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Research Article

A Hybrid Approach for Modular Neural Network Design Using Intercriteria Analysis and Intuitionistic Fuzzy Logic

Sotir Sotirov,[1] **Evdokia Sotirova**,[1] **Vassia Atanassova**,[2] **Krassimir Atanassov**,[1,2] **Oscar Castillo**,[3] **Patricia Melin**,[3] **Todor Petkov**,[1] **and Stanimir Surchev**[1]

[1]*Intelligent Systems Laboratory, "Prof. Dr. Asen Zlatarov" University, Burgas, Bulgaria*
[2]*Bioinformatics and Mathematical Modelling Department, IBPhBME-Bulgarian Academy of Sciences, Sofia, Bulgaria*
[3]*Tijuana Institute of Technology, Tijuana, BC, Mexico*

Correspondence should be addressed to Oscar Castillo; ocastillo@tectijuana.mx

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Intercriteria analysis (ICA) is a new method, which is based on the concepts of index matrices and intuitionistic fuzzy sets, aiming at detection of possible correlations between pairs of criteria, expressed as coefficients of the positive and negative consonance between each pair of criteria. Here, the proposed method is applied to study the behavior of one type of neural networks, the modular neural networks (MNN), that combine several simple neural models for simplifying a solution to a complex problem. They are a tool that can be used for object recognition and identification. Usually the inputs of the MNN can be fed with independent data. However, there are certain limits when we may use MNN, and the number of the neurons is one of the major parameters during the implementation of the MNN. On the other hand, a high number of neurons can slow down the learning process, which is not desired. In this paper, we propose a method for removing part of the inputs and, hence, the neurons, which in addition leads to a decrease of the error between the desired goal value and the real value obtained on the output of the MNN. In the research work reported here the authors have applied the ICA method to the data from real datasets with measurements of crude oil probes, glass, and iris plant. The method can also be used to assess the independence of data with good results.

1. Introduction

One of the open and important questions in biology is the ability of biological systems to adapt to new environments, a concept termed evolvability [1]. A typical feature of evolvability is the fact that many biological systems have modularity; especially many biological processes and structures can be modeled as networks, such as metabolic pathways, gene regulation, protein interactions, and brains [1–5]. This feature has motivated important concepts in intelligent systems, such as modular neural network and evolutionary computation.

Neural networks are considered modular if they are comprised of highly connected clusters of nodes that are connected to nodes in other clusters [4, 6, 7]. Despite importance and continuous research in this area, there is no agreement on why modular biological systems can evolve [4, 8, 9]. There is evidence that modular systems look more adaptable in nature [10] than the monolithic networks [11, 12]. Consequently, there are many papers dedicated to this problem, for example, the work in [12].

In this paper, we introduce a hybrid combination between the intercriteria analysis (ICA, see [13–18]) method and modular neural network models. The ICA employs the apparatus of the intuitionistic fuzzy sets (IFS) for detecting possible correlations between pairs of criteria. Introduced in [19], IFSs are one of the extensions of Zadeh's fuzzy sets [20]. In contrast to fuzzy sets, IFS [21–24] have two degrees: of membership (validity, etc., μ_A) and of nonmembership (nonvalidity, etc., ν_A), so that for each element x of the universe, over which an IFS A is defined, the following inequality is valid: $0 \leq \mu_A(x) + \nu_A(x) \leq 1$. In this case, a pair $\langle a, b\rangle$, where $a, b, a + b \in [0, 1]$, is called an intuitionistic fuzzy pair (IF pair). The ICA method produces the so-called positive and negative consonance coefficients between the different criteria used for evaluation of different objects.

The main contribution of the paper is the proposed hybrid approach combining intuitionistic fuzzy logic (through the ICA method) with modular neural networks for designing a powerful neural model for classification. The neural network model is tested with benchmark problems and a real world case to show the advantages of the proposed approach. As regards existing works that could be considered similar to this one, we can mention that intuitionistic fuzzy logic has not been considered in conjunction with modular neural networks previously, so it can be considered an original contribution to the area of computational intelligence that combines the advantages of the two methods. For the purpose of testing the proposed method for preprocessing the information going into MNNs, we use data from the LUKOIL Neftochim Burgas AD from the measurements of a set of crude oil probes (objects, in terms of ICA) against a set of technological properties (criteria, in terms of ICA), which precedes and conditions the process of production of petrochemical products from the crude oil [25], dataset for iris plant [26], and glass types [27].

The remainder of the paper is organized as follows. In Section 2 some short remarks about the intercriteria analysis method are given, which is based on intuitionistic fuzzy logic. Section 3 describes basic concepts about modular neural networks. Section 4 describes the simulations and a discussion of the results. Finally, Section 5 offers the conclusions and outlines future work in this area.

2. Short Remarks on the Index Matrices and Intercriteria Analysis Method

As we mentioned above, the ICA method [13, 14] is based on two main concepts: intuitionistic fuzzy sets and index matrices. A brief description is offered below for completeness. Index matrices allow summarizing the criteria relevant to a particular decision making problem.

Let I be a fixed set of indices and let R be the set of the real numbers. An index matrix (IM) with sets of indices K and L $(K, L \subset I)$ is defined by (see [13])

$$\left[K, L, \left\{a_{k_i,l_j}\right\}\right] \equiv \begin{array}{c|cccc} & l_1 & l_2 & \cdots & l_n \\ \hline k_1 & a_{k_1,l_1} & a_{k_1,l_2} & \cdots & a_{k_1,l_n} \\ k_2 & a_{k_2,l_1} & a_{k_2,l_2} & \cdots & a_{k_2,l_n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ k_m & a_{k_m,l_1} & a_{k_m,l_2} & \cdots & a_{k_m,l_n}, \end{array} \quad (1)$$

where $K = \{k_1, k_2, \ldots, k_m\}$, $L = \{l_1, l_2, \ldots, l_n\}$, for $1 \le i \le m$, and $1 \le j \le n : a_{k_i,l_j} \in R$.

For any two IMs, a series of relations, operations, and operators have been defined. The theory behind the IMs is described in a more detailed fashion in [13].

Here, following the description of the ICA approach, given by [14], we will start with the IM called M with index sets with m rows $\{O_1, \ldots, O_m\}$ and n columns $\{C_1, \ldots, C_n\}$, where for every p, q $(1 \le p \le m, 1 \le q \le n)$, O_p is an evaluated object, C_q is an evaluation criterion, and e_{O_p,C_q} is the evaluation of the pth object against the qth criterion, defined as a real number that is comparable according to relation R with all the remaining elements of the IM M.

$$M = \begin{array}{c|ccccccc} & C_1 & \cdots & C_k & \cdots & C_l & \cdots & C_n \\ \hline O_1 & e_{O_1,C_1} & \cdots & e_{O_1,C_k} & \cdots & e_{O_1,C_l} & \cdots & e_{O_1,C_n} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots & \ddots & \vdots \\ O_i & e_{O_i,C_1} & \cdots & e_{O_i,C_k} & \cdots & e_{O_i,C_l} & \cdots & e_{O_i,C_n} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots & \ddots & \vdots \\ O_j & e_{O_j,C_1} & \cdots & e_{O_j,C_k} & \cdots & e_{O_j,C_l} & \cdots & e_{O_j,C_n} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots & \ddots & \vdots \\ O_m & e_{O_m,C_1} & \cdots & e_{O_m,C_j} & \cdots & e_{O_m,C_l} & \cdots & e_{O_m,C_n}, \end{array} \quad (2)$$

From the requirement for comparability above, it follows that for each i, j, k the relation $R(e_{O_i,C_k}, e_{O_j,C_k})$ holds. The relation R has a dual relation $\overline{R}$, which is true in the cases when the relation R is false, and vice versa. For instance, if R is "greater," the dual relation $\overline{R}$ is "less."

For the requirements of the proposed method, pairwise comparisons between every two different criteria are made along all evaluated objects. During the comparison, a counter is maintained for the number of times when the relation R holds, as well as another counter for the dual relation.

Let $S^{\mu}_{k,l}$ be the number of cases in which the relations $R(e_{O_i,C_k}, e_{O_j,C_k})$ and $R(e_{O_i,C_l}, e_{O_j,C_l})$ are simultaneously satisfied. Let also $S^{\nu}_{k,l}$ be the number of cases in which the relations $R(e_{O_i,C_k}, e_{O_j,C_k})$ and the dual $\overline{R} = (e_{O_i,C_l}, e_{O_j,C_l})$ are simultaneously satisfied. As the total number of pairwise comparisons between the objects is given by $m(m-1)/2$, it can be verified that the following inequalities hold:

$$0 \le S^{\mu}_{k,l} + S^{\nu}_{k,l} \le \frac{m(m-1)}{2}. \quad (3)$$

For every k, l, such that $1 \le k \le l \le n$ and for $m \ge 2$ two numbers are defined:

$$\mu_{C_k,C_l} = 2\frac{S^{\mu}_{k,l}}{m(m-1)}, \qquad \nu_{C_k,C_l} = 2\frac{S^{\nu}_{k,l}}{m(m-1)}. \quad (4)$$

The pair constructed from these two numbers plays the role of the intuitionistic fuzzy evaluation of the relations that can be established between any two criteria C_k and C_l. In this way, the IM M that relates evaluated objects with evaluating criteria can be transformed to another IM M^* that gives the relations detected among the criteria, where stronger

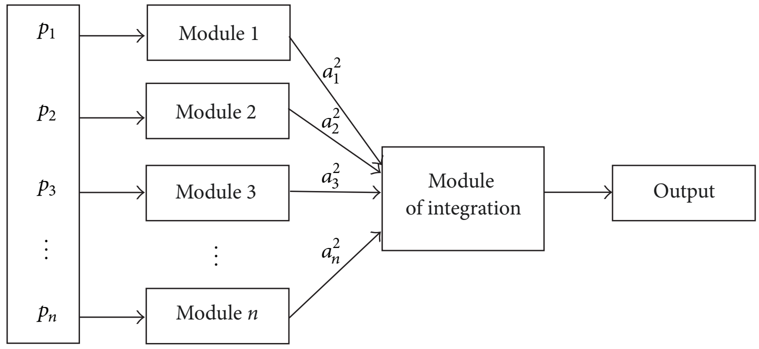

Figure 1: The structure of the MNN.

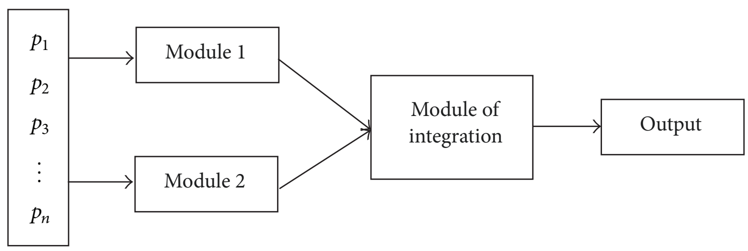

Figure 2: The structure of the MNN with 2 modules.

correlation exists where the first component μ_{C_k,C_l} is higher while the second component ν_{C_k,C_l} is lower.

$$M^* = \begin{array}{c|ccc} & C_1 & \cdots & C_n \\ \hline C_1 & \langle \mu_{C_1,C_1}, \nu_{C_1,C_1} \rangle & \cdots & \langle \mu_{C_1,C_n}, \nu_{C_1,C_n} \rangle \\ \cdots & \cdots & \cdots & \cdots \\ C_n & \langle \mu_{C_n,C_1}, \nu_{C_n,C_1} \rangle & \cdots & \langle \mu_{C_n,C_n}, \nu_{C_n,C_n} \rangle . \end{array} \quad (5)$$

From practical considerations, it has been more flexible to work with two IMs M^μ and M^ν, rather than with the IM M^* of IF pairs. IM M^μ contains as elements the first components of the IFPs of M^*, while M^ν contains the second components of the IFPs of M^*. Once the intercriteria pairs have been calculated, for example, using the software described in [28], the question arises about defining the thresholds against which the membership and the nonmembership parts are evaluated [29, 30].

As has been discussed in some publications on ICA, for example, in [31, 32], the ICA results are very close to those obtained with the correlation analyses of Spearman, Pearson, and Kendall. It is worth noting the so far empirically observed fact that when in the data there are mistakes (e.g., shift of the decimal separator) these three correlation analyses give a larger deviation of the value than ICA; that is, ICA is less sensitive, so the use of them together can be used as a way of detecting errors in the input data.

3. Modular Neural Networks

Modular neural networks [33, 34] are one of the models that can be used for object recognition, classification, and identification (see Figure 1). A modular neural network can be viewed as a set of monolithic neural networks [35–37] that deal with a part of a problem, and then their individual outputs are combined by an integration unit to form a global solution to the complete problem. The main idea is that a complex problem can be divided into simpler subproblems that can be solved by simpler neural networks and then the total solution will be a combination of the outputs of the simple monolithic neural networks.

In the proposed hybrid approach each of the MNN Modules takes as its input the result of the application of ICA method over three datasets (dataset for production of petrochemical products from the crude oil [25], iris plants [26], and glass types [27]). Every module is a two-layer Multilayer Perceptron and the output of the second layer of the ANN is a_i^2 (for $i \in \{1, \dots, n\}$), where n is the maximal number of modules.

The output O is calculated according to the following equation, which basically performs a weighted integration of the module outputs:

$$O = \frac{\sum_{i=1}^{n} a_i^2 g_i k_i}{\sum_{i=1}^{n} g_i}, \quad (6)$$

where a_i^2 is output of the module $i \in [1, 2, \dots, n]$; g_i is average deviation of the output values of the module i; k_i is coefficient of existence of module i. The coefficient of existence of every module shows the presence/absence of the respective module, with respect to the need of that module in the particular case.

For illustration purposes and simplifying calculations, we can choose to reduce the structure of the MNN and use 2

Table 1: Membership parts of the intuitionistic fuzzy pairs, giving the intercriteria correlations between measurements of crude oil probes.

μ	1	2	3	4	5	6	7	8
1	1.000	0.699	0.770	0.658	0.956	0.176	0.446	0.703
2	0.699	1.000	0.787	0.597	0.676	0.408	0.640	0.775
3	0.770	0.787	1.000	0.777	0.728	0.394	0.665	0.921
4	0.658	0.597	0.777	1.000	0.627	0.468	0.674	0.771
5	0.956	0.676	0.728	0.627	1.000	0.134	0.404	0.661
6	0.176	0.408	0.394	0.468	0.134	1.000	0.730	0.473
7	0.446	0.640	0.665	0.674	0.404	0.730	1.000	0.743
8	0.703	0.775	0.921	0.771	0.661	0.473	0.743	1.000

Table 2: Nonmembership parts of the intuitionistic fuzzy pairs, giving the intercriteria correlations between measurements of crude oil probes.

ν	1	2	3	4	5	6	7	8
1	0.000	0.288	0.217	0.326	0.042	0.822	0.552	0.295
2	0.288	0.000	0.204	0.391	0.312	0.580	0.348	0.213
3	0.217	0.204	0.000	0.212	0.261	0.595	0.325	0.068
4	0.326	0.391	0.212	0.000	0.359	0.518	0.312	0.215
5	0.042	0.312	0.261	0.359	0.000	0.866	0.596	0.339
6	0.822	0.580	0.595	0.518	0.866	0.000	0.270	0.527
7	0.552	0.348	0.325	0.312	0.596	0.270	0.000	0.257
8	0.295	0.213	0.068	0.215	0.339	0.527	0.257	0.000

modules from the structure from Figure 2 ($k_1 = 1$, $k_2 = 1$, $k_3 = 0, \ldots, k_n = 0$).

The first module considers all independent inputs (weak dissonance, dissonance, and strong dissonance). The second module takes the inputs that have strong negative consonance, negative consonance, and weak negative consonance, and weak positive consonance, positive consonance, and strong positive consonance.

In the second module, we can reduce some of the inputs if they have very strong positive consonance. In this case, we can remove one of the inputs. In the case that they have strong negative consonance, this means that we can also remove some of the inputs. Other configurations for the modular neural network are possible, depending on how the inputs are selected.

4. Discussion of Results

For verifying the accuracy of the proposed method the data of the real dataset with measurements of crude oil probes, glass, and iris plants were used.

4.1. Testing with Data for Crude Oil Probes. For the learning process of MNN, we set the following parameters: performance (MSE) = 0.00001; validation check = 15. The dataset was divided into three different parts: training (from 1 to 100); validation (from 101 to 120), and testing (from 121 to 140). For the purpose of learning algorithms, one of the variants of the backpropagation algorithm is used, namely, Levenberg-Marquardt. As a target for the model, the values from the databases were used.

In the MNN, the data for 140 crude oil probes, measured against 8 physical properties ("criteria" in the ICA terminology) were used (for the input data, see [34]). The eight criteria are as follows: (1) density at 15°C g/cm^3; (2) 10% (v/v) ASTM D86 distillation, °C; (3) 50% (v/v) ASTM D86 distillation, °C; (4) 90% (v/v) ASTM D86 distillation, °C; (5) refractive index at 20°C; (6) H_2 content, % (m/m); (7) aniline point, °C; (8) molecular weight g/mol. Using the ICA approach, we are seeking for correlations between these eight criteria on the basis of the 140 crude oil probes ("objects" in ICA). Using the ICA software [28] applied to the whole 140 × 8 matrix with measurements, we obtain 28 IF pairs, giving the pairwise correlations between the eight criteria. For easier processing of the result of ICA application, the output is given in the form of two IMs, containing the membership and the nonmembership parts of the IF correlations discovered between each pair of criteria (Tables 1 and 2), which in Table 3 are sorted in descending order according to the membership part of the intercriteria pairs, from strong positive consonance (i.e., pair 1-5 with degree $\langle 0.956; 0.042\rangle$), through dissonance, to negative consonance (i.e., pair 5-6 with degree $\langle 0.134; 0.866\rangle$).

On this basis, we separate these 28 intercriteria pairs in two groups, where *Module 1* of the MNN takes as input the dissonant pairs, and *Module 2* takes as input the consonant pairs, either positive or negative. In this way, we aim to reduce the number of input parameters of the MNN, yet keeping high enough level of precision.

In Table 4 we are presenting the values from 22 neural network simulations and the identifiers of criteria that we provide at the input on each module. These 22 simulations

Table 3: Relations among the criteria with specific values.

IF pair	Criteria	Type of intercriteria relation
⟨0.956; 0.042⟩	1-5	Strong positive consonance
⟨0.921; 0.068⟩	3-8	Positive consonance
⟨0.787; 0.204⟩	2-3	Weak positive consonance
⟨0.777; 0.212⟩	3-4	Weak positive consonance
⟨0.771; 0.215⟩	4-8	Weak positive consonance
⟨0.770; 0.217⟩	1-3	Weak positive consonance
⟨0.743; 0.257⟩	7-8	Weak dissonance
⟨0.730; 0.270⟩	6-7	Weak dissonance
⟨0.728; 0.261⟩	3-5	Weak dissonance
⟨0.703; 0.295⟩	1-8	Weak dissonance
⟨0.699; 0.288⟩	1-2	Weak dissonance
⟨0.676; 0.312⟩	2-5	Weak dissonance
⟨0.674; 0.312⟩	4-7	Weak dissonance
⟨0.665; 0.325⟩	3-7	Dissonance
⟨0.661; 0.339⟩	5-8	Dissonance
⟨0.658; 0.326⟩	1-4	Dissonance
⟨0.640; 0.348⟩	2-7	Dissonance
⟨0.627; 0.359⟩	4-5	Dissonance
⟨0.597; 0.391⟩	2-4	Dissonance
⟨0.473; 0.527⟩	6-8	Strong dissonance
⟨0.468; 0.518⟩	4-6	Strong dissonance
⟨0.446; 0.552⟩	1-7	Strong dissonance
⟨0.408; 0.580⟩	2-6	Dissonance
⟨0.404; 0.596⟩	5-7	Dissonance
⟨0.394; 0.595⟩	3-4	Dissonance
⟨0.394; 0.594⟩	3-6	Dissonance
⟨0.176; 0.822⟩	1-6	Weak negative consonance
⟨0.134; 0.866⟩	5-6	Negative consonance

are all the possible combinations of criteria, where *Module 2* obtains as input at least one criterion, starting with all of the consonant criteria (1, 3, 5, 6, and 8 in row 1) down to at least one of the consonant criteria (1, 3, 5, 6, or 8, in rows 18–22). Based on the values from Table 3, we offer the use of the relations of positive consonance and negative consonance, since both affect in the same way the inputs of the neural network. The parameters g_1, g_2, and g_3 are the average deviations of the output values of *Module 1*, *Module 2*, and whole neural network, respectively. A detailed discussion of the results follows in Section 4.4.

4.2. Testing with Data for Iris Plants. As another test case for the proposed method, we also consider the dataset [26] that contains four parameters (criteria): (1) sepal length in cm, (2) sepal width in cm, (3) petal length in cm, and (4) petal width in cm. There are 3 classes of 50 instances each [26], where each class refers to a type of iris plant. The targets are *Iris setosa*, 1, *Iris versicolor*, 2, and *Iris virginica*, 3.

The ICA method was applied to the 150 × 4 matrix in the same fashion as previously (see Tables 5, 6, and 7), and the results are given in Table 5, sorted in descending order according to the membership part of the intercriteria pairs.

In the neural network inputs were assumed with the following parameters: parameter 2 (in the first neural network input) and parameters 1, 3, and 4 in consonance (in the second neural network input). In Table 8 the values from 7 neural network simulations are presented and a number of parameters that we defined for each module are described.

4.3. Testing with Data for Glass. Finally, as a third case for testing the proposed approach we consider the benchmark glass data. In this case, in the input of this modular neural network, we use the experimental data from [27] for obtaining the type of glass. We work with data for 214 building and vehicle window glasses, measured against 9 criteria: (1) RI: refractive index; (2) Na: sodium (unit measurement: weight percent in corresponding oxide); (3) Mg: magnesium; (4) Al: aluminium; (5) Si: silicon; (6) K: potassium; (7) Ca: calcium; (8) Ba: barium; (9) Fe: iron. In the output (as a target) we give information about the glass type.

As was done in the previous sections, the input parameters (criteria) are divided in two groups: parameters in dissonance (parameters 2, 3, 4, 5, 6, and 9) and parameters in consonance (see Table 9), with the results sorted in

Table 4: Results from the simulations.

Number	Description	Number of the inputs	g_1	g_2	g_3	Number of weight coefficients
1	Module 1—2, 4, and 7 Module 2—1, 3, 5, 6, and 8	8	2.2971	2.1991	2.2330	315
2	Module 1—2, 4, and 7 Module 2—3, 5, 6, and 8 (without 1)	7	2.2139	2.1650	2.1562	280
3	Module 1—2, 4, and 7 Module 2—1, 5, 6, and 8 (without 3)	7	2.2023	2.1498	2.1672	280
4	Module 1—2, 4, and 7 Module 2—1, 3, 6, and 8 (without 5)	7	2.2032	2.1559	2.1564	280
5	Module 1—2, 4, and 7 Module 2—1, 3, 5, and 8 (without 6)	7	2.1352	2.2455	2.1593	280
6	Module 1—2, 4, and 7 Module 2—1, 3, 5, and 6 (without 8)	7	2.1703	2.1578	2.1638	280
7	Module 1—2, 4, and 7 Module 2—5, 6, and 8 (without 1 and 3)	6	2.1844	2.1196	2.1457	245
8	Module 1—2, 4, and 7 Module 2—1, 3, and 6 (without 5 and 8)	6	2.1881	2.1500	2.1572	245
9	Module 1—2, 4, and 7 Module 2—1, 6, and 8 (without 3 and 5)	6	2.2057	2.2465	2.1572	245
10	Module 1—2, 4, and 7 Module 2—3, 5, and 6 (without 1 and 8)	6	2.1715	2.1531	2.1437	245
11	Module 1—2, 4, and 7 Module 2—3, 6, and 8 (without 1 and 5)	6	2.1679	2.1536	2.1370	245
12	Module 1—2, 4, and 7 Module 2—1, 3, and 5 (without 6 and 8)	6	2.2181	2.1415	2.1398	245
13	Module 1—2, 4, and 7 Module 2—1, 3, and 8 (without 5 and 6)	6	2.1883	2.1624	2.1551	245
14	Module 1—2, 4, and 7 Module 2—3 and 6 (without 1, 5, and 8)	5	2.1478	2.1885	2.1485	210
15	Module 1—2, 4, and 7 Module 2—3 and 5 (without 1, 6, and 8)	5	2.1542	2.1210	2.0914	210
16	Module 1—2, 4, and 7 Module 2—1 and 3 (without 5, 6, and 8)	5	2.1436	2.2551	2.1580	210
17	Module 1—2, 4, and 7 Module 2—3 and 8 (without 1, 5, and 6)	5	2.1777	2.2327	2.1981	210
18	Module 1—2, 4, and 7 Module 2—1 (without 3, 5, 6, and 8)	4	2.2006	7.0510	5.6472	210
19	Module 1—2, 4, and 7 Module 2—3 (without 1, 5, 6, and 8)	4	2.1554	6.6392	5.2857	175
20	Module 1—2, 4, and 7 Module 2—5 (without 1, 3, 6, and 8)	4	2.1856	6.8357	5.4230	175
21	Module 1—2, 4, and 7 Module 2—6 (without 1, 3, 5, and 8)	4	2.1873	3.6355	2.7732	175
22	Module 1—2, 4, and 7 Module 2—8 (without 1, 3, 5, and 8)	4	2.2109	6.1718	4.9165	175

descending order according to the membership part of the intercriteria pairs.

In Table 10, the values from 7 neural network simulations are presented with the respective identifiers of the criteria that are feeding the inputs of each module.

The information is divided into two groups: the first part is the group of independent evaluation criteria (see Tables 11 and 12): criteria 2, 4, and 7 (see Table 4 for the crude oil probes data), criterion 2 (see Table 5 for the iris plant data), and criteria 2, 3, 4, 5, 6, and 9 (see Table 8 for the glass types data). These data were used on the inputs of the first module of the neural networks. The other criteria (dependent parameters) were considered on the inputs of the second module of the neural networks.

The inputs on the first module are not removable, because the ICA approach tests the independence of the criteria. The

Table 5: Relations among the criteria.

IF pair	Criteria	Type of intercriteria relation
⟨0.843; 0.538⟩	3-4	Weak positive consonance
⟨0.819; 0.504⟩	1-3	Weak positive consonance
⟨0.764; 0.486⟩	1-4	Weak positive consonance
⟨0.416; 0.139⟩	1-2	Dissonance
⟨0.366; 0.121⟩	2-4	Dissonance
⟨0.364; 0.070⟩	2-3	Dissonance

Table 6: Membership parts of the intuitionistic fuzzy pairs, giving the intercriteria correlations between measurements of iris plant.

μ	1	2	3	4
1	1.000	0.416	0.819	0.764
2	0.416	1.000	0.364	0.366
3	0.819	0.364	1.000	0.843
4	0.764	0.366	0.843	1.000

Table 7: Nonmembership parts of the intuitionistic fuzzy pairs, giving the intercriteria correlations between measurements of iris plant.

ν	1	2	3	4
1	0.000	0.486	0.121	0.139
2	0.486	0.000	0.538	0.504
3	0.121	0.538	0.000	0.070
4	0.139	0.504	0.070	0.000

results from applying the ICA method over tree types of data show that most of the parameters are selected in a proper way (criteria in dissonance). For some of the parameters that were provided on the inputs of the second module, an approach for reasonable elimination of some of these criteria can be adopted.

4.4. Discussion. In the first step we use neural networks without any removal of information and without removing of the inputs. The corresponding results can be found on the first rows in Tables 4, 8, and 10.

On the second step the data that have the highest and lowest consonance coefficients (strong positive consonance, positive consonance, strong negative consonance, and negative consonance) were removed. For example, in Table 4 we use parameters 2, 4, and 7 in *Module 1* and parameters 3, 5, 6, and 8 (without 1) in *Module 2*. In the study, parameter 1 is removed due to the high value of membership coefficient $\mu = 0.956$ (between parameters 1 and 5). After simulating the neural network an average deviation of the MNN $g_3 = 2.1562$ ($g_1 = 2.2139$, $g_2 = 2.1650$) is obtained.

The removed parameters do not have substantial influence on the result, because of decreasing the number of the weight coefficients, and along with this the error of the output values also decreases.

In the same way the second group of parameters (from the pairs) were successively removed. This process continues until finishing the pairs in the highest and lowest consonance.

The next step is to remove two parameters, for example, in row 5 (Table 8) the situation with all parameters on *Module 1*, and parameter 4 (without 1 and 3) in *Module 2* was presented. In the study, parameters 1 and 3 are removed due to the high value of membership coefficient $\mu = 0.81852$ (between parameters 1 and 3). After simulation of the neural network, an average deviation of the MNN $g_3 = 0.5846$ ($g_1 = 0.5725$, $g_2 = 0.0631$) is obtained. The removed parameters 1 and 3 do not have substantial influence on the result, because of decreasing the number of the weight coefficients, and along with this the error of the output values also decreases.

The process can continue iteratively in the same way. In summary, a new approach for building modular neural networks based on ICA, which uses intuitionistic fuzzy logic, has been proposed and tested with three benchmark databases. The simulation results are good, in this way verifying the advantages of the hybrid method.

In Table 13 comparative analysis of the results of the three different datasets is made. The table includes a short description of each dataset, the initial number of inputs (number of the inputs before reduction), the number of inputs after reduction, and average deviation of the output values of the neural networks (g_3), as well as minimal value of average deviation of the output values of the neural networks (g_3, min), the number of weight coefficients without reduction and with reduction, the percentage ratio between the average deviation of the output values of the neural networks and the minimal value of average deviation of the output values of the neural networks, respectively, and the number of weight coefficients without and with reduction.

From the data in the table, it is seen that reducing the number of input parameters and, respectively, the number of inputs of the MNN, the value of average deviation of the output values of the MNN decreases (93,65%–98,2%). On this basis, we further observe decrease of the number of weight coefficients (60%–80%).

5. Conclusions

The number of the neurons is one of the major parameters that need to be defined during the realization of the MNN. Of course, the higher number of neurons in a neural network has the effect of slowing down the learning process. Here, we use the intuitionistic fuzzy logic based method of intercriteria analysis to reduce the number of input parameters of the modular neural network. This leads to reduction of the weight matrices and thus allows implementation of the neural network in limited hardware, saving time and resources in training. The method can also be used to assess the independence of the criteria against which data are measured. Three different real datasets with measurements of glass types, crude oil probes, and iris plant specimens were used to verify the accuracy and efficiency of the proposed approach. As future work, we envision using the proposed approach with other types of complex problems or more real life situations, like in the design of intelligent controllers for robotic systems

Table 8: Results from the simulations.

Number	Description	Number of the inputs	g_1	g_2	g_3	Number of weight coefficients
1	Module 1—2 Module 2—1, 3, 4	4	0.5725	0.0084	0.5726	175
2	Module 1—2 Module 2—3, 4 (without 1)	3	0.5725	0.0321	0.5749	140
3	Module 1—2 Module 2—1, 4 (without 3)	3	0.5725	0.6667	1.2898	140
4	Module 1—2 Module 2—1, 3 (without 4)	3	0.5725	0.0527	0.5793	140
5	Module 1—2 Module 2—4 (without 1, 3)	2	0.5725	0.0631	0.5846	105
6	Module 1—2 Module 2—3 (without 1, 4)	2	0.5725	0.0807	0.5907	105
7	Module 1—2 Module 2—1 (without 3, 4)	2	0.5725	0.6667	1.2898	105

Table 9: Relations among the criteria.

IF pair	Criteria	Type of intercriteria relation
⟨0.760; 0.234⟩	1-7	Weak positive consonance
⟨0.564; 0.423⟩	4-5	Dissonance
⟨0.547; 0.409⟩	4-6	Strong dissonance
⟨0.532; 0.455⟩	2-4	Strong dissonance
⟨0.532; 0.404⟩	3-6	Strong dissonance
⟨0.527; 0.425⟩	1-3	Strong dissonance
⟨0.513; 0.481⟩	1-2	Strong dissonance
⟨0.497; 0.493⟩	2-7	Strong dissonance
⟨0.488; 0.470⟩	5-6	Strong dissonance
⟨0.441; 0.509⟩	2-3	Strong dissonance
⟨0.419; 0.571⟩	5-7	Dissonance
⟨0.410; 0.090⟩	8-9	Dissonance
⟨0.384; 0.604⟩	4-7	Dissonance
⟨0.383; 0.607⟩	2-6	Dissonance
⟨0.371; 0.579⟩	3-7	Dissonance
⟨0.368; 0.594⟩	1-6	Dissonance
⟨0.353; 0.596⟩	3-5	Dissonance
⟨0.318; 0.672⟩	1-4	Weak dissonance
⟨0.316; 0.237⟩	6-9	Weak dissonance
⟨0.314; 0.645⟩	6-7	Weak dissonance
⟨0.311; 0.236⟩	3-9	Weak dissonance
⟨0.304; 0.240⟩	7-9	Weak dissonance
⟨0.300; 0.693⟩	1-5	Weak dissonance
⟨0.299; 0.245⟩	1-9	Weak dissonance
⟨0.288; 0.659⟩	3-4	Weak dissonance
⟨0.272; 0.057⟩	4-8	Weak dissonance
⟨0.262; 0.697⟩	2-6	Weak dissonance
⟨0.257; 0.070⟩	2-8	Weak dissonance
⟨0.253; 0.291⟩	4-9	Weak dissonance
⟨0.253; 0.291⟩	5-9	Weak dissonance
⟨0.210; 0.334⟩	2-9	Weak negative consonance
⟨0.203; 0.123⟩	5-8	Weak negative consonance
⟨0.162; 0.164⟩	7-8	Weak negative consonance
⟨0.123; 0.202⟩	1-8	Negative consonance
⟨0.113; 0.213⟩	6-8	Negative consonance
⟨0.059; 0.249⟩	3-8	Negative consonance

Table 10: Results from the simulations.

N:	Description	Number of the inputs	g_1	g_2	g_3	Number of weight coefficients
1	*Module 1*—2, 3, 4, 5, 6, 9 *Module 2*—1, 7, 8	9	0.7658	0.8796	1.6721	350
2	*Module 1*—2, 3, 4, 5, 6, 9 *Module 2*—7, 8 (without 1)	8	0.7658	0.8696	1.6584	315
3	*Module 1*—2, 3, 4, 5, 6, 9 *Module 2*—1, 8 (without 7)	8	0.7658	0.9277	1.7492	315
4	*Module 1*—2, 3, 4, 5, 6, 9 *Module 2*—1, 7 (without 8)	8	0.7658	1.5826	2.8488	315
5	*Module 1*—2, 3, 4, 5, 6, 9 *Module 2*—8 (without 1, 7)	7	0.7658	0.8756	1.6626	280
6	*Module 1*—2, 3, 4, 5, 6, 9 *Module 2*—7 (without 1, 8)	7	0.7658	1.7190	3.0898	280
7	*Module 1*—2, 3, 4, 5, 6, 9 *Module 2*—1 (without 7, 8)	7	0.7658	1.6378	2.9400	280

Table 11: Membership parts of the intuitionistic fuzzy pairs, giving the intercriteria correlations of glass.

μ	1	2	3	4	5	6	7	8	9
1	1.000	0.513	0.527	0.318	0.300	0.368	0.760	0.123	0.299
2	0.513	1.000	0.441	0.532	0.383	0.262	0.497	0.257	0.210
3	0.527	0.441	1.000	0.288	0.353	0.532	0.371	0.059	0.311
4	0.318	0.532	0.288	1.000	0.564	0.547	0.384	0.272	0.253
5	0.300	0.383	0.353	0.564	1.000	0.488	0.419	0.203	0.253
6	0.368	0.262	0.532	0.547	0.488	1.000	0.314	0.113	0.316
7	0.760	0.497	0.371	0.384	0.419	0.314	1.000	0.162	0.304
8	0.123	0.257	0.059	0.272	0.203	0.113	0.162	1.000	0.410
9	0.299	0.210	0.311	0.253	0.253	0.316	0.304	0.410	1.000

Table 12: Nonmembership parts of the intuitionistic fuzzy pairs, giving the intercriteria correlations.

ν	1	2	3	4	5	6	7	8	9
1	0.000	0.481	0.425	0.672	0.693	0.594	0.234	0.202	0.245
2	0.481	0.000	0.509	0.455	0.607	0.697	0.493	0.070	0.334
3	0.425	0.509	0.000	0.659	0.596	0.404	0.579	0.249	0.236
4	0.672	0.455	0.659	0.000	0.423	0.409	0.604	0.057	0.291
5	0.693	0.607	0.596	0.423	0.000	0.470	0.571	0.123	0.291
6	0.594	0.697	0.404	0.409	0.470	0.000	0.645	0.213	0.237
7	0.234	0.493	0.579	0.604	0.571	0.645	0.000	0.164	0.240
8	0.202	0.070	0.249	0.057	0.123	0.213	0.164	0.000	0.090
9	0.245	0.334	0.236	0.291	0.291	0.237	0.240	0.090	0.000

Table 13: Results from the simulations.

Number	Description	Number of the inputs before reduction	Number of the inputs after reduction	g_3	g_3 min	Number of weight coefficients without reduction	Number of weight coefficients with reduction	g_3 %	Number of weight coefficients %
1	Data with parameters of crude oil	8	5	2.2330	2.0914	315	210	93,65	66,67
2	Data of iris plant parameters	4	2	0.5726	0.5446	175	105	95,11	60
3	Data of glass parameters	9	7	1.6721	1.6626	350	280	98,2	80

or in the design of pattern recognition systems for human identification based on biometric measures. We believe that for real world situations some pertinent modifications or improvements to our model could be needed, but the essence of the solution to the problems is already provided in the proposed approach. As another leg of future investigation in the proposed direction, we consider a three-module MNN, which will be fed with the following inputs: one with the intercriteria pairs exhibiting positive consonance, another with the intercriteria pairs exhibiting negative consonance, and the third one with the pairs exhibiting dissonance.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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