A SOFT FUZZY ALGORITHM OF THE MOBILE ROBOT CONTROL

Context. The task of a mobile robot control on the base of soft algorithm fuzzy inference has been solved. The objective is the creation of soft algorithm of the fuzzy inference which allows to provide additivity of fuzzy control system. Method. A soft algorithm of fuzzy inference used to control the mobile robot is suggested. Given algorithm allows to compensate errors inherent to the traditional models of fuzzy inference. Errors include: the curse of dimensionality, the absence of additivity and the fuzzy partition. This soft algorithm of fuzzy inference at the expense of rational allocation of premises and conclusions in a matrix of fuzzy relations, reduces the number of operations of the fuzzy inference. Another distinctive feature of the proposed soft algorithm is that in fuzzy inference to find minima and maxima used soft arithmetic operators. The paper shows that during the work of hard formulas for the implementation of these formulas while controlling the mobile robot the situations will appear when the robot loses control. The article points out that the implementation of the possibility in soft algorithm of fuzzy inference option of changes in parameters of sigmoidal membership functions will minimize the error at fuzzy system output. Dynamics of changing RMSE ratio from the varying parameters of sigmoidal membership functions proves it. The additional simulations presented in the article shows that during varying the parameters of sigmoidal membership function, during in increasing of the parameter $a$, is being observed decrease in the value of RMSE. The effectiveness of the proposed soft algorithm is confirmed by numerical simulation and experiments in the researching of a mobile robot movement along a line.

Results. The specialized software for microcontroller Arduino Uno is developed and it realizes the proposed soft algorithm which allows to carry out an experimental study of its properties. Conclusions. The software realizing proposed algorithm has been developed and used in computational experiments investigating the properties of the algorithm. The experiments confirmed the efficiency of the proposed algorithm and software.

Keywords: fuzzy inference system, fuzzy set theory, RMSE, soft computing, mobile robot.

NOMENCLATURE

- $\text{RMSE}$ is a root mean square error;
- $\text{MF}$ is a membership functions;
- $\text{MISO}$ is a multi input single output;
- $\text{FR}$ is a fuzzy rules;
- $\text{FIS}$ is a fuzzy inference system;
- $y$ is an output parameter;
- $x_i$ is an input parameter;
- $n$ is a number of input parameters;
- $X$ is a vector of the input parameters;
- $k$ is a number of fuzzy rules;
- $m$ is a number of terms;
- $l$ is a number input parameters;
- $a, b, c$ are the parameters of the Gaussian membership function;
- $\delta$ is a softness operator;
- $\gamma$ is an operator of the parameterization;
- $M$ is the number of observations in the learning sample.

1 INTRODUCTION

Algorithms of the fuzzy-logic inference are successfully applied in modeling of difficult technological processes of the modern control systems [1, 2, 3]. The algorithms allow increasing accuracy of the control process by balancing outside effects in real-time mode. However, in practice, implementation of the system based on algorithms of the fuzzy-logic inference has some problems concerning continuous differentiability of MF. They are curse of dimensionality [4, 5, 6]; non-observance of the condition of the partition of unity condition [7] and non-compliance of the condition of additivity [8].

The main purpose in the article is to design a soft algorithm of fuzzy inference that allows to control robotic systems in real time.
2 PROBLEM STATEMENT

Fuzzy inference systems, based on the Zadeh rule, are used for modeling modern systems [12, 13, 14, 15]. For example, when MISO-system with n-input and one output parameter is designated, then dependence between these is defined as

\[ y = f(X) = f(x_1, x_2, \ldots, x_n), \]

where \( y \) – an output parameter, \( x_i \) – input parameters, \( i=1\ldots n \), \( n \) – number of input parameters.

The vector \( X \) of the input parameters is shown on the Cartesian product of the determination of input parameters \( X_1 \times X_2 \times \ldots \times X_n ; X = [x_1, x_2, \ldots, x_n] \). At the same time, the function \( f \) shows a condition multiplicity of the output parameter \( Y \) in the area of the determination of the input parameters \( X \)

\[ f : X_1 \times X_2 \times \ldots \times X_n \rightarrow Y. \]

According to the Zadeh rule the fuzzy multiplicity in a MISO-system is determined as

\[ Y(y) = \bigvee_{x \in x_1 \times x_2 \times \ldots \times x_n} (X_1(x_1) \land \ldots \land X_n(x_n)), \]

where \( \vee \) is a symbol, which means the operation of the hard fuzzy maximum; \( \land \) is a symbol, which means the operation of the hard fuzzy minimum.

At the same time, the membership function of the output parameter takes the form

\[ \mu_f(y) = \bigvee_{x_1 \times x_2 \times \ldots \times x_n} (\mu_{X_1}(x_1) \land \ldots \land \mu_{X_n}(x_n)). \]

The disadvantage of the MF relation, based on the Zadeh rule using hard formulas is evident. When the equation (2) \( \min(x; y)=\min(0.7; 0)=0, \) the result at the output is zero. Therefore, a fuzzy system will be non-sensitive to changes of the input parameter \( x_i \), because its value will depend on the second parameter \( x_1 = 0 \); if \( x_1 = 0.2 \) and the output is 0. Thus, the FIS does not possess additivity. Therefore, values of the RMSE parameter are increasing when modeling. For example, in [16] when modeling a similar system, RMSE (without training) is more than 120.

Another huge disadvantage of ANFIS models, which are created on the Zadeh rule, is existence of empty decisions in conclusions of the fuzzy inference. They increase with the conclusion of input parameters and FR, which are the knowledge base. The growth of the conclusion of FR is so fast, that it causes an error, which is concerned the dimension damnation. In recommendation [17], the conclusion of fuzzy rules \( k \) should be the same as the conclusion of terms \( m \). They describe a fuzzy input parameter. For example, if MISO-system has 2 input parameters and each of them is described by 3 terms, than the amount of FR will be defined as \( k=m^m=3^3=9 \). If the fuzzy MISO-system has 12 input parameters and each of them consists of 3 terms, than the amount of FR will be defined as \( k=531441 \). The growth of the conclusion of input parameters from 2 to 12 will increase the conclusion of fuzzy rules in 59049 times [18].

To compensate for the above drawbacks is solved the following task: the development of a fuzzy algorithm uses of soft arithmetic operations. A comparison of the proposed method with the traditional models of fuzzy inference is implemented based on the RMSE evaluation.

3 REVIEW OF THE LITERATURE

Currently, there are a large number FIS used as a decision-making system [3,4,9]. However, these FIS in the composite rule Zadeh use hard arithmetic operations of finding the minimum and maximum [12, 13, 14, 15]. Typically, such systems are not additive, and are not monotone [8, 15]. Also hard fuzzy inference system may cause such error as the curse of dimensionality [4,6]. This leads to the fact that in some cases FIS cannot learned. In some cases, FIS do not provide the condition of the partition of unity [7]. To resolve this issue we recommend to use parameterized MF for ensuring the partition of unity condition and continuity through the intersection point of the adjustment linguistic terms which equal 0.5. Also, to overcome the above errors in the studies recommended to use soft arithmetic operations [9, 10, 11, 21].

4 MATERIALS AND METHODS

A soft algorithm of the fuzzy logic inference includes the following steps:

Step 1. Fuzzification of the input parameters. The fuzzy MISO-system \( \gamma = f(x_1, x_2) \), which has 2 input and 1 output parameters should be considered. If each input parameter has 3 fuzzy terms (Fig. 1) with a MF then the output parameter has 5 fuzzy terms

\[ \mu(y) = \frac{1}{1 + \left(\frac{x-c}{a}\right)^b}, \]

where \( a, b, c \) are the parameters of the MF; \( x \) is a quantitative value of the input parameter.
Step 2. Determination of values of MF for every implication of the input parameters, based on the information received from sensors of active control systems, for example (Fig.1), if \( x_1 = 140 \) then \( x_2 = 262 \):

\[
\begin{align*}
    x_1' &= (x_{11}, x_{12}, x_{13}, \ldots) = (0.9; 0,144; 0), \\
    x_2' &= (x_{21}, x_{22}, x_{23}, \ldots) = (0; 0.25; 0.79).
\end{align*}
\] (4)

Step 3. Synthesis of the knowledge base, which contains fuzzy rules of the type «If … then» (see Table 1) [19].

Step 4. Creation of a fuzzy ratio matrix. Soft arithmetic operations are used while calculating MIN and MAX [8].

The operation of determination the soft MIN is obtained as follows:

\[
\min(\delta, x_i) = x_i + \delta^2 - \sqrt{(\delta - x_i)^2 + \delta^2}, \quad \text{where} \quad \delta = 0.05. \quad \text{(5)}
\]

The Eq. (5) demonstrates that

\[
\min(0.7; 0) = 0.7 + 0 + 0.05^2 - \sqrt{(0.7 - 0)^2 + 0.05^2} = 0.0076.
\]

Therefore, the soft MISO-system, will give the value different from zero and respond to the changing parameter \( x_i \), if the second parameter is \( x = 0 \). In this case the fuzzy system will be additive in the whole range of input parameters.

The equation of parameterized soft maximum capture is obtained as follows

\[
\max(\delta, x_i) = \left| \gamma \cdot \max(x_1, x_2) + 0.5(1 - \gamma)(x_1 + x_2) \right|, \quad \text{(6)}
\]

where \( \gamma \) is an operator of the parameterization. If \( \gamma = 1 \), then Eq. (6) will apply operations of hard-MAX. If \( \gamma = 0 \), then Eq. (6) will apply arithmetic operations.

The Eq. (6) can be applied only with 2 operands. If there are more than 2 operands, then it is necessary to apply the soft-MAX operator

\[
\text{soft-MAX} = \max_{i=1}^{n} (\max(x_{ii}, x_{ij})). \quad \text{(7)}
\]

Taking into consideration the (Eqs. (5), (6), (7)) the fuzzy ratio matrix is given as in Table 2.

The conclusion of conclusions equals to the conclusion of conclusions of the output parameters, i.e. 5. In a hard model of the fuzzy inference the conclusion of conclusions will be equal to 9. Therefore, a rational location of elements in the fuzzy ration matrix will be of the curse dimension.

Step 5. Truncation of output parameter terms, according to the equation

\[
\mu(y)_i = \text{soft-MIN} = \min_{i=1}^{n} (y_i; \mu(y)_i), \quad \text{(8)}
\]

where \( i = 1 \ldots n \) is the conclusion of the conclusion of the fuzzy logic inference; \( n \) is the amount of conclusions of the fuzzy logic inference.

Step 6. Integration of the transformed terms of the output parameters

\[
\mu(y)' = \text{soft-MAX} = \max_{i=1}^{n} [\mu(y)_1; \mu(y)_2; \mu(y)_3; \mu(y)_4; \mu(y)_5]. \quad \text{(9)}
\]

Step 7. The obtained result is defuzzification by the weighted average method [20, 21]

\[
y^* = \frac{\sum_{i=1}^{n} y_i \mu(y)_i}{\sum_{i=1}^{n} \mu(y)_i}. \quad \text{(10)}
\]

Therefore (Eqs. (3)-(10)) present a soft algorithm of the fuzzy logic inference.

4 EXPERIMENTS

The task of estimation of the created soft algorithm of the fuzzy logic inference assumes finding an optimal decision where RMSE is MIN [22, 23]

\[
\text{RMSE} = \sqrt{\frac{1}{M} \sum_{i=1}^{n} (y - y^*)} \rightarrow \min. \quad \text{(11)}
\]

Experimental data \( y = f(x_1, x_2, \ldots x_n) \) is given in Table 3.

Calculation of RMSE in the hard fuzzy inference system.

The data obtained from the defuzzification of the output result. Table 4 shows applying the hard algorithm of the fuzzy logic inference.

Table 1 – Knowledge base with FR

| Fuzzy rule | if | then | Fuzzy rule | if | then | Fuzzy rule | if | then |
|------------|----|------|------------|----|------|------------|----|------|
| FR 1       | \( x_{11} \) | \( x_{21} \) | \( y_3 \) | FR 4 | \( x_{12} \) | \( x_{21} \) | \( y_4 \) | FR 7 | \( x_{13} \) | \( x_{21} \) | \( y_3 \) |
| FR 2       | \( x_{11} \) | \( x_{22} \) | \( y_4 \) | FR 5 | \( x_{12} \) | \( x_{22} \) | \( y_4 \) | FR 8 | \( x_{13} \) | \( x_{22} \) | \( y_2 \) |
| FR 3       | \( x_{11} \) | \( x_{23} \) | \( y_3 \) | FR 6 | \( x_{12} \) | \( x_{23} \) | \( y_2 \) | FR 9 | \( x_{13} \) | \( x_{23} \) | \( y_3 \) |

Table 2 – Fuzzy ratio matrix

| Output term | Composition | Maximum |
|-------------|-------------|---------|
| \( y'_5' \) | \( b_7 = \text{soft-MIN}(x_{11}; x_{21}) \) | \( b_7 \) |
| \( y'_3' \) | \( b_2 = \text{soft-MIN}(x_{11}; x_{22}) \) | \( b_2 \) |
| \( y'_2' \) | \( b_1 = \text{soft-MIN}(x_{11}; x_{23}) \) | \( b_1 \) |
| \( y'_4' \) | \( b_3 = \text{soft-MIN}(x_{12}; x_{21}) \) | \( b_3 \) |
| \( y'_1' \) | \( b_6 = \text{soft-MIN}(x_{12}; x_{22}) \) | \( b_6 \) |
| \( y'_5 \) | \( b_4 = \text{soft-MIN}(x_{12}; x_{23}) \) | \( b_4 \) |
| \( y'_2 \) | \( b_5 = \text{soft-MIN}(x_{13}; x_{21}) \) | \( b_5 \) |
| \( y'_3 \) | \( b_6 = \text{soft-MIN}(x_{13}; x_{22}) \) | \( b_6 \) |
| \( y'_1 \) | \( b_5 = \text{soft-MIN}(x_{13}; x_{23}) \) | \( b_5 \) |
Calculation of the RMSE parameter with the use of the experimental data (see Table 3) and the data, obtained from the modeling of the hard fuzzy inference model (see Table 4) is designated as RMSE_{hf} = 247.54.

Calculation of RMSE in the soft fuzzy inference system.

RMSE of with the appliance of soft arithmetic operations is calculated in (Eqs. (3)÷(10)). The obtained data is given in Table 5.

As shown in Table 5 there are no non-sensitive zones. Thus, soft fuzzy model reacts to all changes of the input parameters and becomes additive. It helps to minimize the value of the RMSE parameter.

Calculation of the RMSE parameter with the use of the experimental data (see Table 3) and data, obtained from the modeling of the soft fuzzy inference model (see Table 5) is defined as RMSE_{sf} = 16.19.

It is shown that the soft model of the fuzzy logic inference is in 15.3 times more corresponded to the experimental selection in Table 3.

A graphic version of the modeling is shown in Fig. 2.

Several numerical experiments are necessary to perform to study the soft algorithm of the fuzzy inference system.

Additional imitation modeling of RMSE calculation.

Some additional experiments, which allow proving effectiveness of the introduced soft algorithm, are to be performed with the random conclusions from 430 to 470. It is necessary to fill values of the output parameter in Table 3 and to calculate RMSE for hard and soft algorithms of the FIS. It is necessary to change only the values of the coefficients a and b of the output MF \( y \) if using fuzzy logic modeling Eq. (3). The value of the parameter c is not changed (see Table 6).

MIN RMSE for the soft fuzzy logic inference is obtained in the 3\textsuperscript{rd} experiment: RMSE=11.14. MIN RMSE of the hard fuzzy logic inference is obtained in the 4\textsuperscript{th} experiment: RMSE=244.88, then a=40, then b=2 (see Eq. (3)).

A graphic version of the best variants for the RMSE parameter is illustrated in Fig. 3.

The data, which show dynamics of RMSE depend on the parameter \( a \) (see Table 7).

Interpretation of the data (see Table 7) is given in Fig. 4.

### Table 3 – Experimental selection

| \( x_2 \) | \( x_1 \) | 210 | 220 | 230 | 240 | 250 | 260 | 270 | 280 | 290 | 300 |
|-------|-------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| 110   | 457   | 432 | 460 | 440 | 466 | 468 | 440 | 451 | 459 | 444 |
| 120   | 451   | 446 | 464 | 452 | 452 | 470 | 442 | 443 | 438 | 445 |
| 130   | 470   | 456 | 463 | 452 | 453 | 469 | 434 | 432 |
| 140   | 470   | 457 | 465 | 448 | 434 | 431 | 442 | 435 | 435 | 467 |
| 150   | 435   | 455 | 467 | 464 | 468 | 455 | 458 | 464 | 462 | 430 |
| 160   | 461   | 443 | 442 | 439 | 462 | 439 | 458 | 457 | 466 | 434 |
| 170   | 435   | 448 | 465 | 442 | 445 | 446 | 443 | 455 | 442 | 447 |
| 180   | 446   | 436 | 456 | 434 | 452 | 464 | 432 | 445 | 444 | 450 |
| 190   | 446   | 453 | 463 | 447 | 441 | 435 | 435 | 465 | 446 | 465 |
| 200   | 461   | 462 | 455 | 444 | 446 | 432 | 452 | 445 | 436 | 463 |

### Table 4 – Defuzzification on the hard fuzzy model

| \( x_2 \) | \( x_1 \) | 210 | 220 | 230 | 240 | 250 | 260 | 270 | 280 | 290 | 300 |
|-------|-------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| 110   | 473   | 472 | 466 | 465 | 459 | 456 | 456 | 450 | 450 | 450 |
| 120   | 474   | 481 | 481 | 473 | 466 | 457 | 456 | 450 | 450 | 449 |
| 130   | 476   | 475 | 478 | 470 | 462 | 454 | 447 | 443 | 443 | 449 |
| 140   | 467   | 475 | 478 | 470 | 462 | 454 | 447 | 443 | 443 | 449 |
| 150   | 461   | 465 | 465 | 457 | 450 | 442 | 434 | 434 | 434 | 438 |
| 160   | 457   | 453 | 452 | 445 | 437 | 429 | 421 | 422 | 422 | 425 |
| 170   | 450   | 450 | 450 | 442 | 434 | 426 | 418 | 418 | 418 | 426 |
| 180   | 450   | 449 | 443 | 443 | 434 | 427 | 428 | 426 | 426 | 438 |
| 190   | 0     | 0    | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   |
| 200   | 0     | 0    | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   |

### Table 5 – Defuzzification on the soft fuzzy model

| \( x_2 \) | \( x_1 \) | 210 | 220 | 230 | 240 | 250 | 260 | 270 | 280 | 290 | 300 |
|-------|-------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| 110   | 450   | 450 | 458 | 450 | 450 | 441 | 450 | 450 | 450 |
| 120   | 450   | 473 | 474 | 466 | 464 | 456 | 450 | 450 | 450 |
| 130   | 473   | 481 | 481 | 473 | 466 | 458 | 450 | 450 | 450 |
| 140   | 469   | 477 | 478 | 470 | 462 | 454 | 447 | 443 | 443 |
| 150   | 464   | 465 | 465 | 458 | 450 | 441 | 434 | 434 | 434 |
| 160   | 455   | 453 | 452 | 445 | 437 | 429 | 421 | 422 | 422 |
| 170   | 450   | 450 | 450 | 442 | 434 | 426 | 418 | 418 | 418 |
| 180   | 450   | 449 | 443 | 443 | 434 | 427 | 428 | 426 | 426 | 438 |
| 190   | 0     | 0    | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   |
| 200   | 0     | 0    | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   |
УПРАВЛІННЯ У ТЕХНІЧНИХ СИСТЕМАХ

Figure 2 – Modeling: a – experimental selection; b – hard FIS; c – soft FIS

Table 6 – Imitation modeling of RMSE

| No. of experiment | RMSE<sub>HF</sub> | RMSE<sub>SF</sub> |
|-------------------|-------------------|-------------------|
|                   | a=8 b=4          | a=20 b=4         | a=40 b=4 |
|                   | a=8 b=2          | a=20 b=2         | a=40 b=2 |
| 1                 | 247.54           | 247.42           | 247.3   |
|                   | 16.19            | 14.21            | 11.99   |
| 2                 | 247.55           | 247.35           | 247.19  |
|                   | 17.95            | 14.65            | 11.74   |
| 3                 | 247.65           | 247.46           | 247.33  |
|                   | 17.1             | 13.8             | 11.14   |
| 4                 | 245.04           | 244.88           | 244.69  |
|                   | 18.84            | 15.95            | 12.6    |
| 5                 | 247.43           | 247.26           | 247.1   |
|                   | 17.07            | 14.37            | 11.42   |
| 6                 | 247.35           | 247.39           | 247.28  |
|                   | 17.15            | 14.12            | 11.98   |
| 7                 | 246.78           | 246.59           | 246.45  |
|                   | 17.87            | 14.52            | 11.9    |
| 8                 | 247.23           | 247.04           | 246.88  |
|                   | 19.22            | 15.67            | 12.71   |
| 9                 | 247.33           | 247.2            | 247.09  |
|                   | 16.44            | 13.73            | 11.44   |
| 10                | 247.63           | 247.51           | 247.37  |
|                   | 16.76            | 14.87            | 12.38   |
| Average           | 247.17           | 247.01           | 246.87  |
|                   | 17.46            | 14.59            | 11.93   |

Figure 3 – a – 3<sup>rd</sup> experiment for the soft FIS; b – 4<sup>th</sup> for the hard FIS (experiment)

Figure 4 – Dynamics of RMSE when the parameter <i>a</i> is changed
The process of mobile robot control, which is moving along the line, is illustrated in Fig. 5. The decision of this task is made for 2 lengths: 2 meters and 2.5 meters. There are a lot of ways to solve the task [27, 28]. A robot based on the two-wheeled platform mini Q is applied in the experiment.

Scheme and the principle of the mobile robot operation.

Mobile robot includes the following elements: A microcontroller, based on the Arduino Uno scheme, made on ATmega328p processor with 16 MHz CPU speed with 32 Kb memory; A two-wheeled platform mini Q with a disc, 2 wheels 42H19 mm and 2 micro motors with 3–9 V; A Motor Shield card for Arduino Uno, based on L298P driver, which allows controlling two micro motors with 5–24 V voltage; Troyka Shield card connects necessary sensors to the mobile robot; Two digital line sensors. A structural scheme of the mobile robot is shown in Fig. 6.

The line sensors, which determine the colour of the surface under the mobile robot, should be used for the robot moving along the line. The output signal from the sensor is a binary signal: logical 0 or 1 depends on the colour under the mobile robot. 1 means “black”, 0 means “white”. The use of the Troyka Shield card allows connecting to the Motor Shield. Three different signals are transmitted through the three-wire loopback: G means “ground”; V means “voltage”; S means “signal”. The Motor Shielis is used to control two wheel rotation. Its work is similar to the scheme H-bridge, for example L293d. Two pins are applied to indicate the direction of the wheel rotation. For example, if there is a signal 1:1, then the mobile robot moves straight ahead.

If the signal 1:0, then the mobile robot rotates around its axis. If the signal 0:0, then the mobile robot moves back. The other two pins are used to supply the voltage to the micro motors ranging from 0 to 5 V. The process of control is implemented with the help of pulse-wide modulation. If the pin is under 5V, then the mobile robot moves at the maximum speed. If V=0, then the mobile robot does not move. The Motor Shield card is put on the Arduino Uno.

Fuzzy system of the mobile robot control.

Input parameters for the mobile robot control are linguistic variables: power supply voltage – u (V) and robot’s weight – m (gr). It is possible to use the range of values of linguistic variables. If the power voltage is within the range from 6 to 9 V (see Fig. 7, a) then a FM of the linguistic variables of the power voltage is defined as \( U = [u_1] + [u_2] + [u_3] \). The weight of the mobile robot depends both on the conclusion of its sensors and a type of the voltage supply. The presented weight is within the range from 180 to 270 grams. FM of the linguistic variables of the mobile robot weight is defined as \( M = [m_1] + [m_2] + [m_3] \) (see Fig. 7, b). The MF is designated as Eq. (3).

The MF of the output linguistic variable Speed, depends on the ADC precision. Therefore its range is occurred as [0 … 255] [see Fig. 7, c]. This variable is also defined by the sigmoidal function Eq. (3) \( Speed = [s_1] + [s_2] + [s_3] + [s_4] \).

Hard and soft algorithms of the fuzzy logic inference should be used for calculation the variable Speed. A matrix should be created for the robot with a FIS applying the (Eqs. (5)– (7)) outlined in Table 8.

Defuzzification uses a method of the center of gravity to determine the output variable Speed outlined in Table 9 and Table 10.

Calculation of the RMSE by the methods presented in Section 4 shows that RMSE$_{p}$=11.93 in modeling of the soft model of the fuzzy inference and RMSE$_{s}$=35.59 in modeling of the hard model of FIS. The area, which is grey (see Table 10), is an area of non-sensitivity of the mobile robot with a FIS. The output of the MISO system will be the same if the robot’s weight is in the range from 180 to 190 grams. It will also influence its work. Therefore, the robot will not move if the variable Speed equals 0. The results are illustrated in Fig. 8 and in Table 9 and Tables 10.

Figure 6 – Structural scheme of the mobile robot

Table 7 – Dynamics of RMSE when the parameter a is changed

| a  | 10  | 20  | 30  | 40  | 50  | 60  | 70  | 80  | 90  | 100 |
|----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| RMSE | 15.73 | 14.21 | 13.22 | 12.42 | 11.96 | 11.72 | 11.63 | 11.61 | 11.61 | 11.63 |

Table 8 – Fuzzy ratio matrix

| Output term | Composition | Maximum |
|-------------|-------------|---------|
| \( s'1 \) | \( b_1 = \text{soft-min}(u_1; m_1) \) | \( b_1 = \text{soft-max}(b_2, b_3) \) |
| \( s'2 \) | \( b_2 = \text{soft-min}(u_2; m_2) \) | \( b_2 = \text{soft-min}(m_2) \) | \( b_2 = \text{soft-MAX}(b_0, b_1, b_2) \) |
| \( s'3 \) | \( b_3 = \text{soft-min}(u_3; m_3) \) | \( b_3 = \text{soft-min}(u_3; m_3) \) | \( b_3 = \text{soft-max}(b_0, b_3) \) |
| \( s'4 \) | \( b_4 = \text{soft-min}(u_4; m_4) \) | \( b_4 = \text{soft-min}(u_4; m_4) \) | \( b_4 = \text{soft-max}(b_2, b_4) \) |
The moving time of the mobile robot along the line \( t \) (see Fig. 5) and the amount of successful robot’s passes are estimated within the experiment. The experimental data of the mobile robot when it moves along the first track (see Fig. 5, a) are given in Table 11. The experimental data of the mobile robot when it moves along the second track are given in Fig. 5, b (see Table 12).

The analysis of the experimental results (see Table 11) shows that the mobile robot has not done a move along the track in the experiment no. 1, when using the hard FIS. However, the mobile robot has successfully done all the movements along the track in all experiments (see Table 11), when using the soft FIS.

| Table 9 – Defuzzification variable \( Speed \) based on the soft fuzzy inference algorithm |
|----|----|----|----|----|----|----|----|----|----|----|----|----|----|
| \( m \) | 180 | 190 | 200 | 210 | 220 | 230 | 240 | 250 | 260 | 270 |
|----|----|----|----|----|----|----|----|----|----|----|----|
| 6.1 | 75 | 75 | 75 | 75 | 90.36 | 85.89 | 80.14 | 76.85 | 75 | 75 |
| 6.4 | 75 | 75 | 75 | 75 | 95.15 | 90.49 | 84.11 | 79.68 | 75 | 75 |
| 6.7 | 75 | 75 | 88.9 | 93.71 | 99.17 | 94.53 | 85.99 | 80.14 | 79.6 | 75 |
| 7 | 84.2 | 84.2 | 89.89 | 93.29 | 99.06 | 94.49 | 84.79 | 79.86 | 79.84 | 79.56 |
| 7.3 | 75 | 75 | 84.51 | 89.31 | 94.5 | 89.8 | 80.02 | 75.13 | 75.14 | 74.45 |
| 7.6 | 75 | 75 | 83.23 | 87.58 | 88.72 | 84.2 | 74.29 | 69.34 | 70.87 | 71.26 |
| 7.9 | 72.76 | 72.76 | 78.4 | 81.19 | 82.11 | 76.93 | 67.23 | 62.88 | 65.12 | 65.86 |
| 8.2 | 69.88 | 69.88 | 77.52 | 78.91 | 79.68 | 74.85 | 65.22 | 60.58 | 62.39 | 64.09 |
| 8.5 | 75 | 75 | 79.55 | 79.37 | 74.56 | 65.55 | 60.87 | 61.72 | 75 |
| 8.8 | 75 | 75 | 75 | 75 | 79.37 | 75.53 | 66.9 | 62.37 | 75 | 75 |
Table 10 – Defuzzification variable *Speed* based on the hard fuzzy inference algorithm

| m | 180 | 190 | 200 | 210 | 220 | 230 | 240 | 250 | 260 | 270 |
|---|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| 6.1 | 0 | 0 | 88.9 | 86.74 | 82.39 | 81.25 | 81.25 | 81.25 | 80.02 | 78.74 |
| 6.4 | 0 | 0 | 88.9 | 93.09 | 89.79 | 86.2 | 85.02 | 83.35 | 80.01 | 78.74 |
| 6.7 | 0 | 0 | 86 | 92.2 | 99.09 | 94.41 | 84.98 | 80.27 | 79.58 | 77.1 |
| 7.0 | 0 | 0 | 84.39 | 88.57 | 98.53 | 94.02 | 84.68 | 79.85 | 75.29 | 75 |
| 7.3 | 0 | 0 | 81.88 | 88.06 | 94.37 | 89.52 | 80.01 | 75.23 | 75.27 | 74.91 |
| 7.6 | 0 | 0 | 80.03 | 83.05 | 88.33 | 83.83 | 74.44 | 69.55 | 69.21 | 73.72 |
| 7.9 | 0 | 0 | 80.03 | 82.89 | 82.16 | 76.95 | 67.51 | 63.1 | 67.13 | 71.6 |
| 8.2 | 0 | 0 | 80.03 | 80.81 | 79.73 | 74.87 | 65.46 | 60.77 | 65.51 | 69.97 |
| 8.5 | 0 | 0 | 78.84 | 78.68 | 79.05 | 74.4 | 65.85 | 61.29 | 63.15 | 68.12 |
| 8.8 | 0 | 0 | 78.74 | 77.76 | 74.48 | 71.53 | 71.53 | 68.71 | 64.46 | 65.61 |

Table 11 – The robot moving along the track no. 1

| Experiment no. | Hard fuzzy inference | Soft fuzzy inference |
|----------------|---------------------|---------------------|
| u, V | m, gr. | Speed | t, sec. | u, V | m, gr. | Speed | t, sec. |
| 1 | 6.1 | 180 | 0 | – | 6.1 | 180 | 75 | 11.49 |
| 7.5 | 180 | 0 | – | 7.5 | 180 | 75 | 6.97 |
| 9 | 180 | 0 | – | 9 | 180 | 75 | 6.19 |
| 2 | 6.1 | 230 | 81 | 12.84 | 6.1 | 230 | 86 | 6.01 |
| 7.5 | 230 | 85 | 5.88 | 7.5 | 230 | 85 | 5.88 |
| 9 | 230 | 75 | 5.59 | 9 | 230 | 78 | 5.37 |
| 3 | 6.1 | 260 | 80 | 11.45 | 6.1 | 260 | 75 | 12.11 |
| 7.5 | 260 | 71 | 7.53 | 7.5 | 260 | 71 | 7.14 |
| 9 | 260 | 63 | 5.62 | 8.5 | 260 | 62 | 5.37 |

Table 12 – The robot moving along the track no. 2

| Experiment no. | Hard fuzzy inference | Soft fuzzy inference |
|----------------|---------------------|---------------------|
| u, V | m, gr. | u, V | m, gr. | u, V | m, gr. |
| 1 | 6.1 | 180 | – | – | 6.1 | 180 | 75 | 27.61 |
| 7.5 | 210 | 84 | 10.29 | 7.5 | 210 | 88 | 9.93 |
| 9 | 250 | 72 | 9.31 | 9 | 250 | 64 | 11.08 |

The result of the robot moving along the track no.2 are similar to the above mentioned result. Thus, the experiments show that the process of the mobile robot control is unstable.

Analyzing the results given in Table 12 one can conclude that if the power voltage supply of the mobile robot increases then the time of its passing the track decreases (see Fig. 9).

6 DISCUSSION

Different methods are possible to minimize RMSE. For example, ANFIS technology of finding the optimal conclusion of fuzzy rules is described in paper [24, 25, 26]. Nevertheless, the present research proves that it is possible to decrease RMSE at 30 % off if change the parameters *a* and *b* of the sigmoidal function Eq. (3). RMSE should be...
calculated for experimental values (see Table 3), if the parameters \( a \) and \( b \) of the sigmoidal function are changed (see Eq.(3)). Other parameters (see Table 3) are constant.

According to the results of the experiments, it is possible to conclude that: RMSE is 20.7 times less when using a soft fuzzy algorithm in comparison with a hard one. It is possible to minimize RMSE in 1.46 times if the parameters of the sigmoidal MF are changed. The mobile robot does not always accomplish a task if the hard FIS is used. The decision time for a track is minimized if the power voltage supply is increased. Therefore, a soft fuzzy system of decision-making is recommended to apply for a mobile robot control.

**CONCLUSION**

The problem of building a soft algorithm of fuzzy inference used to control a mobile robot is solved in the paper.

Scientific novelty of the results obtained in the article is that for the first time proposed soft algorithm, which in fuzzy inference to find minima and maxima uses soft arithmetic operators that provides additive of fuzzy control systems.

The practical significance of these results is that for the movement of the mobile robot along a line the specialized software based on the soft fuzzy algorithm is developed.

Prospects for further research consist in the fact that the improvement of the developed software for control of a mobile robot will allow to study given soft algorithm of fuzzy inference for a wide class tasks to control mobile robots.

**REFERENCES**

1. Shrovba S. D. Fuzzy classifier learning based on distance between the main competitors / S. D. Shrovba, A. V. Galushchak // Radio Electronics, Computer Science, Control. – 2016. – № 2. – P. 70–76. DOI: 10.15588/1607-3274-2016-2-9
2. Subbotin S. A. The neuro-fuzzy network synthesis with the ranking and specific encoding of features for the diagnosis and automatic classification on precedents / S. A. Subbotin // Radio Electronics, Computer Science, Control. – 2016. – №1. – P. 50–57. DOI: 10.15588/1607-3274-2016-1-6
3. Fateh M. M. A precise robust fuzzy control of robots using voltage control strategy / M. M. Fateh, S. Fateh // International Journal of Automation and Computing. – 2013. – № 10. – P. 64–72. DOI:10.1007/s11633-013-0697-x
4. High dimensional neurofuzzy systems: overcoming the curse of dimensionality / [M. Brown, K. M. Bossley, D. J. Mills, C. J. Harris] // Proceedings IEEE International Conference. – 1995. – №4. – P. 2139–2146. DOI: 10.1109/fuzzy.1995.409776
5. METSK-HDe: A multiobjective evolutionary algorithm to learn accurate TSK-fuzzy systems in high-dimensional and large-scale regression problems / [M. J. Gactoa, M. Galendeb, R. Alcalde, F. Herrera] // Information Sciences. – 2014. – Vol. 276. – P. 63–79. DOI:10.1016/j.ins.2014.02.047
6. Vernieuwea H. Comparison of clustering algorithms in the identification of Takagi–Sugeno models: A hydrological case study / H. Vernieuwea, B. De Baetsa, N. E. C. Verhoest // Fuzzy Sets and Systems. – 2006. – Vol. 157. – P. 2876–2896. DOI:10.1016/j.fss.2006.04.007
7. Bodianskyi Ye. V. Multilayer adaptive fuzzy probabilistic neural network in classification problems of text documents / Ye. V. Bodianskyi, N. V. Ryabova, O. V. Zolotukhin // Radio Electronics, Computer Science, Control. – 2015. – № 1. – P. 39–45. DOI: 10.15588/1607-3274-2015-1-5
8. Piegat A. Fuzzy modelling and control / A. Piegat – Physica-Verlag. Heidelberg, 2001. – 728 p. DOI:10.1007/978-3-7908-1824-6
9. Shin M. Reinforcement learning approach to goal-regulation in a self-evolutionary manufacturing system / M. Shin, K. Ryu, M. Jung // Expert Systems with Applications. – 2012. – Vol. 39. – P. 8736–8743. DOI: 10.1016/j.eswa.2012.01.207
10. Zadeh L. A. Some reflections on soft computing, granular computing and their roles in the conception, design and utilization of information/intelligent systems / L. A. Zadeh // Soft Computing. – 1998. – №2. – P. 23-25. DOI:10.1007/s005000050030
11. Bobyr M. V. Analysis of the use of soft arithmetic operations in the structure of fuzzy logic inference / M. V. Bobyr, N. A. Milostnaya // Vestnik kompyuternykh i informatsionnykh tekhnologii. – 2015. – Vol. 133. – P. 7–15. DOI:10.14489/ VKIT.2015.07.PP.007-015
12. Zadeh L. A. Fuzzy sets / L.A. Zadeh // Information and Control. – 1965. – № 8. – P. 338–353. DOI: 10.1016/S0019-9958(65)90241-X
13. Zadeh L. A. Fuzzy sets as a basis for a theory of possibility / L. A. Zadeh // Fuzzy Sets and Systems. – 1999. – Vol.100. – P. 9–34. doi:10.1016/S0165-0114(98)00004-9
14. Bobyr’ M. V. Automation of the cutting-speed control process based on soft fuzzy logic computing / M. V. Bobyr’, V. S. Titov, A. A. Nasser // Journal of Machinery Manufacture and Reliability. – 2015. – Vol. 44. – No. 7. – P. 61–69. DOI: 3.1013/ S1052618815070067
15. Stepniacka M. Implication-based models of monotone fuzzy rule bases / M. Stepniacka, B. De Baets // Fuzzy Sets and Systems. – 2013. – Vol. 232. – № 1. – P. 134–155. DOI: 10.1016/j.fss.2013.07.019
16. Kumanan S. Application of multiple regression and adaptive neurofuzzy inference system for the prediction of surface roughness / S. Kumanan, C. P. Jesuthanam, R. Ashok Kumar //
1. Bobyr M. V. The International Journal of Advanced Manufacturing Technology. – 2008. – Vol. 35. – P. 778–788. DOI: 10.1007/s00170-006-0755-4
2. Bobyr M. V. Effect of conclusion rule on training of fuzzy-logic systems / M. V. Bobyr // The International Journal of Advanced Manufacturing Technology. – 2012. – Vol. 63. – P. 373–390. DOI: 10.1007/s00170-012-3914-9
3. Bobyr M. V. Mobile Fuzzy System of Distribution of Braking Forces on the Engines of a Mobile Robot / M. V. Bobyr, V. S. Titov, A. Belyaev // MATEC Web of Conferences. – 2016. – Vol. 79. – P. 01052 DOI: 10.1051/matecconf/20167901052

Bobyr M. V. 1, Milostная H. A. 2
1 Д-р техн. наук, доцент, профессор кафедры вычислительной техники, Юго-Западный государственный университет, Курск, Россия
2 Канд. техн. наук, доцент, заведующий кафедрой вычислительной техники, Юго-Западный государственный университет, Курск, Россия

МАЯЧНЫЙ НЕЧЕТКИЙ АЛГОРИТМ ДЛЯ УПРАВЛЯЮЩЕГО МОБИЛЬНОГО РОБОТА

Актуальность. Решена задача управления мобильным роботом на основе мягкого алгоритма нечеткого логического вывода.

Цель работы – создание мягкого алгоритма нечеткого логического вывода, позволяющего обеспечить аддитивность нечеткой системы управления.

Метод. Предложен мягкий алгоритм нечеткого логического вывода, использующийся для управления мобильным роботом. Данный алгоритм позволяет компенсировать ошибки присущие традиционным моделям нечеткого вывода. К ошибкам относятся: промахи размерности, отсутствия аддитивности и условия разбиения единицы. Данный мягкий алгоритм нечеткого вывода, за счет рационального разбиения пределов и заключений в матрице нечетких отношений, позволяет сократить число операций необходимых для реализации нечеткого вывода. Другая отличительная особенность предложенного мягкого алгоритма заключается в том, что для нахождения в нечетком выводе минимумов и максимумов используются мягкое арифметическое моделирование. В статье показано, что при использовании жестких формул для реализации этих же формул в процессе управления мобильным роботом будут возникать ситуации в которых робот потеряет управляемость. В статье указано, что реализация возможности в мягким алгоритме нечеткого вывода опции изменения параметров сигмоидальных функций принадлежностей, позволяет минимизировать погрешности на его выходе. Об этом свидетельствует динамика изменения коэффициента RMSE от варьирования параметров сигмоидальной функции. Дополнительное имитационное моделирование представленное в статье показывает, что при варьировании коэффициентов погрешности сигмоидальной функции, в частности при увеличении параметра a наблюдается уменьшение значения RMSE. Эффективность предложенного мягкого алгоритма подтверждена представленное в статье численное моделирование и эксперименты исследования перемещения мобильного робота вдоль линии.

Результаты. Разработано специализированное программное обеспечение для микроконтроллера Arduino Uno, реализующее предложенный алгоритм, и позволяющее осуществить экспериментальное исследование его свойств.

Выводы. Проведенные численные и экспериментальные исследования подтвердили работоспособность предложенного мягкого алгоритма и реализующего его программного обеспечения, а также позволяют рекомендовать их для применения на практике для управления мобильными роботами.

Ключевые слова: нечеткая система вывода, нечеткие множества; RMSE; мягкое вычисления; мобильный робот.

Бобарь М. В. 1, Милостная Н. А. 2
1 Д-р техн. наук, доцент, профессор кафедры обчислительной техники, Пивденно-Західний державний університет, Курск, Росія
2 Канд. техн. наук, викладач кафедри обчислительной техники, Пивденно-Західний державний університет, Курск, Росія
формул в процесі управління мобільним роботом виникають ситуації в яких робот втратить керованість. Також в статті показано, що реалізація можливості в якому алгоритмі нечіткого виведення опції зміна параметрів сигмодальних функцій приналежностей, дозволить мінімізувати пограничність на його вихід. Про це свідчить динаміка зміни коефіцієнта RMSE від варіювання параметрів сигмодальної функції. Додаткове імітаційне моделювання представлене в статті показує, що при варіюванні коефіцієнтів сигмодальної функції приналежності, зокрема при збільшенні параметра а спостерігається зменшення значення коефіцієнта RMSE. Ефективність запропонованого мобільного алгоритму підтверджена представлено в статті чисельне моделювання і експерименти дослідження пере- міщення мобільного робота відносно ліній.

Результати. Розроблено спеціалізоване програмне забезпечення для мікроконтролера Arduino Uno, що реалізовує запропонован- ний алгоритм, і що дозволяє здійснити експериментальне дослідження його властивостей.

Висновки. Проведені чисельні і експериментальні дослідження підтвердили працездатність запропонованого мобільного алгоритму і реалізованого програмного забезпечення, а також дозволяють рекомендувати їх для вживання на практиці для управління мобільними роботами.

Ключові слова: нечітка система виведення, нечіткі множини; RMSE; м’які обчислення; мобільний робот.

REFERENCES

1. Shitova S. D., Galushchak A. V. Fuzzy classifier learning based on distance between the main competitors, Radio Electronics, Computer Science, Control, 2016, No. 2, pp. 70–76. DOI: 10.15588/1607-3274-2016-2-9
2. Subborin S. A. The neuro-fuzzy network synthesis with the ranking and specific encoding of features for the diagnosis and automatic classification on precedents, Radio Electronics, Computer Science, Control, 2016, No. 1, pp. 50–57. DOI: 10.15588/1607-3274-2016-1-6
3. Fateh M. M., Fateh S. A precise robust fuzzy control of robots using voltage control strategy, International Journal of Automation and Computing, 2013, No. 10, pp. 64–72. DOI:10.1007/s11633-013-0697-x
4. Brown M., Bossley K. M., Mills D. J., Harris C. J. High dimensional neuro-fuzzy systems: overcoming the curse of dimensionality, Proceedings IEEE International Conference, 1995, No. 4. pp. 2139–2146. DOI: 10.1109/fuzz.1995.409976
5. Gactoa M. J., Galende M., Acalific R., Herrera F. METSK-HDE: A multiobjective evolutionary algorithm to learn accurate TSK-fuzzy systems in high-dimensional and large-scale regression problems, Information Sciences, 2014, Vol. 276, pp. 63–79. DOI:10.1016/j.ins.2014.02.047
6. Vernieuwea H., De Baetsb B., Verhoest N.E.C. Comparison of neuro-fuzzy probabilistic network in classification problems of text documents, Radio Electronics, Computer Science, Control, 2015, No. 1, pp. 39–45. DOI: 10.15588/1607-3274-2015-1-5
7. Piegat A. Fuzzy modelling and control. Physica-Verlag, Heidelberg, 2001, 728 p. DOI:10.1007/978-3-7908-1824-6
8. Shin M., Ryu K., Jung M. Reinforcement learning approach to goal-regulation in a self-evolutionary manufacturing system, Expert Systems with Applications, 2012, Vol.39, pp. 8736–8743. DOI: 10.1016/j.eswa.2012.01.207
9. Zadeh L. A. Some reflections on soft computing, granular computing and their roles in the conception, design and utilization of information/intelligent systems, Soft Computing, 1998, No. 2., pp. 23–25. DOI:10.1007/s005000050303
10. Bobyr M. V., Milostnaya N. Analysis of the use of soft arithmetic operations in the structure of fuzzy logic inference, Vestnik kumtv ‘untuerych i informatsionnyh tekhnologii, 2015, Vol. 133, pp. 7–15. DOI:10.14489/VKIT.2015.07.PP.007-015
11. Zadeh L. A. Fuzzy sets, Information and Control, 1965, No. 8, pp. 338–353. DOI:10.1016/S0019-9958(65)90241-X
12. Zadeh L. A. Fuzzy sets as a basis for a theory of possibility, Fuzzy Sets and Systems, 1999, Vol.100, pp. 9–34. DOI: 10.1016/S0165-0114(99)00004-9
13. Bobyr M. V., Titov V. S., Nasser A. A. Automation of the cutting-speed control process based on soft fuzzy logic computing, Journal of Machinery Manufacturing and Reliability, 2015, Vol. 44, No.7, pp. 61–69. DOI: 10.3103/S1052618815070067.
14. Stepnicka M., De Baets B. Implication-based models of monotone fuzzy rule bases, Fuzzy Sets and Systems, 2013, Vol. 232, No.1, pp. 134–155. DOI: 10.1016/j.fss.2013.07.019
15. Kumanan S., Jesuthanam C. P., Ashok R. Kumar Application of multiple regression and adaptive neurofuzzy inference system for the prediction of surface roughness, The International Journal of Advanced Manufacturing Technology, 2009, Vol. 35, pp. 778–789. DOI:10.1007/s00170-006-0755-4
16. Chernova I. V., Sumin S. A., Bobyr M. V., Seregin S. P. Forecasting and Diagnosing Cardiovascular Disease Based on Inverse Fuzzy Models, Biomedical Engineering, 2016, Vol. 49, No. 5, pp. 263–267. DOI:10.1007/s10527-016-9545-y.
17. Driankov D., Hellendoorn H., Reinfrank M. An introduction to fuzzy control. Springer, Berlin, 1996, 316 p. DOI:10.1007/978-3-662-03284-8
18. Neshat M., Adeli A., Sepidnarm G., Sargolzaei M. Predication of concrete mix designing using adaptive neuro-fuzzy inference systems and fuzzy inference systems, The International Journal of Advanced Manufacturing Technology, 2012, Vol.63, pp. 373–390. DOI:10.1007/s00170-012-3914-9
19. Palani S., Natarajan U., Chellamalai M. On-line prediction of micro-turning multi-response variables by machine vision system using adaptive neuro-fuzzy inference system (ANFIS), Machine Vision and Applications, 2013, Vol.24, pp. 19–32. DOI: 10.1007/ s00138-011-0378-0
20. Deng X., Wang X. Incremental learning of dynamic fuzzy neural networks for accurate system modeling, Fuzzy Set and System, 2009, Vol. 60, pp. 972–987. DOI:10.1016/j.fss.2008.09.005
21. Banakara A., Azem M. F. Parameter identification of TSK neuro-fuzzy models, Fuzzy Sets and Systems, 2011, Vol. 179, pp. 62–82. DOI: 10.1016/j.fss.2011.05.003
22. Bobyr M. V. Effect of conclusion rule on training of fuzzy-logic systems, Vestnik kumtv ‘untuerych i informatsionnyh tekhnologii, 2014, Vol. 125, pp. 28–35. DOI: 10.14489/vkt.2014.11.pp.028-035
23. Azadeh A., Neshat N., Kazemi A., Saberi M. // Predictive control of drying process using an adaptive neuro-fuzzy and partial least squares approach, The International Journal of Advanced Manufacturing Technology, 2012, Vol.58, pp. 585–596. DOI: 10.1007/s00170-011-3415-2
24. Selekwfa M. F., Dunlap D. D., Shi D., Collins Jr. E. G. Robot navigation in very cluttered environments by preference-based fuzzy behaviors, Robotics and Autonomous Systems, 2008, Vol. 56, pp. 231–246. DOI:10.1016/j.robot.2007.07.006
25. Mo H., Tang Q., Meng L. Behavior-Based Fuzzy Control for Mobile Robot Navigation, Mathematical Problems in Engineering, 2013, 10 p. DOI: 10.1155/2013/561451