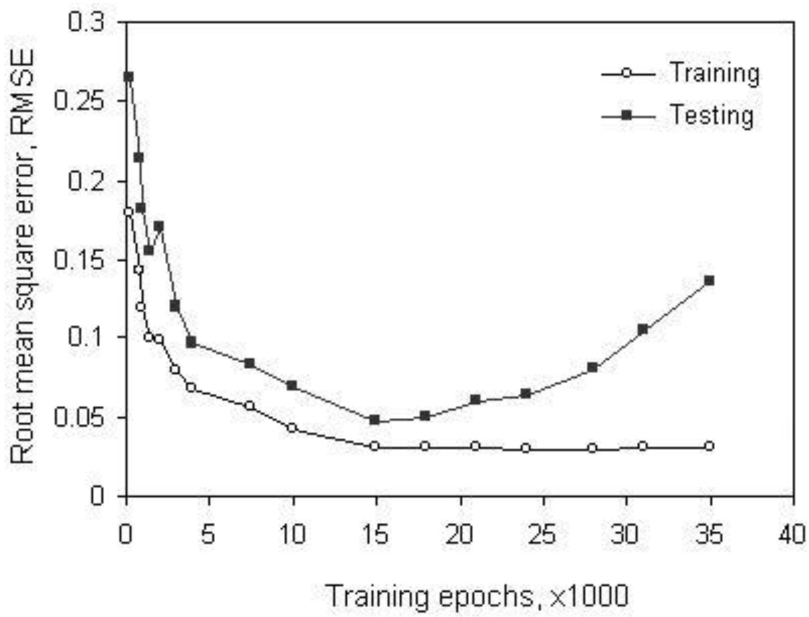

Figure 11. Convergence of the root mean square errors during training of the final selected ANN.

significant (P = 0.05).

In this study, multi-linear regression (MLR) models with the salinity level as the input variable was also employed to evaluate the results with ANN model. The regression models did not predict wheat yield and yield components with the same level of accuracy as ANN models (Table 7). A comparison between the coefficients of determination, R^2, of the ANN model (Table 6) with those for the 6 regression models (Table 7) indicates that the ANN model, in many cases, has been very close to, or even higher, accuracy than regression models in predicting the yield and yield components data to wheat.

DISCUSSION

Salinity is one of the important stresses affecting plant growth and productivity, results of Soltania et al. (2006); Mahajan and Tuteja (2005); Faroop and Azam (2005); Reddy et al. (2003); Allakhverdiev et al. (2000) confirmed our results. The result of Khatun and Flowers (1995) confirmed this result; opposite of Na+ and Cl- at all levels of applied salinity, where they were minimal, K+ concentration was maximal in the flag leaf. Results of Katerji et al. (2005); Faroop and Azam (2005); Francois et al. (1986) were similar to these results; their results confirmed that salinity caused to decrease grain yield. Among genotypes, Ho and Ler had the maximum and minimum Number of grain, respectively (Table 3), similar to these results Katerji et al. (2005) showed different tolerance of two durum wheat varieties. Similar to this results, Faroop and Azam (2005); Marschner (1995); Sadat and Harati (2005) showed a negative correlation between Na+ and K+ concentration. Increase of Na^+ result a decrease in K+, since K+ is an important element for protein synthesis and enzyme activation (Marschner, 1995), plants can't tolerate salinity stress. With increase of salinity levels, Na^+/K^+ ratio in the first leaf below the flag increased (Figure 8), similar results were observed by Yang et al. (2002) and Botella et al. (1997). Among genotypes, Caj x Ho had the maximum Na^+/K^+ ratio (Table 3). Maintaining a low Na^+/K^+ ratio is one of the determinants of plant salt tolerance (Zhu et al., 1998). Analyzing the impacts of number of hidden neurons on the training and prediction performance of the ANN model showed that as the number of hidden neurons increased, the training accuracy improved.

The prediction performance was optimum when 28 neurons were used in the hidden layers (Figure 10). However, no improvement in the prediction performance was noticed when the number of neurons in the hidden layer was increased beyond 28. The reason for this may be attributed to the memorization of training data by networks with too many neurons. In back-propagation networks, the number of hidden neurons determines how well a problem can be learned. If too many are used, the network will tend to try to memorize (also called overtraining) the problem, and thus not generalize well when presented with test data sets. If too few are used, the network will generalize well but may not have enough power to learn the patterns well. There is no formal procedure to determine number of hidden neurons. Typically, it is determined by a combination of previous expertise, amount of data available, dimensionality,

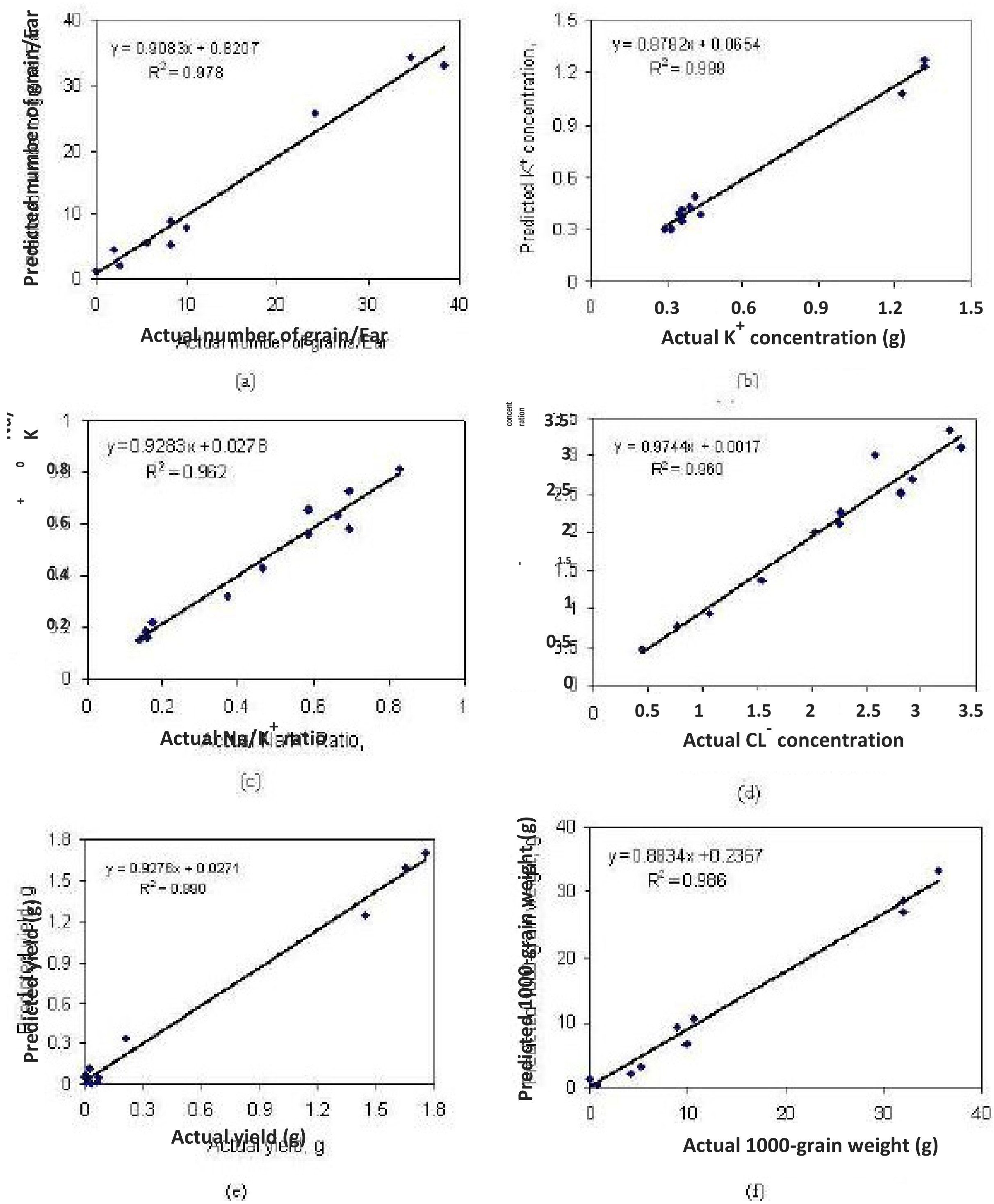

Figure 12. Comparison between the observed value and that predicted by the artificial neural network for. a) number of grain per ear and b)K+ concentration, c) NA+/K+ ratio, d)Cl- concentration, e) Yield , f) 1000-grain weight.

complexity of the problem, and trial and error. The results showed that epoch size directly affected the learning ability of the network. The training and testing data sets followed a very similar trend up to a 15×10^3 epochs. At that point, overfitting (''memorizing'' of data) started to occur and the prediction errors for the two data sets diverged, continuing to decrease for training data, but increasing for testing data as previously reported in the literature (Haykin, 1994). Anyway, the optimal network was found at 15×10^3 epochs.

Table 6. The mean values of RMSE, *T* value, mean relative error, and R^2 of the ANN model to predict yield and yield components to wheat.

	RMSE	*T* value	Mean relative error	R^2
K^+ concentrations (mg 100^{-1}g biomass)	0.053	0.975	-0.086	0.988
Na^+/ K^+ ratio	0.047	0.961	-0.038	0.962
CL^- concentration	0.048	0.957	0.022	0.960
Number of grains /Ear	0.050	0.973	-0.154	0.978
1000-grain weight, g	0.053	0.968	-0.052	0.986
Yield, g	0.036	0.986	-0.110	0.990

Table 7. Six regression models to predict six yield and yield components parameters to wheat.

	MLR Model	RMSE	Mean relative error	R^2
K^+ concentration (mg 100^{-1}g biomass)	y=-0.6391Ln(x)+1.0926	0.14	0.11-	0.816
Na^+/ K^+ ratio	y=3.5246Ln(x)+0.3474	0.71	-3.5	0.897
CL^- concentration	y=1.6233Ln(x)+0.6397	0.2	0.0109	0.986
Number of grains/Ear	$y=280.03e^{-1.8401x}$	0.82	0.041	0.893
1000-grain weight, g	$Y=5.231X^2-36.292X+63.037$	0.29	-0.77	0.946
Yield, g	$Y=2.5335\ X^{-5.2887}$	0.47	0.31	0.886

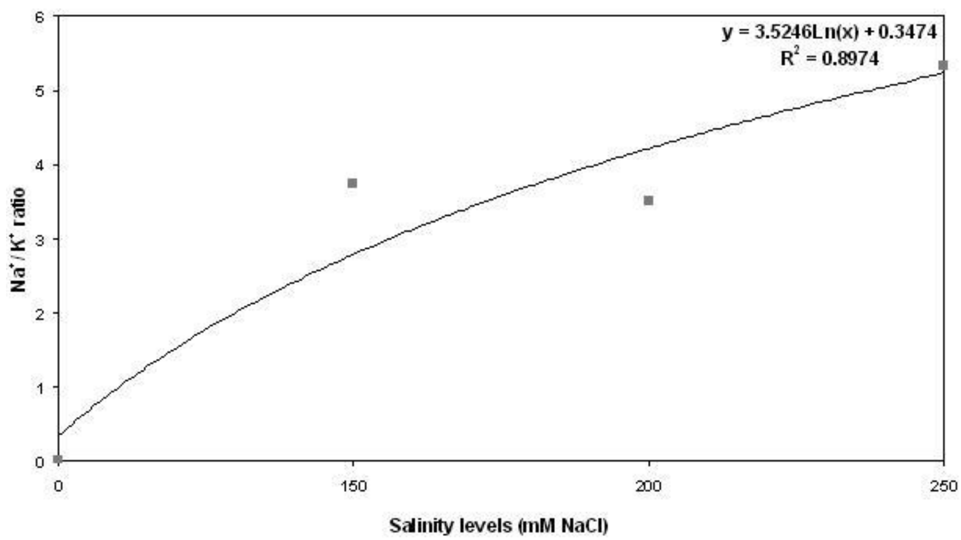

Figure 8. The effect of Salinity Levels on Na+ K+ ratio in the first leaf below the flag of wheat genotypes.

The result implied that the designed ANN was able to properly learn the relationship between the input and output parameters. In fact, a well-trained ANN model is the key to design and analysis input and output relations. Means were thus accurately predicted in a wide range of number of input vectors and output variables. The small difference between measured and predicted data provides a clear insight into the generalization ability of ANN models. These results also confirm the fact that a properly trained ANN model (in this study a 2-28-6 ANN structure) is able to predict simultaneously more than one dependent variables (Table 5 and Figure 12), unlike traditional mathematical models where one regression was required for each dependent variable (Table 7). This ability of ANNs could significantly reduce the computation time and the amount of practical work required to build

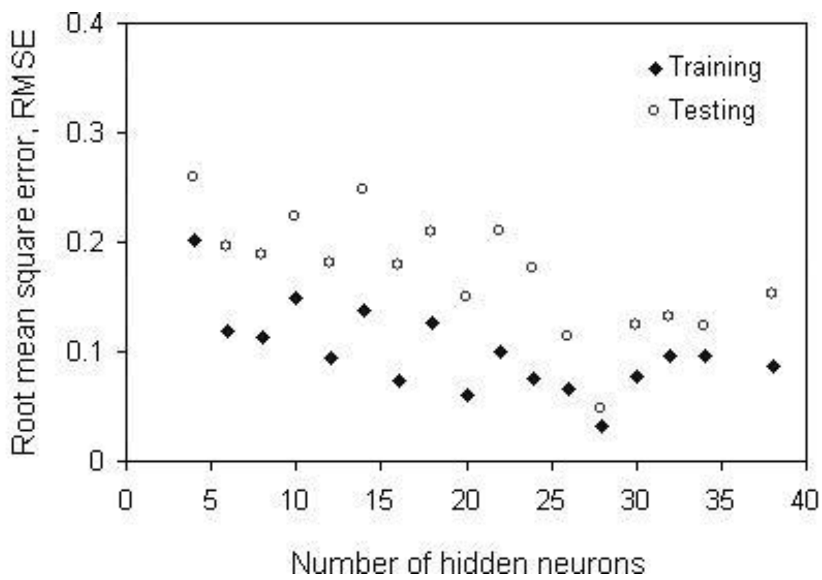

Figure 10. Effect of the number of hidden neurons on the mean RMSE errors for training and testing data.

the mathematical models. Moreover, as it was explained, a single ANN model had better predictions performances than the six regression models for the noisy experimental data (Tables 6 to 7). Hence, it is recommended that ANNs can potentially be used as an alternative technique to predict noisy yield and yield components data in agriculture.

The results showed that for the ANN model trained by 15 x 103 epochs the mean value of the relative errors was -0.069, which indicates a good model performance. These results show that the network successfully learned the relationship between the input factors and wheat yield and yield components as output for all range of data. This indicates that the ANN model used in this study can potentially be used to estimate yield and yield components of agricultural products. This indicates that the obtained ANN model can assuredly replace the mathematically constitutive models for yield and yield components prediction, since it takes acceptable performance into account with experimental data and automatically improves itself through learning. Figure 13 shows the relationship between the relative errors and values estimated by the ANN model for all the six outputs. It is clear that the slope of correlation between estimated data and residuals were close to zero. The residuals were well distributed on either side of the horizontal line (ordinate) representing the residual mean. Some over- and under-estimates of some weak values were possibly observed. This was the consequence of the scarcity of high and low values in the database for an effective learning of the model. The results obtained from this study showed that, the network parameters affected the ANN significantly. The learning rate and momentum term were adjusted to yield a model with the least error. As clear from Table 5, a large learning rate and smaller momentum were desirable so that the achieved result was as precise as possible.

Figure 14 shows the effects of the learning rate and momentum value on the RMSE. It is evident that, as the learning rate was increased the RMSE tended to drop. It was revealed that the learning rate ranged from 0.1 to 0.5 tended to produce larger RMSE, while values ranged from 0.6 to 0.9 were quite similar and tended to give smaller errors. This indicates that in this range the necessary weight adjustments were appropriate. However, at this range of learning rate, the effect of different values of momentum in the range of 0.1 to 0.3 on the performance of the networks was negligible. The optimized values of learning rate and momentum were 0.7 and 0.2, respectively.

Conclusions

An ANN approach was successfully applied to predict six yield and yield components of wheat by considering the effects of the salinity level and wheat genotype. The comparison of the ANN predictions with the experimental measurements was satisfactory. It was found that a single ANN model had better predictions performances than six regression models for the noisy experimental data. These results confirm the fact that a properly trained ANN model (in this study a 2-28-6 ANN structure) can be used to predict simultaneously more than one dependent variables, unlike traditional regression models where one regression is required for each dependent variable. This ability of ANN models could significantly reduces the computation time and the amount of practical

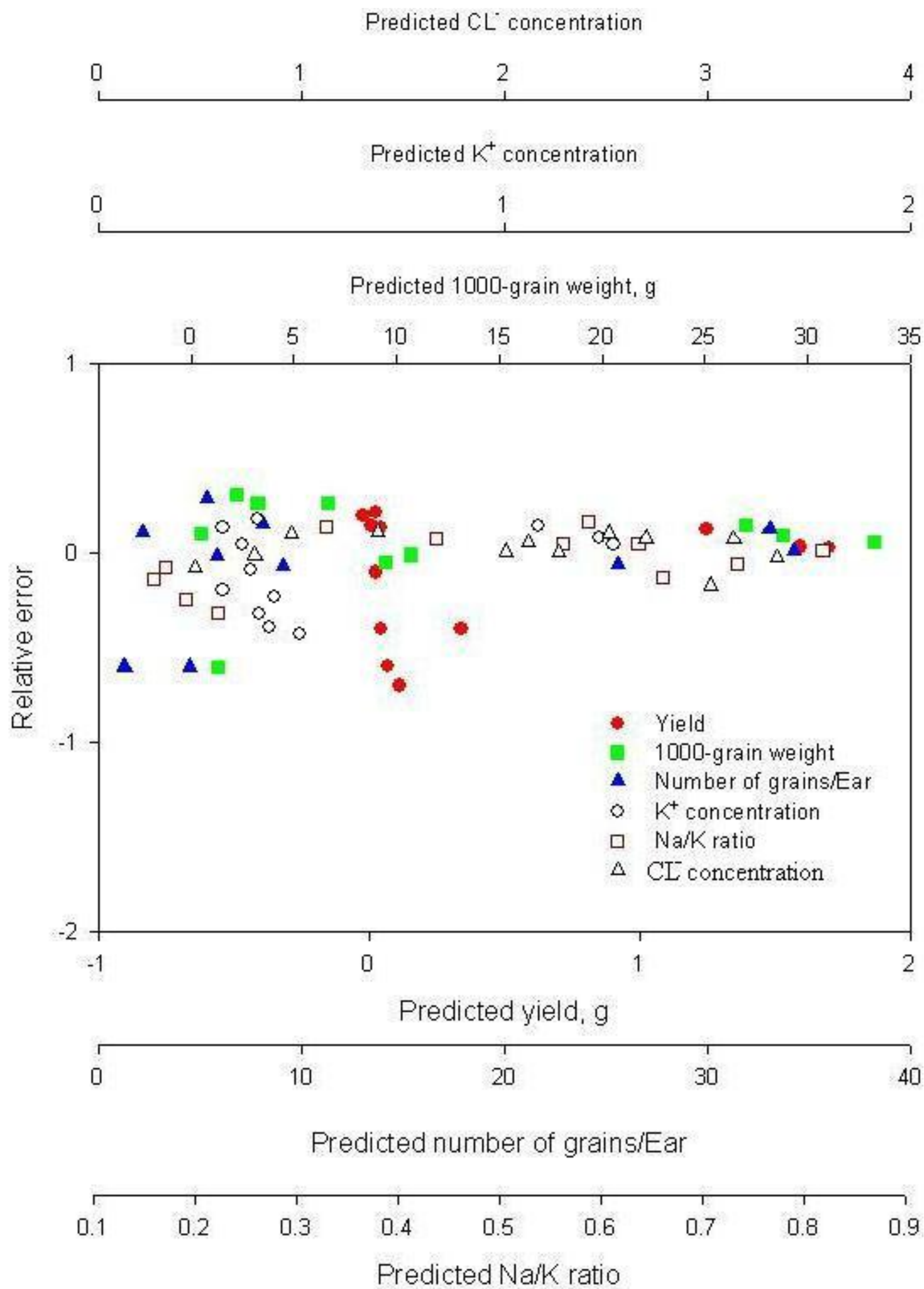

Figure 13. Error distribution of the ANN model for the prediction of the wheat seed yields and yield components.

work required to build the mathematical models. Hence, it is recommended that ANNs can potentially be used as an alternative technique to predict noisy yield and yield components data in agriculture.

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