Neuro-fuzzy concepts applied for planning of the cereal crops: applications to the maize hybrids growing in a Romanian region

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ABSTRACT
The aim of our study is to improve the crop planning procedures using neuro-fuzzy concepts. In this paper we design a neuro-fuzzy procedure that offers the suitable maize hybrid, from a set of preferred hybrids, which must be organically farmed in the current year. Our method is a statistical one, on the one hand it processes data provided by the previous years and on the other hand it takes in account the vague character of the environmental factors. Also we present here some experimental results obtained by us on a certain set of real data, results which prove the efficiency of our approach.

1. Introduction
One of the issues of interest for ecologic maize crops is to choose the best hybrids that ensure both a high level and a better quality of production. Considering that in a specific geographical area, the evolution of climatic factors may present significant variations from year to year or from season to season, the choosing of the right variety can be difficult because a variety which has been suitable under climatic conditions of a year may be less suitable in another. A strong fluctuation of climatic conditions can lead to an unpredictable development of certain factors, pests or plant disease, which may have a negative influence on plant growth even when strategies and technologies for plant growing are applied. Besides authors such as Rusu et al. [12] and Serban [15] showed that the climatic changes have a direct influence on the morpho-physiological features of some maize hybrids. An important research direction in the field of agronomy is the environmental factors pursuit during crop development. The aim is to improve any unfavourable situations by applying dynamic technology strategies. As a consequence new methods have been developed both for monitoring environmental changes and for dynamic adaptation of the crops’ technological processes. Prasannakumar et al. [11] and Judd et al. [7] provide methods to monitor the development and pest influence in a certain crop using for damages evaluations the spectral indices given by remote sensing. A significant contribution in this direction is brought by the monitoring procedures for plant growth that use satellite observations. Some authors such as Bunce et al. [2] suggest surveillance and
monitoring procedures based on spatial data analysis. There are also authors who combine these methods with classical methods for crops pursuit and thus they obtain better results. For example, Ecker et al. [3] use simultaneously methods that process both data from traditional sources at the ground level and data provided by satellite images.

Another approach of the agricultural system research consists in utilization of the artificial intelligence theory. The performance and benefits of neural networks and genetic procedures for data analysis persuaded a lot of biotechnologist researchers to focus on adaptation and application of artificial learning methods in modelling, observation, control and optimization of agricultural processes [5,6,9,10,14].

We underline two aspects that led us to our approach for maize crops planning. On the one hand, the crops monitoring methods lead to strategies applied during crops development, these strategies increase the productions level but also up their costs. The improving planning methods used in variety choosing can significantly reduce additional costs due to the unpredictable variation of the environmental factors or pests. On the other hand, the majority of existing methods, designed for choosing the most suitable variety to be cultivated, use the experimental results comparison of hybrids performance from a specific geographical area and in the climatic conditions of some years without taking into account the vague characteristics. In this paper we model these vague characteristics using fuzzy theory concepts.

In the following section we present the particular conditions in which experimental data used were obtained and the neuro-fuzzy algorithm was designed to choose the best hybrid. The third section contains the obtained results after applying the proposed procedure and also a comparative discussion that highlights the advantages of our method. Finally, we conclude some aspects related to our research.

2. Materials and methods

2.1. Field experiment

The purpose of our research is to choose from a set of maize hybrids recommended for growing in a certain region, the hybrid that in organic cultivation ensures the highest level of production.

The maize experiments were developed at the Variety Testing Centre of Targoviste on the experimental fields, over the years 2013–2015 in the geographical area of the north Romanian Plain, at 262 m altitude where the soil type is luvisol.

Three types of maize hybrids were grown: EF5209, KXA7482 and NJ5481. These three hybrids have been chosen among the best performing varieties grown in this region of Romania [4,13]. The seed time was: 11 May 2013, 8 May 2014 and 4 May 2015, respectively, and the used density was 102 plants per plot (51,000 pl/ha). Each hybrid was cultivated for three years. In the first two years, each variety was grown in 10 plots, 5 plots of these were chemically fertilized and the other five were organically fertilized (with manure), Tables 1 and 2 contain the data obtained in the first two years. Using all the data provided by observing crops during 2013 and 2014 (both with chemical and organic fertilizers) we made forecasts to choose the hybrid that will be grown organically in the next year, 2015. For the data processing we used a neuro-fuzzy algorithm presented in the next subsection. In 2015 we used only organic crops for the three investigated hybrids and the observed data
Table 1. Production data for 2013 corresponding to all experimental plots (P1, P2, P3, P4, P5).

| Variety          | EF 5209 (code 557) | KXA 7482 (code 552) | NJ 5481 (code 555) |
|------------------|--------------------|---------------------|--------------------|
| Data for the current year 2013 | Chemical fertilizers | Manure | Chemical fertilizers | Manure | Chemical fertilizers | Manure |
| Production for P1 (kg) | 24.3 | 20.2 | 27.8 | 18.1 | 24.1 | 17.9 |
| Production for P2 (kg) | 23.8 | 19.6 | 27.9 | 17.6 | 23.9 | 18.2 |
| Production for P3 (kg) | 23.9 | 20.5 | 26.9 | 17.5 | 23.2 | 18.1 |
| Production for P4 (kg) | 24.7 | 19.8 | 27.6 | 18 | 23.5 | 17.8 |
| Production for P5 (kg) | 24.3 | 20.9 | 27.9 | 17.3 | 23.3 | 18 |
| Total production (kg) | 121 | 101 | 138.1 | 88.5 | 118 | 90 |
| Hectolitre weight | 69.4 | 70.5 | 71.2 | 68.1 | 71.6 | 72.8 |
| Efficiency | 82 | 83 | 82.8 | 81.1 | 86.3 | 86.1 |

Table 2. Production data for 2014 corresponding to all experimental plots (P1, P2, P3, P4, P5).

| Variety          | EF 5209 (code 557) | KXA 7482 (code 552) | NJ 5481 (code 555) |
|------------------|--------------------|---------------------|--------------------|
| Data for the current year 2014 | Chemical fertilizers | Manure | Chemical fertilizers | Manure | Chemical fertilizers | Manure |
| Production for P1 (kg) | 18.6 | 15.1 | 20.8 | 18.9 | 25.8 | 17.6 |
| Production for P2 (kg) | 18.5 | 14.9 | 21 | 18.6 | 26.3 | 17.9 |
| Production for P3 (kg) | 19.2 | 14.4 | 21.2 | 18.7 | 26.1 | 16.9 |
| Production for P4 (kg) | 18.9 | 14.8 | 20.9 | 17.9 | 25.9 | 17.4 |
| Production for P5 (kg) | 18.8 | 13.8 | 20.6 | 17.8 | 26.9 | 16.6 |
| Total production (kg) | 94 | 73 | 104.5 | 91.9 | 131 | 86.4 |
| Hectolitre weight | 69.8 | 71.4 | 71 | 72.3 | 70.9 | 72.5 |
| Efficiency | 81 | 83.6 | 83.6 | 84.7 | 84.1 | 86.3 |

Table 3. Production data for 2015 corresponding to all experimental plots (P1, P2, P3, P4, P5).

| Variety          | EF 5209 (code 557) | KXA 7482 (code 552) | NJ 5481 (code 555) |
|------------------|--------------------|---------------------|--------------------|
| Data for the current year 2015 | Manure | Manure | Manure |
| Production for P1 (kg) | 16.2 | 17.9 | 18.9 |
| Production for P2 (kg) | 16.5 | 17.3 | 18.9 |
| Production for P3 (kg) | 15.9 | 18.2 | 19.3 |
| Production for P4 (kg) | 15.8 | 18 | 18.8 |
| Production for P5 (kg) | 16.8 | 17.9 | 19.2 |
| Total production (kg) | 81.2 | 89.3 | 95.1 |
| Hectolitre weight | 70.4 | 72.6 | 71.8 |
| Efficiency | 83 | 81.4 | 86.2 |

for the crops of this year (see Table 3) were used to validate our results, to check if the hybrid chosen using our algorithm was indeed the one which had the highest harvest.

All 30 experimental plots had each a cultivated area of 20 m². Regarding the fertilization of experimental maize crops, for chemical fertilization 120 kg N/ha and 80 kg Si P₂O₅/ha were used and for organic fertilization manure 40 t/ha was used.

General climatic conditions of the experimental years were as follows (see website of National Meteorology Administration, NMA [16]): in 2013 there was an average temperature of 10.1°C, this value is about 1.3°C higher than the average of the years for this
region and the yearly amount of precipitations was 619.5 mm. In 2014 there was an average temperature of 10.2°C, with about 1.4°C higher than the average of the years and the yearly amount of precipitations was 801 mm, highlighting three months: April, May and July that exceeded the average rainfall for this geographical area. Regarding the climatic conditions corresponding to the current year 2015, we can highlight that in the summer season the temperature was higher than the average by about 1.5–2.5°C and the amount of precipitations was lower by about 50–150 mm.

2.2. Data analysis

This subsection contains the description of the neuro-fuzzy algorithm used for processing of experimental data obtained during 2013 and 2014. We begin by arguing the need to approach the data analysis using this algorithm. Therefore, we could use a classical preference relation to take a decision on choosing the best variety, for example we can choose the preferred variety as that which had the highest production in the crops’ conditions with organic fertilizer. Using data of 2013 and 2014 crops’ production (Tables 1 and 2) we have the following results: for EF 5209 production was $101 + 73$ kg for a surface of $5 \times 20 + 5 \times 20 = 200$ m$^2$, or 0.87 kg/m$^2$, for KXA 7482 production was 0.902 kg/m$^2$ and for NJ 5481 production was 0.882 kg/m$^2$. Ordering the varieties by production size would mean that next year, 2015, KXA 7482 should be used because it is expected to produce a higher harvest. Comparing with validation data (Table 3) it is observed that the decision was not a correct one because in 2015, KXA did not have the highest production. Therefore, to achieve the mathematical algorithm used in software development, we used a fuzzy concept of choice theory described by Luo [8]. The approach with fuzzy theory is justified by the fact that the preference relationship that has to be applied to the choice of the optimum variety can be rather considered an imprecise one because there are a number of criteria, factors such as climate and its consequences in the evolution of pests that require a vague character for the mathematical preference relation. Hence, we designed a sum fuzzy rational choice function $C$, which describes the choice behaviour from a set of alternatives $X = \{x_1, x_2, x_3\}$ when the preference relation $r^*$ is fuzzy binary [1].

For our situation, $x_1$ is EF 5209, $x_2$ is KXA 7482 and $x_3$ is NJ 5481.

To specify, the preference relation $r^*$ is necessary previously to determine the associated representation matrix $M(r^*)$. According to Luo [8] to find the matrix representation we can use the artificial learning theory.

For a choice function $C$ on $X$, if $A \in P(X)$ and $I(A) = \{i | x_i \in A\}$ is the index set corresponding to $A$, Luo [8] provides the sets:

\[
U[C(A)] = \bigcup_{l \in I(C(A))} \bigcup_{k \in I(A) - l} \{ x \in R^I | x_{ij} = \delta_{ij}^l(A), i, j = 1, \ldots, I \},
\]

\[
U[C^+(A)] = \bigcup_{l \in I(C(A))} \bigcup_{k \in I(A) - l} \{ x \in R^I | x_{ij} = \delta_{ij}^l(A), i, j = 1, \ldots, I \},
\]

\[
U(C) = \bigcup_{A \in P(X)} U[C(A)] \quad \text{and} \quad U^+(C) = \bigcup_{A \in P(X)} U^+[C(A)],
\]
where

\[ x = (x_{11}, \ldots, x_{1j}, \ldots, x_{I1}, \ldots, x_{II}) \quad \text{and} \quad \delta_{ij}^l = \begin{cases} 1 & \text{if } i = l, j \in I(A), \\ -1 & \text{if } i = k, j \in I(A), \\ 0 & \text{else.} \end{cases} \]

Extending the work done in Badea et al. [1] we design a new algorithm that gives \( M(r^*) \) with the following decision function:

\[ g(x) = \sum_{k=1}^{I^2} q_k \left( \frac{c}{\|x^k\|} - \frac{c}{\|x^k\|^2} (x - x^k) \right) = \sum_{k=1}^{I^2} q_k g(x, x^k). \]

The function \( g(x) \) is an approximation of the potential function.

To implement the algorithm we started from a Matlab computing achieved in Badea et al. [1]. Here we used a different decision function, other than the potential function of the learning rule procedure.

First, we define using Matlab [17] the functions: \text{indexsetA.m} and \text{indexsetC(A)} to compute the sets of indexes.

To determine the learning set for the learning procedure of our algorithm we designed the function: \text{reunitCA.m}. This is a set of vectors \( x \in I^2 \) with components \( x_{ij} \in \{-1, 0, 1\} \) computed by using relations (1), (2) and (3). These vectors are input parameters of the training function.

We use the function: \text{modpotentialK.m} to train the network on the learning set. This function changes the machine decision function until this becomes stable. The correction applied for the decision function is

\[ g_{k+1}(x) = \begin{cases} g_k(x) + g(x, x^{k+1}) & \text{if } x^{k+1} \in U(C) - U^+(C) \text{ and } g_k(x^{k+1}) \neq 0, \\ g_k(x) - g(x, x^{k+1}) & \text{if } x^{k+1} \in U^+(C) \text{ and } g_k(x^{k+1}) \leq 0, \\ g_k(x) & \text{if } x^{k+1} \in U(C) - U^+(C) \text{ and } g_k(x^{k+1}) = 0, \\ \text{or} & \text{if } x^{k+1} \in U^+(C) \text{ and } g_k(x^{k+1}) > 0. \end{cases} \]

The output parameter for function \text{modpotentialK.m} is \text{gopt.m} that gives the representation matrix \( M(r^*) \).

3. Results

Using a PC at 2.53 GHz, for 30 individuals in a total time around 3.5 min after 41 algorithm repetitions we obtained the following optimum representation matrix:

\[ M(r^*) = \begin{pmatrix} 0.545 & 0.112 & 0.204 \\ 0.684 & 0.029 & 0.348 \\ 0.580 & 1.000 & 0.836 \end{pmatrix}. \]

The choice function \( C \) that corresponds to matrix \( M(r^*) \) is given in Table 4.

From the previous table we get that the order of preference is \( x_3 \succ x_2 \succ x_1 \). Therefore, the hybrid NJ 5481 is the most preferable alternative from our alternative sets.
Table 4. The choice function for $M(r^*)$.

| $P(X)$ | $x_1$ | $x_2$ | $x_3$ | $x_1x_2$ | $x_1x_3$ | $x_2x_3$ | $x_1x_2x_3$ |
|--------|-------|-------|-------|----------|----------|----------|-------------|
| $C$    | $x_1$ | $x_2$ | $x_3$ | $x_2$    | $x_3$    | $x_3$    | $x_3$       |

The results of data processing using Matlab software development of our neuro-fuzzy choice approach concur with the results of 2015 (year in which the crop has been observed with the purpose to use the obtained data to validate our results). From the data given in Table 3, after applying our algorithm, it would be decided to cultivate the variety NJ 5481 next year; this choice would have been the right one because harvest amounts were respectively: 95.1 kg/100 m² for NJ 5481, 89.3 kg/100 m² for KXA 7482 and 81.2 kg/100 m² for EF 5209.

By comparing with the classical method, and using the observed data, the hybrid KXA 7482 would be the preferred option for next year cultivation, and our method provides results that lead to a better decision for planning of organic maize crops. Thus, our approach can be used to improve the forecasts and the planning decisions, it does not exclude the classical methods because the varieties chosen to form the set of alternatives needed to apply our method are actually formed with the best performing varieties of these classical methods.

Another result which comes out from our testing procedures is that tracking and using of the experimental data both from organic fertilization crops and chemical fertilization crops improve predictions and decisions about the future ecological crops because, in terms of mathematical statistics, they provide data needed to model vague factors such as climate and its consequences.

Also, using the results of our experimental work (see Tables 1 and 2) we can observe that hectoliter weight of the organic crops have higher values than hectoliter weight of the chemical fertilized crops, for most of the tracked hybrids. The best results for hectoliter weight were obtained in organic farming of hybrids NJ 5481 and KXA 7482. Concerning the crops efficiency, we notice that the values are close for both fertilization methods. Finally, even if the production levels are higher in crops with chemical fertilizer, we notice that the experimental hybrids production provides good values also in the case of organic fertilization.

4. Conclusions

A strong variation of environmental factors makes it necessary to adapt and improve cultivation technologies but at the same time it requires a careful planning of varieties that will be sown in the coming years. A suitable variety seeding can help in reducing losses in agriculture more, it represents a basic component of the efforts being made to achieve technological or economical optimum.

Up to the present, the methods used to determine the varieties to be grown in a specific geographical area are based on farming, observing and testing them in advance in certain climatic conditions. These methods are continued by monitoring and application of certain phytotechnic technologies. There is always a vague component that can influence the results of these classical methods, so our approach that uses the neuro-fuzzy concept can
be applied to improve decisions related to both organic maize crop planning and other culture planning.

**Disclosure statement**

No potential conflict of interest was reported by the author.

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