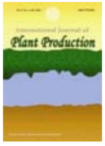

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The optimization of root nutrient content for increased sugar beet productivity using an artificial neural network

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Abstract

Conventional procedures are inadequate for optimizing the concentrations of nutrients to increase the sugar yield. In this study, an artificial neural network (ANN) was used to optimize the Ca, Mg, N, K and Na content of the storage root to increase sugar yield (Y) by increasing both sugar content (SC) and root yield (T). Data from three field experiments were used to produce a wide range of variation in nutrient content, SC and T. In the training phase of the ANN, R^2 was 0.91 and 0.94 for SC and T, respectively. The high R^2 values obtained demonstrating the ability of the ANN to predict SC and T. The obtained optimum values were 0.37%, 0.35%, 0.97%, 4.67 (meq/100 g) and 0.33% for Ca, Mg, N, K and Na, respectively. Optimization increased the potential Y by 17%.

Keywords: Artificial neural network; Nutrient content; Optimization; Sugar beet.

Introduction

The term "agronomic efficiency" was introduced by De Wit (1992). Agronomic efficiency can be improved by fine tuning the inputs to the crop in relation to the anticipated yield. Fine tuning could also reduce the environmental impacts (e.g., nitrogen (N) leaching) of agricultural practices and could increase the profitability of crop production. Nutrients are one of the important inputs in agriculture. They are essential for the normal growth and development of crops.

The complex response of sugar beet productivity to nutrients has two components, the sugar content of the root and the root yield per ha, which usually have an inverse relationship. In addition, sugar extraction is affected adversely by surplus N, which increases the concentrations of α-amino N compounds within the storage root (Pocock et al., 1990; Tsialtas and Maslaris, 2008).These compounds significantly reduce the proportion of the sugar which can be crystallized (Dutton and Huijbregts, 2006). Furthermore, the effect of N tends to be considerably affected by weather (De Koeijer et al., 2003) and by the levels of other nutrients (Cai and Ge, 2004; Pocock, et al., 1990). For example, Voth and Christenson (1980) found that Mn-deficient leaves of sugar beet contained above-average nitrate concentrations; this was not true for Mn-sufficient leaves. An increased N application depressed the Mn concentration in the leaf tissue (Bravo et al., 1992) and decreased the content of P in the leaves by approximately 2% (Cai and Ge, 2004). Bonilla et al. (1980) observed that boron deficiency and toxicity could cause more NO_3-N accumulation in the sap of sugar beet owing to a decrease in the activity of the N-Rase enzyme. Increasing N application has produced increases in S, Na and Mn and decreases in Ca and K in sugar beet plants (Bravo et al., 1989). El-Sheikh and Ulrich (1970) measured the concentrations of some nutrients in the leaves and petioles and found that Rb can increase the growth of sugar beets suffering from K deficiency. These authors stated that Na increased the growth of sugar beet plants if they were either K deficient or adequately supplied with K. The simultaneous supply of Na and Rb resulted in synergistic effects only in K-deficient plants.

A more complex aspect of these interactions is that they tend to vary from one organ to another. For example, the zinc content of the leaf blades tends to show a linearly increasing trend as the level of N fertilizer increases from 0 (N_0) to 300 (N_{300}) lb per A (Bravo et al., 1992). In contrast, the zinc content decreases in the petioles and remains constant in the crown and root. N100 increases the boron content of the crown but decreases that of the root. The boron content of the petioles is not affected by N application. These variations are the topic of a general review by Tariq and Mott (2007).

Many useful procedures and mathematical equations have been proposed for optimizing nutrient ratios or concentrations for increased crop yield. These methods have previously been reviewed (e.g., Trionfo, 2000). However, these techniques are not capable of optimizing the nutrient levels to simultaneously increase root yield and sugar content in the presence of the interactions cited.

Problems of this kind can be solved with an alternative approach involving the artificial neural network (ANN) technique.

An ANN model is a network of simple units, each having a local memory. These units, known as neurons, are connected by unidirectional links that transmit data for use in discrimination (Nagy et al., 2002). The model provides a random mapping from an input vector to an output vector by mimicking the biological cognition processes of the brain (Azmathullah et al., 2005). Neurons are defined as mathematical expressions that filter the signal through the net. The net is formed by successive layers of neurons, and each neuron is connected to each of the neurons in the previous layer (Caamaño et al., 2006).

A multi-layer perceptron is a typical ANN. It is constructed from a number of nodes that are organized according to a particular arrangement (Figure 1). The optimization problems including both single-and multi-objective problems can be found in studies of many researchers such as Goldberg (1989), Rauch and Harremoes (1999) and Huang (2010). The aim of this study is to use ANN to optimize the content of 5 root nutrients, Ca, Mg, N, K and Na, to increase the potential root yield and the extractable sugar content of sugar beet.

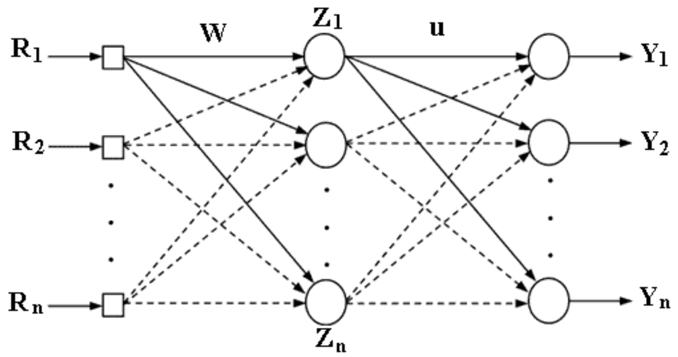

Figure 1. Configuration of the MLP with one hidden layer (Vakil-Baghmisheh, 2002).

Materials and Methods

Experimentation

Three field experiments were conducted to gather the data required for this study. Two of the three experiments were carried out at the Research Farm of Shahrood University of Technology, Shahrood (36° 25' N, 55° 01' E and 1345 m asl), Iran on April 21, 2004 (1st experiment) and May 26, 2007 (2nd experiment). The 3rd experiment was conducted at Rudasht Research Station (32° 5' N, 52° ' E and 1450 m asl), Isfahan, Iran on April 23, 2008. The experiment followed a complete randomized-block design with three replications per treatment for all three experiments.

In the 1st experiment, the treatments were the factorial combinations of 3 N (165 kg ha^{-1}) resources (urea, ammonium nitrate and ammonium sulfate), 3 application times ((I) application of 1/3 of the fertilizers at the time of thinning the plants and 2/3 one month later, (II) ½ at thinning and ½ one month later, and (III) 2/3 at thinning and 1/3 one month later), and 2 weed control strategies (control by hand (both within and between rows) and control with a cultivator (only between rows)). A split-plot experiment was used in the 2nd study. The irrigation levels (8- (control), 12- and 16-day intervals) represented the main plots. Factorial combinations of 3 salicylic acid concentrations (0 (control; only water was applied), 0.4 and 0.8 millimole) and 2 application times (applying the salicylic acid once, at the stage of leaf fascicle formation (#7.4) or twice, at the #7.4 and #8.15 stages (the epacme of the root tuber)) were used. These combinations represented the subplots. The treatments in the 3rd experiment consisted of factorial arrangements of 4 N (0, 80, 120 and 160 kg urea ha^{-1}) and 4 K levels (0, 125, 190 and 250 kg K_2SO_4 ha^{-1}).

In the 1st experiment, the soil composition was 36% clay, 48% silt and 16% sand. The percentages of these materials were 34, 44 and 32%, respectively, for the 2nd experiment and 39, 45, and 16%, respectively, for the 3rdexperiment. Other characteristics of the soils are presented in Table 1. At the time of harvest, in addition to the root (say tuber) and the percentage of sugar, the concentrations of Ca, Mg, N, K and Na in the root were measured. These variables were used as inputs (regressors).

Table 1. The properties of the soil used in the three experiments discussed in the text.

Year	EC (dS/m)	pH	OC (%)	N (%)	P (ppm)	K (ppm)	Na (ppm)	Mn (ppm)	Cu (ppm)	Zn (ppm)	Fe (ppm)
2004	1.92	8.15	0.40	0.04	20.8	280	--	4.60	0.62	0.5	2.60
2007	1.50	7.89	0.79	0.06	14	143	22.2	--	--	--	--
2008	5.00	7.80	0.63	0.06	12.3	268	28	2.72	1.27	0.32	4.53

Artificial Neural Network and Genetic Algorithm analysis

The data set was randomly shuffled and split into a training set (70% of the total data) and a test set (30%). These percentages were determined by trial and error using MATLAB software (Bateni et al., 2007). The

Multilayer Perceptron (MLP) approach was used. Among ANN models, this method offers the highest practical significance. Figure 2 shows a MLP with one hidden layer. The transfer function serves to normalize a node's output signal strength to values between 0 and 1. Each node multiplies every input by its interconnection weight, sums the product, and then passes the sum through a transfer function to produce its result. This transfer function is usually a steadily increasing S-shaped curve called a sigmoid function. Under this threshold function, the output y_j from the j^{th} neuron in a layer is (Bateni et al., 2007):

$$y_j = f(\Sigma w_{ij} x_i) = \frac{1}{1+e^{-(\Sigma w_{ij} x_i)}} \tag{1}$$

where w_{ij} is the weight of the connection joining the j^{th} neuron in a layer with the i^{th} neuron in the previous layer and x_i is the value of the i^{th} neuron in the previous layer.

Different transfer functions, such as Sigmoid, Gaussian, Haperbolic Tangent, and Hyperbolic Secant, were used in this study (Kreyszig, 2006). Many MLP training methods are available. The back-propagation method was used in this study. In this algorithm, neural networks process the information in interconnecting processing elements (often termed neurons, units or nodes). To compare the performance of various ANN configurations, three statistical parameters were used. These parameters were standard deviation (Std), root mean-squared error (RMSE) and the coefficient of determination, R^2:

$$RMSE = \sqrt{\frac{\Sigma_{i=1}^{n}(X_i - Y_i)^2}{n}} \tag{2}$$

$$R^2 = \left(\frac{\Sigma_{i=1}^{n}(x_i - y_i)^2}{\sqrt{\Sigma_{i=1}^{n} x_i^2 \, \Sigma_{i=1}^{n} y_i^2}} \right) \tag{3}$$

Where $x = (X - \overline{X})$, $y = (Y - \overline{Y})$, X=observed values, Y=predicted values, $\overline{Y}$=mean of Y, $\overline{X}$=mean of X, and n=the number of testing patterns.

The training of the ANN models was ended when either the acceptable level of error was achieved or the number of iterations exceeded a prescribed maximum of 10000. A learning rate of 0.01 was used. The models that minimized the error, i.e., RMSE and Std, and had high R^2 values were selected as the optimum models. After the satisfactory performance of the ANN model was confirmed, the relative contributions of the regressors to the determination of the sugar content and the root yield were estimated.

Optimization

No linear relationships were found between root yield or sugar content and any of the 5 nutrient contents of the root (data not shown). Therefore, the following 3-stage approach was used.

Stage 1

Initially, two of the five regressors, Mg and Ca, which tended to have a more obvious direct effect on sugar content, were used with an ANN having 2 inputs (root yield and sugar content) and 1 output. Separate ANN models were developed for Mg as the output and for Ca as the output. Eighty percent of the original data (the values obtained from the three experiments) were used to train the ANN model, and 20% were used to test the model. The satisfactory performance of the ANN was confirmed, and the values of Ca and Mg were then predicted. Each of these values could potentially be the optimum value for increased sugar content and root yield. From these values, those that were within the range of the original data were selected and used as the sample data set (Table 2).

Stage 2

The goal of this stage was to include the remaining regressors, i.e., K, Na and N, in the ANN model using the sample data set obtained from the previous stage. An ANN with 4 inputs and 3 outputs was used. In this stage, the inputs were root yield, sugar content, Mg, and Ca and the outputs were K, Na, and N. As in the previous stage, 80% of the original data were used for the training phase and the remaining data for the testing phase. The trained neural network was then used to find the values of K, Na and N and thereby complete the estimation of the values of the 5 regressors. These values, consisting of 37 data samples, are presented in Table 2. These 37 samples do not necessarily correspond to the desired productivity of the sugar beet. Hence, in the next stage the 37 samples of the 5 regressors obtained in the two previous stages were examined.

Table 2. The sample datasets used to select the nutrient parameters for optimum sugar beet production. $\hat{S}$ and $\hat{W}$ are the initial values used to estimate the five essential nutrient parameters, and S and W are the estimated crop specifications resulting from the use of the estimated five parameters for sugar beet production.

$\hat{S}$ %	$\hat{W}$ ton ha^{-1}	Ca %	Mg %	N %	K meq/100g	Na %	S %	W ton ha^{-1}
11.3	50.0	0.36675	0.34977	0.97069	4.66778	0.32537	17.09708	74.65979
11.5	50.4	0.36675	0.34993	0.97175	4.76385	0.38282	17.05924	73.88203
11.7	50.8	0.36675	0.35010	0.97282	4.86908	0.45179	17.00657	72.96751
11.9	51.2	0.36675	0.35026	0.97387	4.98080	0.53178	16.93633	72.19231
12.1	51.6	0.36675	0.35043	0.97491	5.10042	0.62501	16.84311	71.84670
12.3	52.0	0.36675	0.35059	0.97592	5.22445	0.72982	16.72549	72.19687
12.5	52.4	0.36675	0.35076	0.97693	5.35409	0.84815	16.57980	73.30322
12.7	52.8	0.36676	0.35092	0.97789	5.48484	0.97650	16.41259	74.69269
12.9	53.2	0.36678	0.35108	0.97883	5.61638	1.11473	16.23115	75.18347
13.1	53.6	0.36682	0.35124	0.97974	5.74668	1.26070	16.05061	73.18631
13.3	54.0	0.36692	0.35139	0.98059	5.87135	1.40882	15.89213	68.28378
13.5	54.4	0.36711	0.35154	0.98139	5.98940	1.55683	15.76836	61.93313
13.7	54.8	0.36742	0.35169	0.98212	6.09890	1.70101	15.68561	56.16951
11.3	50.0	0.36785	0.35184	0.98279	6.19933	1.83926	15.64100	52.01969
13.9	55.2	0.36829	0.35198	0.98340	6.29253	1.97296	15.62669	49.48779
14.3	56.0	0.36838	0.35210	0.98401	6.38677	2.11380	15.63652	48.28585
14.5	56.4	0.36754	0.35220	0.98471	6.49344	2.28049	15.67254	48.48956
14.7	56.8	0.36506	0.35225	0.98556	6.61487	2.48052	15.73500	50.16492
14.9	57.2	0.36048	0.35221	0.98646	6.73427	2.69016	15.80466	52.52722
15.1	57.6	0.35421	0.35201	0.98714	6.81522	2.84511	15.85611	54.95565
15.3	58.0	0.34776	0.35154	0.98718	6.82907	2.88745	15.88491	57.78284
15.5	58.4	0.34344	0.35064	0.98613	6.77080	2.80655	15.88191	59.91567
15.7	58.8	0.34345	0.34918	0.98365	6.64814	2.62232	15.82573	58.75570
15.9	59.2	0.34936	0.34714	0.97935	6.44286	2.31640	15.70095	52.01366
16.1	59.6	0.36141	0.34490	0.97271	6.09241	1.82528	15.61121	45.83491
16.3	60.0	0.37746	0.34356	0.96400	5.64453	1.27851	16.05024	68.71998
16.5	60.4	0.39295	0.34530	0.95599	5.50942	1.15968	16.36326	74.84951
16.7	60.8	0.40356	0.35343	0.95224	6.18559	2.09880	15.74706	34.51236
16.9	61.2	0.40769	0.36875	0.94656	6.97009	3.38281	16.22061	45.81275
17.1	61.6	0.40602	0.37764	0.92873	6.98051	3.47293	16.32138	47.30859
17.3	62.0	0.40020	0.36073	0.90729	6.60371	3.07028	16.28798	41.91203
17.5	62.4	0.39234	0.33761	0.87351	5.01099	1.04443	16.59590	41.24006
17.7	62.8	0.38450	0.33802	0.85410	5.09434	1.30664	16.39336	23.19472
17.9	63.2	0.37801	0.36486	0.83928	5.91064	2.68330	16.50641	28.46876
18.1	63.6	0.37335	0.39780	0.81861	4.69854	1.05732	16.68746	31.92153
18.3	64.0	0.37034	0.41025	0.81025	4.35891	0.60411	17.46926	44.25911
18.5	64.4	0.36857	0.40288	0.80691	4.48452	0.87006	17.01143	30.95036

Stage 3

Another multi-layer ANN with 5 inputs (K, N, Na, Mg and Ca) and 2 outputs (root yield and sugar content) was used to assess the sample data set provided by the previous stages. The training and testing of the ANN with the original data set was performed as in the previous stages. Next, the trained neural network was used to find the values of, K, Na and N, the three other parameters. The developed neural network was then used to assess the data shown in Table 2. In this assessment, the output of the network for each group of inputs was sugar content and root yield, shown in columns S and W of the table, respectively.

Results

The substantial differences in soil properties (Table 1), treatments and weather (data not shown) produced a wide range of variation in the values of the regressors, root yield and sugar content (Table 3). For instance, the tuber Na content and root yield varied as much as 5- and 4.5- fold, respectively. As expected, the root yield and sugar content tended to have an inverse relationship ($r = -0.5$; $P<0.01$). The performance of the MLP tended to improve as the number of hidden neurons increased. However, too many neurons in the hidden layer caused overfitting problems. This situation allowed good network learning and data memorization but also produced a lack of any ability to generalize. However, the network was unable to learn if a small number of neurons were used in the hidden layer. Usually the number of layers and neurons nodes of hidden layer (s) is typically determined by trial-and-error (Eberhart and Dobbins, 1990; Bateni et al., 2007). Therefore the trial and error method were used to determine the best configuration of MLP model. The results show for this data set, a MLP model with one hidden layer and a 5-5-2 configuration (Figure 2) appeared to be suitable for the prediction and optimization of the root yield and sugar content. The convergence results of this model are shown in Figure 7.

Table 3. Some statistical properties of the data, including the regressors, sugar content and root yield used for analysis.

Attribute	Minimum	Maximum	Mean	Range
Ca (%)	0.31	0.42	0.355	0.11
Mg (%)	0.33	0.41	0.371	0.08
N (%)	0.82	0.97	0.900	0.15
K (meq/100g)	4.43	6.70	5.674	2.27
Na (%)	0.62	3.11	1.907	2.49
Root sugar content (%)	14.11	18.36	16.378	4.25
Root yield (kg ha^{-1})	14110	64450	40120	50340

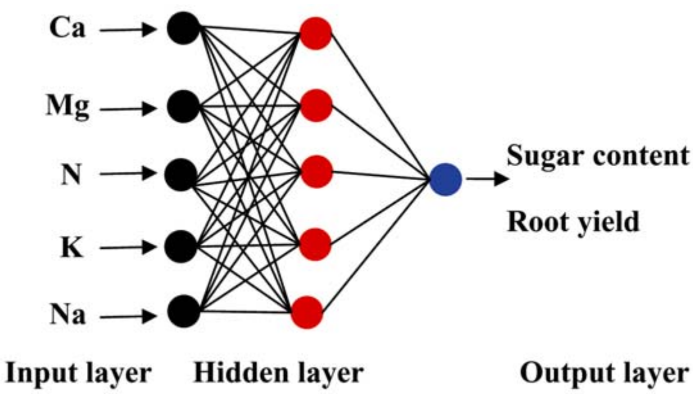

Figure 2. Multilayer neural network used for optimization of the content of some root nutrients to increase both the sugar content and the root yield of sugar beet.

The performance of the ANN with 4 different transfer functions is shown in Table 4. The lower values of RMSE and higher $R^2$for the hyperbolic secant function indicated that this transfer function was more suitable than the others for the current study. The suitability of this choice was also confirmed by the acceptable coincidence of the target network with the output network for different pattern sequences (Figures 3 and 4). The predicted and observed values were evenly distributed throughout the entire range (Figures 5 and 6). Although the results of the training phase were generally better than the test phase, the test phase demonstrated the ability of the MLP neural network to predict the sugar content and root yield from new data. The high R^2 demonstrated that the trained network was reliable and accurate and could therefore be used to predict the sugar yield.

Table 4. Some statistical properties of the results of the MLP model with different transfer functions for sugar content and root yield at the training and verification stages.

Transfer Function	Output	Training phase			Testing stage		
		RMSE	Std	R^2	RMSE	Std	R^2
Sigmoid	Sugar	0.945	0.371	0.879	0.367	1.173	0.737
	Root	25.004	7.879	0.823	8.491	19.817	0.531
Gaussian	Sugar	0.660	0.267	0.939	0.402	0.864	0.868
	Root	11.2064	3.278	0.971	8.448	14.269	0.749
Hyper. Tan.	Sugar	0.740	0.299	0.923	0.352	0.644	0.815
	Root	18.119	6.248	0.893	5.106	7.793	0.870
Hyper. Sec.	Sugar	0.619	0.276	0.935	0.287	0.606	0.931
	Root	10.704	4.205	0.953	6.571	21.429	0.829

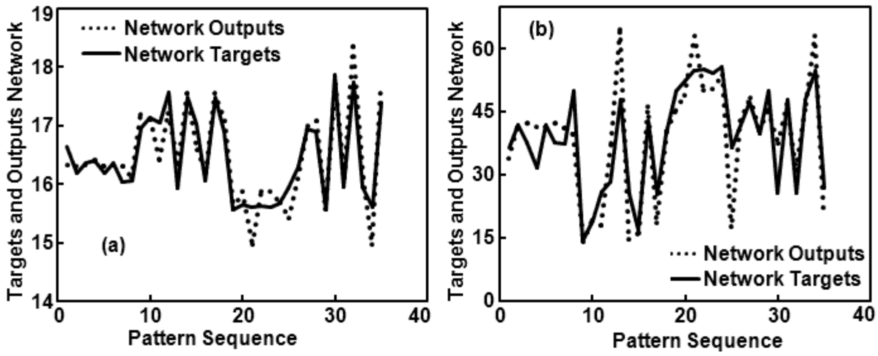

Figure 3. Targets and output network vs. pattern sequence for sugar content (a) and root yield (b) at the training phase.

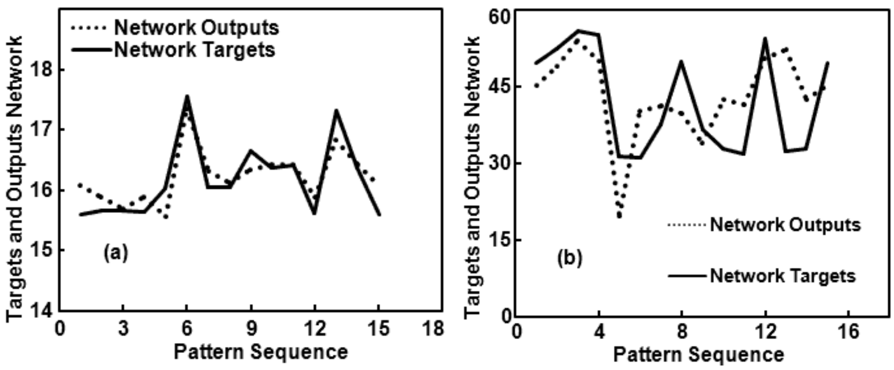

Figure 4. Targets and output network vs. pattern sequence for sugar content (a) and root yield (b) at the testing phase.

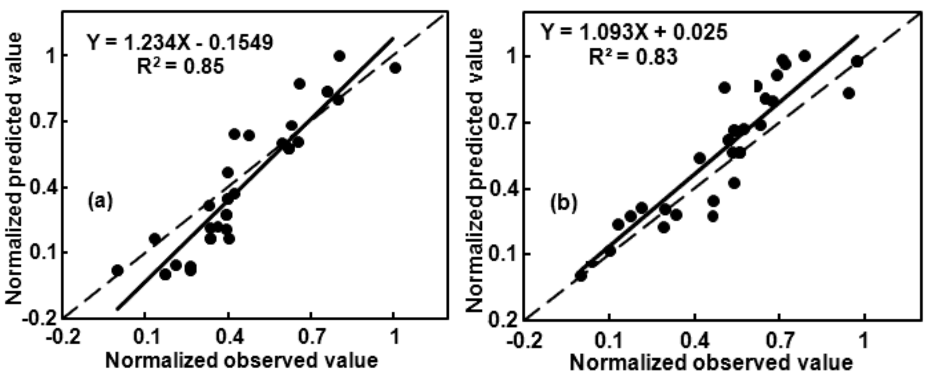

Figure 5. Plot of network output vs. training targets for normalized sugar content (a) and root yield (b) with the hyperbolic secant transfer function at the testing phase.

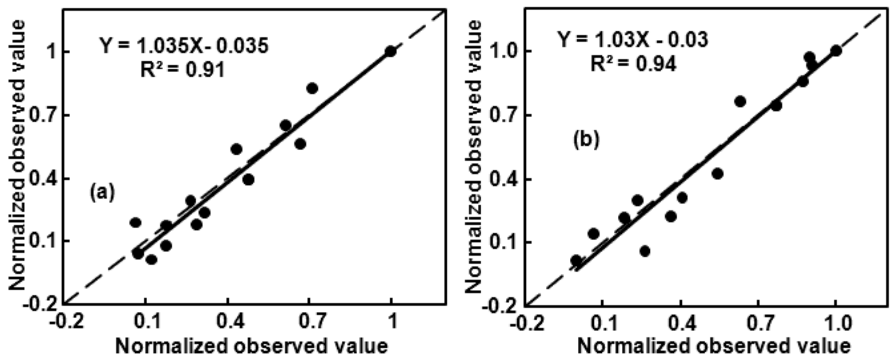

Figure 6. Plot of network output vs. training targets for normalized sugar content (a) and root yield (b) with the hyperbolic secant transfer function at the training phase.

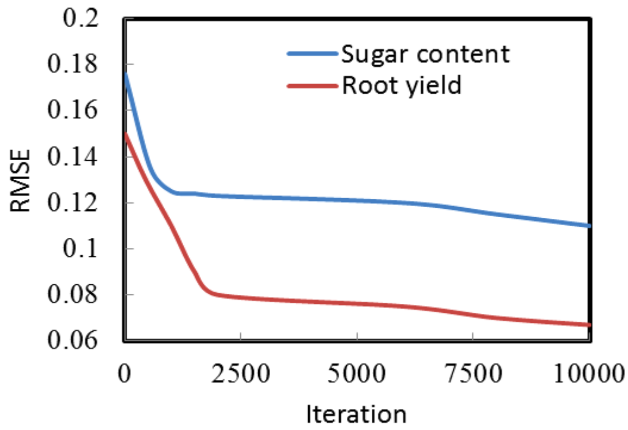

Figure 7. ANN (5-5-2) convergence results for sugar content and root yield.

The relative contributions of the regressors to the prediction of the sugar content and the root yield are shown in Figure 8. Na appeared to have the highest contribution to the sugar content (39.66%), and K appeared to have the highest contribution to the root yield (31.6%). The lowest contribution to the sugar content was found for Ca (9.1%), and the lowest contribution to the root yield was found for Mg (11.47%). Despite the contributions of the other regressors, Mg tended to contribute almost equally to the sugar content and the root yield. The highest root yield obtained by optimization was 75.1835 ton ha^{-1} (Table 2). At this value of root yield, the sugar content was 16.2% (Table 2). At another combination of nutrients, the sugar content reached 17.5%. At this value of sugar content, the root yield was 44.2591 ton ha^{-1}.

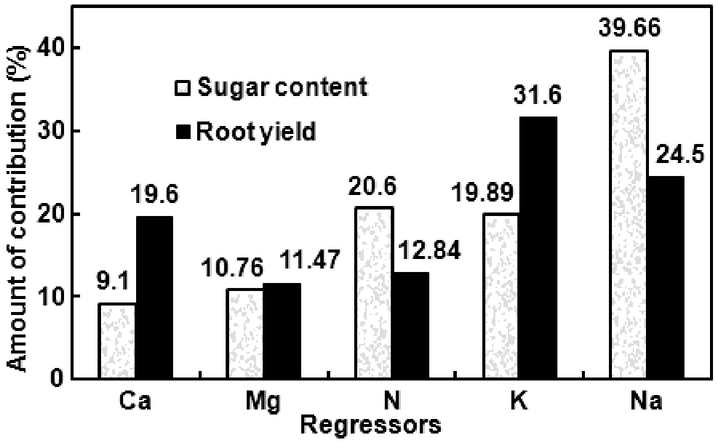

Figure 7. The relative contribution of some nutrients (independent variables) to changes in the sugar content and root yield of sugar beet.

Discussion

The optimization of effective factors, such as nutrients, to obtain simultaneous increases in the sugar content and the root yield of sugar beet is a complex problem whose solution requires an efficient technique. In this study ANN was used to optimize the concentration of 5 nutrients to increase the root yield and the sugar content. The resulting configuration of the ANN produced good predictive ability (Figures 5 and 6; Table 2) and an effective optimization of the regressors.

This study focused on the concentrations of nutrients in the root rather than in the upper parts (leaf and petiole) of the plant. This choice was made because the nutrient content of the upper parts of the plant cannot always be used as an index of the nutrient concentration in the root. This difference has several causes. Generally, the concentrations of nutrients tend to vary over the growth period (e.g., Barbanti et al., 2007; Bravo et al., 1989), and therefore these concentrations would not be the same at different sampling times. Moreover, the remobilization of nutrients from the upper parts of the plant to the root appears to be affected by interactions among nutrients and many other factors such as water availability (Tsialtas et al., 2009). For example, Cai and Ge (2004) found that the pattern of allocation of K to leaves and roots tends to change with changing N availability in the soil. However, this was not the case for P.

The results of optimization indicated that the optimum concentration of nutrients for higher sugar content is substantially different from the optimum for higher root yield (Table 2). Therefore, the predicted sugar content was multiplied by the predicted root yield shown in Table 2 to obtain the higher predicted sugar yield. The row of the table corresponding to the highest value of sugar yield was considered to represent the optimum nutrient content. The highest sugar yield was 12.7668 ton ha^{-1}, the product of 17.1% sugar content and 74.6598 ton ha^{-1} root yield. This potential sugar yield is much higher than the observed maximum sugar yield of 10.5356 ton ha^{-1}. To produce this potential sugar yield, the concentrations of Ca, Mg, N, K and Na in the tuber should be 0.37%, 0.35%, 0.97%, 4.67 (meq/100g) and 0.33%, respectively. Based on a sensitivity analysis (Figure 8), the precise concentrations of Na and K should receive more emphasis than those of the other 3 nutrients because variations in Na and K tend to produce much more dramatic variations in sugar content and root yield, respectively.

The results of this study demonstrated that the precise optimization of nutrients could increase the potential productivity of sugar beet. The study showed that an increase in sugar yield of up to 17% is possible. The analysis included only a few nutrients. Future research should also examine other nutrients. Agronomic management and breeding programs should be used to obtain appropriate combinations of nutrients. Although published reports regarding genetic variation in nutrient uptake and in re-translocation to the root (tuber) are rare, some previous results suggest that such diversity exists. For example, Stevanato et al. (2004) investigated the nutrient uptake of 3 sugar beet varieties and found a substantial difference (approximately 10%) in nitrate uptake rate.

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