UDC 004.891.3 (045)

[1]E. I. Chumachenko,
[2]D. Yu. Koval,
[3]G. A. Sipakov,
[4]D. D. Shevchuk

USING ANFIS AND NEFCLASS NEURAL NETWORKS IN CLASSIFICATION PROBLEMS

Technical Cybernetic Department National Technical University of Ukraine
"Kyiv polytechnic institute", Kyiv, Ukraine
E-mails: [1]chumachenko@tk.kpi.ua, [2]kvl_demon@mail.ru, [3]genasip@mail.ru, [4]shedimon@ya.ru

Abstract*—*The analysis of different neural network topologies on different data sets in classification problems is represented.

Index Terms—Fuzzy logic; neural networks; classification problems.

I. INTRODUCTION

Nowadays the intelligent information systems have become widespread. The base of these is the hybrid neural networks consisting of neural networks of different topologies. One of the types of problems these networks can solve are the classification problem. In this paper a comparative analysis of the classification problems solutions using different network topologies is proposed. The topologies we are using in the paper are: neurofuzzy classification (NEFCLASS) (fuzzy perceptron), adaptive neurofuzzy inference system (ANFIS) (hybrid network that contains fuzzy layer and multilayer perceptron) and a standard multilayer perceptron. The purpose of work is to study the properties of presented topologies on the different subject areas and to determine the best conditions for each network.

II. PROBLEM STATEMENT

Make a structural analysis of the ANFIS and NEFCLASS topologies; examine their learning algorithms and compare the results of solving the classification problem with different data sets with the results obtained by the usage of a multilayer perceptron.

III. DESCRIPTION OF TOPOLOGIES

A. ANFIS[1]

Adaptive neurofuzzy inference system is a five-layer network of direct propagation.

This network have the following structure rules: if $x_1 = A$, $x_2 = B$, …, $x_n = C$, then $y = f(x_1 \ldots x_n)$, where $f(x_1 \ldots x_n)$ is the any functional dependency.

Rules are generated by rundown all possible combinations of the input variables terms.

Adaptive neurofuzzy inference system structural scheme is presented in Fig. 1.

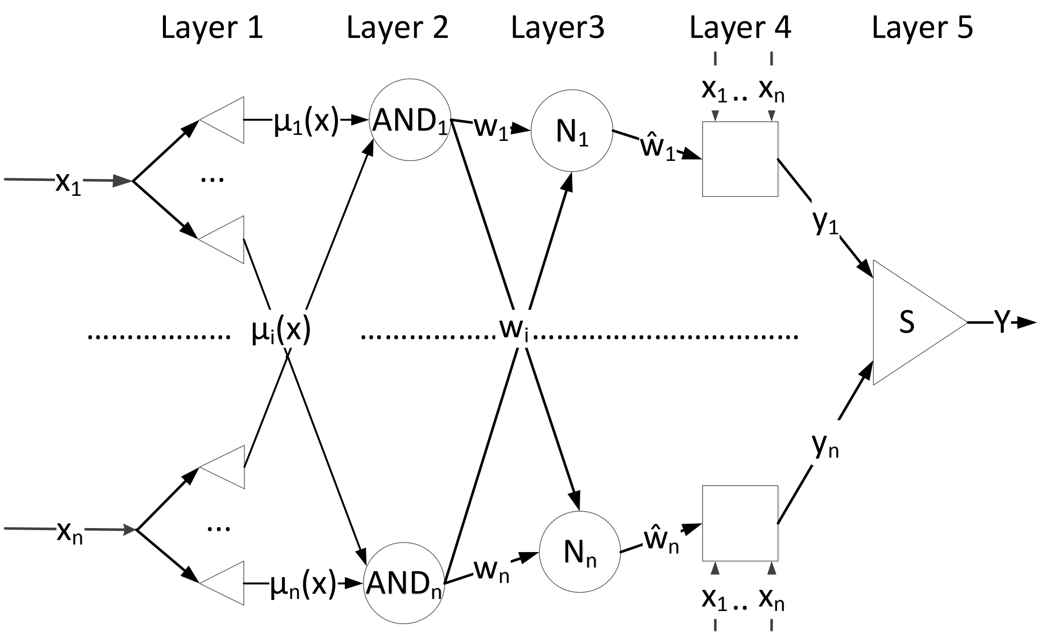

Fig. 1. Structure of ANFIS

Let's examine each layer of the network.

Layer 1. Every neuron of this layer is the neuron which transforms the crisp input signal with the help of the membership function, i.e. results fuzzification is performed.

Layer 2. Neurons of this layer perform the intersection operation (AND) of the input signals and send to the output

$$w_i = \min\left(\mu_{i1}(X_1), ..., \mu_{in}(X_n)\right).$$

In fact, we calculate how much the value of the input variables correspond to the ith rule (e.g. the activating power of the rule) on this layer.

Layer 3. Neurons of this layer calculate the normalized power of the rule

$$\overline{w_i} = \frac{w_i}{\sum_{j=0}^{n} w_i}.$$

Based on the previous results we determine which rule is most appropriate for the input values. Thus the rule with the highest w_i will have the greatest impact on the output.

Layer 4. The value of the output variables is formed on this layer

$$y_i = \overline{w_i} f_i.$$

Now the corresponding output for each rule is calculated.

Layer 5. Each rules outputs are submitted to the input of this layer for the further aggregation. Thereby obtained output signal is

$$Y = \frac{\sum_{i=0}^{n} w_i y_i}{\sum_{i=0}^{n} w_i}.$$

B. NEFCLASS[3]

Fuzzy rules describing the input data are as follows: if x_1 belongs μ_1, …, x_n belongs μ_n, then the sample (x_1, ..., x_n) belongs to the class i, where μ_1, …, μ_n is the membership function.

Neurofuzzy classification system has three-layered consecutive structure shown in Fig. 2.

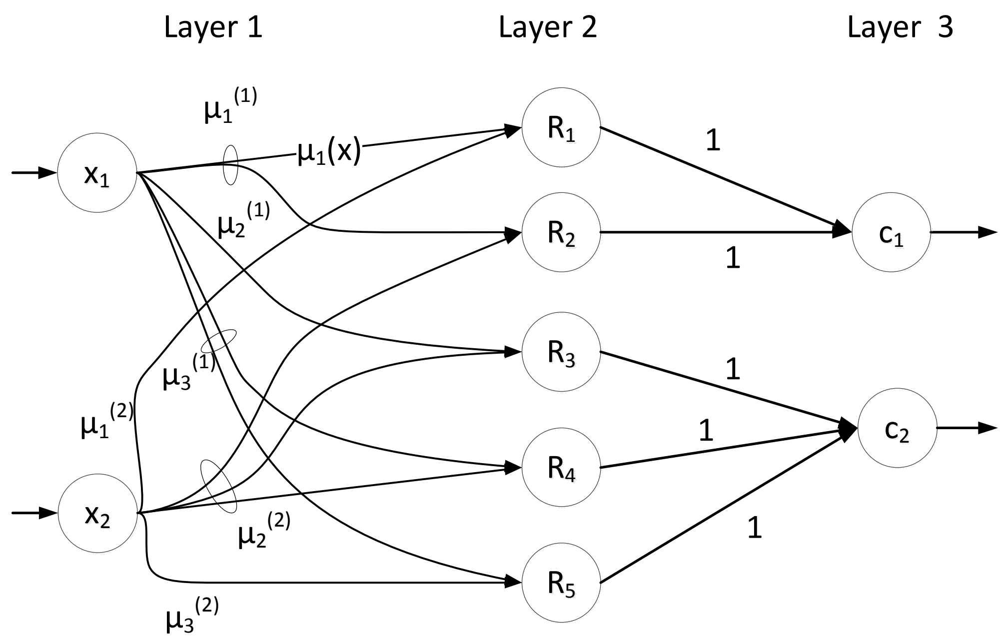

Fig. 2. Structure of NEFCLASS

First layer U_1 contains input neurons that represent the input neurons. Activation a_x of the neuron $x \in U_1$ does not change the input value.

The hidden layer U_2 contains fuzzy rules with the neurons activation function:

$$a_R^{(p)} = \min_{x \in U_1}\left\{W(x,R)\left(a_x^{(p)}\right)\right\},$$

where $W(x, R) = \mu_i(x)$.

Third layer U consists of the input neurons of each class with the activation function:

$$a_c^{(p)} = \max_{R \in U_2}\left\{a_R^{(p)}\right\}.$$

Fuzzy sets and linguistic rules represent approximation and determine the result of the NEFCLASS system. They are obtained from the data sets through the learning. The rule by which for every linguistic value can exist only one representation of a fuzzy set must necessarily fulfilled.

Neurofuzzy classification structural scheme is presented in Fig. 2.

IV. LEARNING ANFIS AND NEFLCASS

To achieve desirable (or, at least, similar to it) set of outputs for some set of inputs the network must be learned. Each input (or output) set is treated as a vector. Learning is implemented by consecutive representation of input vectors with simultaneous adjustment of weights in accordance with a specific procedure. During the process of learning network weights are gradually becoming such that each input vector form desired output vector. Represented topologies are learned similarly to the direct distribution networks.

A. ANFIS learning [2]

Backpropagation method (backward propagation of errors).

During learning the problem of minimizing the neural network errors using the method of least squares is stated. For a network with p outputs error is given by the proportion

$$E = \frac{1}{2}\sum_{j=1}^{p}\left(y_j - d_j\right)^2,$$

where y_j is the output value of the neural network for each component of the input vector and d_j is the desired neural network output.

In case of the ANFIS network number of outputs $p = 1$.

Full learning algorithm of the neural network using the backpropagation procedure as follows.

1. Advance one of possible images to the network input and calculate the values of outputs in a normal neural network operation mode, when the signals propagate from the inputs to the outputs. Neural network output is calculated as follows:

$$s_j^{(n)} = \sum_{i=0}^{M} y_i^{(n-1)} w_{ij}^{(n)},$$

where M is the number of neurons in layer $n-1$; $y_i^{(n-1)} = x_{ij}^{(n)}$ are ith neurons input of the jth layer; $y_j^{(n)} = f(s_j^{(n)})$, where $f()$ – activation function of the neuron; $y_q(0) = I_q$, where I_q – qth component of the input vector.

2. Calculate $\delta^{(N)}$ for the output layer (layer N):

$$\delta_i^{(N)} = \frac{\partial E}{\partial y_i}\frac{dy_i}{ds_i} = \left(y_i^{(N)} - d_i\right)\frac{dy_i}{ds_i}. \qquad (1)$$

In the case of a hyperbolic tangent $\frac{dy}{ds} = 1 - s^2$, in case of sigmoid $\frac{dy}{ds} = s(1-s)$.

3. Calculate the change in weights $\Delta w(n)$ of the layer N.

$$\Delta w_{ij}^{(n)} = -\eta\delta_j^{(n)} y_i^{(n-1)}, \qquad (2)$$

where η is the factor of learning speed, $0 < \eta < 1$.

4. Calculate $\delta(n)$ and $\Delta w(n)$ using equations (1) and (2) respectively for all left layers, $n = N - 1, \ldots, 1$.

5. Adjust all weights in a neural network

$$w_{ij}^{(n)}(t) = w_{ij}^{(n)}(t-1) + \Delta w_{ij}^{(n)}(t),$$

where t is the number of the current iteration; n is the number of the layer.

6. If the network error is greater than specified or the number of learning iterations has not reached a predetermined limit, then go to step 1. Otherwise is the end of the learning.

B. NEFLCASS learning

The learning consists of 2 stages: learning the rules and learning the fuzzy sets.

First layer U_1 contains input neurons, in which the input samples are represented. Activation a_x of the neuron $x \in U_1$ typically does not change the input value. Hidden layer U_2 contains fuzzy rules and third layer U_3 consists of output neurons of each class.

Learning the fuzzy sets

The supervised learning algorithm of the NEFCLASS system must adapt its fuzzy sets running cyclically through all the training set L, the following steps are continued until one of the stopping criteria fulfilled.

Select the following sample (p, t) from L and circulate it through the NEFCLASS system and determine the output vector c.

For each output neuron c_i the δ_{c_i} value is determined

$$\delta_{c_i} = t_i - a_{c_i},$$

$$a_R^{(p)} = \min_{x \in U_1}\left\{W(x,R)\left(a_x^{(p)}\right)\right\},$$

$$a_c^{(p)} = \sum_{R \in U_2} W(c,R) \cdot a_R^{(p)}$$

or alternatively

$$a_c^{(p)} = \max_{x \in U_1}\left\{a_R^{(p)}\right\},$$

where $W(x, R)$ is the fuzzy weight of the input neuron x and the rule neuron R compound, and $W(R, c)$ is the fuzzy weght of the rule neuron R and the output leayer neuron c compound.

1. For every rule neuron R with $a_R > 0$:

a) determine the δ_R value, that equals

$$\delta_R = a_R(1-a_R)\sum_{c\in U_3} W(R,c)\delta_c;$$

b) Find the x', which fulfills

$$W(x',R)(a_{x'}) = \min_{x\in U_1}\{W(x,R)(a_x)\};$$

c) for the fuzzy sets with the membership function of the form:

$$\mu : \mathrm{R} \to \begin{cases} (x-a)/(b-a), & x\in[a,b); \\ (c-x)/(c-b), & x\in[b,c]; \\ 0, & \end{cases}$$

$W(x', R)$, determine δ_a, δ_b, δ_c using the speed of learning $\sigma > 0$:

$$\delta_b = \sigma\delta_R(c-a)\mathrm{sgn}(a_{x'}-b);$$

$$\delta_a = -\sigma\delta_R(c-a)\delta_b;$$

$$\delta c = \sigma\delta_R(c-a)\delta_b,$$

and apply the changes to $W(x', R)$.

d) calculate the rules error:

$$E = a_R(1-a_R)\sum_{c\in U_3}(2W(R,c)-1)\delta_c.$$

As a stopping criterion we can use listed below:

1. During n iterations the error is not reduced.
2. Stop the learning when error reaches a certain (preferably close to zero) value.

V. NUMERICAL EXPERIMENT

To check the accuracy data sets for classification Iris (example 1) and simplified set Wine (example 2) were used.

Description of the Iris set [4].

Input variables.

1. Sepal length in cm.
2. Sepal width in cm.
3. Petal length in cm.
4. Petal width in cm.

The number of possible classes: 3.

Description of the Wine set [5].

Input variables.

1. Alcohol.
2. Malic acid.
3. Ash.
4. Alcalinity of ash.
5. Magnesium.
6. Total phenols.
7. Flavanoids.
8. Nonflavanoid phenols.
9. Proanthocyanins.
10. Color intensity.
11. Hue.
12. OD280/OD315 of diluted wines.
13. Proline.

The number of possible classes: 3.

It should be noted, that in the first set with a small number of variables determined 5 terms for each variable, that increase the number of possible rules. On contrary, in the second set the number of terms for each variable is 3.

The learning time with given data sets, minimal error: 0.01; classical learning algorithms is presented on Table 1.

TABLE 1

LEARNING TIME

Network	Wine, s	Iris, s
ANFIS	4	3,4
NEFCLASS	4,3	3
Multilayer perceptron	5	4

Thus we can conclude that the duration of the NEFCLASS network learning strongly depends on the number of the input variables and their possible terms.

Results of the networks work for the Iris set is presented on Table 2 and for the Wine set on Table 3.

TABLE 2

RESULTS OF NEURON NETWORKS FUNCTIONING FOR EXAMPLE 1

Network	Accuracy, %	Action period, s
NEFCLASS	95,6	0.6
ANFIS	95,1	1.2
Multilayer perceptron	94,8	1.4

TABLE 3

RESULTS OF NEURON NETWORKS FUNCTIONING FOR EXAMPLE 2

Network	Accuracy, %	Action period, s
NEFCLASS	88,6	4
ANFIS	93,9	2.6
Multilayer perceptron	90,2	3

Analyzing the results, we can conclude that the NEFCLASS network works faster and better under the condition that the number of input variables is small though it can have many terms. With the growth of the number of the input variables networks precision subside.

The ANFIS network results demonstrate, that its accuracy depends on the input variables to a lesser extent than the NEFCLASS network.

Standard multilayer perceptron is less accurate and requires more action period with a small number of input variables. On a greater number of input variables multilayer perceptron is more precise but slower than the NEFCLASS network and less accurate comparatively to the ANFIS network.

CONCLUSIONS

In this article we consider the NEFCLASS and ANFIS topologies, methods of their learning and their usage as the classifiers. A comparative analysis with the multilayer perceptron work on different data sets was held.

REFERENCES

[1] Kruglov, V. V.; Dli, M. I.; Golunov, R .Ju. Fuzzy logic and artificial neural networks. Moscow. Fizmatlit, 2001. (in Russian).

[2] Zade, L. The concept of a linguistic variable and its application to approximate reasoning. Moscow. Mir, 1976. (in Russian).

[3] Zajchenko, Ju. P. Fuzzy models and methods in intellectual systems. Kyiv. Slovo, 2008. (in Russian).

[4] http://archive.ics.uci.edu/ml/datasets/Iris

[5] http://archive.ics.uci.edu/ml/datasets/Wine

Received 06 February 2015.

Chumachenko Olena. Candidate of engineering. Associate Professor.
Technical Cybernetic Department, National Technical University of Ukraine “KPI”, Kyiv, Ukraine.
Education: Georgian Politechnic Institute, Tbilisi, Georgia (1980).
Research area: system analysis, artificial neuron nets.
Publications: more than 50 papers.
E-mail: chumachenko@tk.kpi.ua

Koval Dmitro. Student.
Education: NTUU “KPI”, Kyiv, Ukraine.
Research interests: fuzzy logic, neural nets.
Publications: 1.
E-mail: kvl_demon@mail,com

Sipakov Gennadiy. Student.
Education: NTUU “KPI”, Kyiv, Ukraine .
Research interests: fuzzy logic, neural nets.
Publications: 1.
E-mail: genasip@mail.ru

Shevchuk Dmitro. Student.
Education: NTUU “KPI”, Kyiv, Ukraine.
Research interests: fuzzy logic, neural nets.
Publications: 1.
E-mail: shedimon@ya.ru

О. І. Чумаченко, Д. Ю. Коваль, Г. О. Сіпаков, Д. Д. Шевчук. Використання нейронних мереж ANFIS і NEFCLASS у задачах класифікації

Виконано аналіз функціонування нейронних мереж ANFIS і NEFCLASS при вирішенні задач класифікації.

Ключові слова: нечітка логіка; нейронні мережі; задача класифікації.

Чумаченко Олена Іллівна. Кандидат технічних наук. Доцент.
Кафедра технічної кібернетики, Національний технічний університет України «КПІ», Київ, Україна.
Освіта: Грузинський політехнічний інститут, Тбілісі, Грузія (1980).
Напрям наукової діяльності: системний аналіз, штучні нейронні мережі.
Кількість публікацій: більше 50 наукових робіт.
E-mail: chumachenko@tk.kpi.ua

Коваль Дмитро Юрійович. Студент.
Освіта: НТУУ «КПІ», Київ, Україна.
Напрямок наукової діяльності: нечітка логіка, нейронні мережі.
Кількість публікацій: 1.
E-mail: kvl_demon@mail,com

Сіпаков Геннадій Олександрович. Студент.
Освіта: НТУУ «КПІ», Київ, Україна.

Напрямок наукової діяльності: нечітка логіка, нейронні мережі.
Кількість публікацій: 1.
E-mail: genasip@mail.ru

Шевчук Дмитро Дмитрович. Студент.
Освіта: НТУУ «КПІ», Київ, Україна.
Напрямок наукової діяльності: нечітка логіка, нейронні мережі.
Кількість публікацій: 1.
E-mail: shedimon@ya.ru

Е. И. Чумаченко, Д. Ю.Коваль, Г. А. Сипаков, Д. Д. Шевчук. Использование нейронных сетей ANFIS и NEFCLASS в задачах классификации

Выполнен анализ функционирования нейронных сетей ANFIS и NEFCLASS при решении задач классификации.

Ключевые слова: нечеткая логика; нейронные сети; задача классификации.

Чумаченко Елена Ильинична. Кандидат технических наук. Доцент.
Кафедра технической кибернетики, Национальный технический университет Украины «КПИ», Киев, Украина.
Образование: Грузинский политехнический институт, Тбилиси, Грузия (1980).
Направление научной деятельности: системный анализ, искусственные нейронные сети.
Количество публикаций: более 50 научных работ.
E-mail: chumachenko@tk.kpi.ua

Коваль Дмитрий Юрьевич. Студент.
Образование: НТУУ «КПИ», Киев, Украина
Направление научной деятельности: нечеткая логика, нейронные сети.
Количество публикаций: 1.
E-mail: kvl_demon@mail,com

Сипаков Геннадий Александрович. Студент.
Образование: НТУУ «КПИ», Киев, Украина
Направление научной деятельности: нечеткая логика, нейронные сети.
Количество публикаций: 1.
E-mail: genasip@mail.ru

Шевчук Дмитрий Дмитриевич. Студент.
Образование: НТУУ «КПИ», Киев, Украина
Направление научной деятельности: нечеткая логика, нейронные сети.
Количество публикаций: 1.
E-mail: shedimon@ya.ru