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# MODEL OF DECISION SUPPORT SYSTEM FOR BALL POSITIONING RELATIVE TO THE CENTER OF MOBILE BEAM

**Summary**. Article aims to show the possibility of building a decision support system for the control of technical systems based on analysis of the characteristics of the system. Intelligent decision support systems are able to actively assist during operation. In the literature were shown examples of the use of artificial intelligence techniques for effective control of the operation of different systems. Frequently used techniques of artificial intelligence are fuzzy sets and neural networks. This article aims to show the possibility of developing such a system.

# MODEL SYSTEMU WSPOMAGANIA DECYZJI POZYCJONOWANIA UKŁADU KULKI NA RÓWNOWAŻNI

**Streszczenie**. Artykuł ma na celu pokazać możliwość budowania systemu wspomagania kontroli układów technicznych na podstawie analizy wartości z charakterystyk. Inteligentne systemy wspomagania decyzji są w stanie aktywnie pomagać w czasie pracy. W literaturze wskazano wiele przykładów wykorzystania technik sztucznej inteligencji do skutecznego

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kontrolowania funkcjonowania różnych systemów. Najczęściej stosowanymi technikami inteligencji obliczeniowej są zbiory rozmyte i sieci neuronowe. Ten artykuł ma pokazać możliwości opracowania takiego systemu do badania układów technicznych.

## 1. Defining the problem

Designing an intelligent decision support system requires the assembly of sufficient knowledge about the system under study in order to achieve the verification of dynamic characteristics of the respondents. One of the simplest and effective methods of simulation of technical systems is genetic algorithm (GA). Application of GA methods in the simulation system, and thus the accumulation of knowledge about the test system, gives the ability to easily and effectively collect knowledge about the operation of the system as discussed in the literature [1, 5, 8]. Gathered in this way knowledge can be processed in such a way that the computer learns to identify operations on the basis of the facts. Effective learning and verification allow artificial intelligence techniques such as fuzzy sets and neural networks.

Fuzzy inference is based on linguistic values, discussed in the literature [4, 6, 9]. Linguistic value is what we use the most often in everyday life. These include statements such as "too much", "too little", "too high", "too low", "too fast" or "too slow". Such variables are mapped to values understood by the computer by appropriate membership functions. They allow to "blur" the specific value that describes the characteristics of the investigated system. Prepared in this way decision-making variables are pursued by the fuzzy inference rules. Fuzzy inference rule corresponds to a decision that a man could take on the basis of existing knowledge in the form of statements of "too fast" or "too slow". Fuzzy rule is implemented through the appointment of the acceptance by the appropriate model.

Neural networks allow to build a framework of knowledge usable by the computer in the way shown in literature [1, 8]. Knowledge about the system under study is absorbed by the computer during the learning process. The learning process is a mathematical algorithm that allows to built a decision-making network in a specific topic. Neural network itself is a set of consecutive coefficients of the matrix of network and the activation function representing the knowledge stored. Implementation of decisions by such structure shall be constructed on the basis of determining the values of the signal transmitted through the network, which perform respectively designated patterns.

For a system in which the ball is on the moving beam, ball movement along the beam is unaffected by external factors. Beam can rotate in a vertical plane around the center of the system. In the middle of the beam was used a support. The proposed decision support model will be designed to determine whether the specific values of the characteristics of the system can lead to loss of balance in the system under study. So this issue of designing a decision model can be described as determination of fuzzy or neural control that could put the ball in the equilibrium position regardless of where on the beam it resides.

## 2. Fuzzy system design

Fuzzy inference is based on the construction of a suitable set of rules for fuzzy linguistic values, what is described in literature [2, 4, 3, 7, 9]. A fuzzy set in $X$ is called a set of pairs

$$A = \{(x, \mu_A)\, x \in X, A \subseteq X\}\,, \tag{1}$$

where

$$\mu_A : X \to [0, 1] \tag{2}$$

is a function of $x$. The most commonly used in the literature [2, 4, 3, 7] are gaussian function class $s$ function. Gaussian function is described by the following formula

$$\mu_A\left(x\right) = \exp\left(-\left(\frac{x-c}{\sigma}\right)^2\right), \tag{3}$$

where the symbols mean $c$ – center of the function, $\sigma$ – span parameter of Gaussian curve. Class $s$ function is continuous for all values of the parameters $a$, $b$, $c$, and differentiable only if the equation $c - b = b - a$ is satisfied for the following formula

$$\mu_A(x) = \begin{cases} 0 & \text{for } x < a, \\ \frac{1}{2}\left(\frac{x-a}{c-a}\right)^2 & \text{for } a \leqslant x \leqslant c, \\ 1 - \frac{1}{2}\left(\frac{x-b}{c-b}\right)^2 & \text{for } c \leqslant x \leqslant b, \\ 1 & \text{for } x \geqslant b, \end{cases} \tag{4}$$

where symbols mean $c$ – middle range of membership, $a$ – distance to the left of center, $b$ – distance to the right of center.

To test the value of selected characteristics have been established factors in the Table 1.

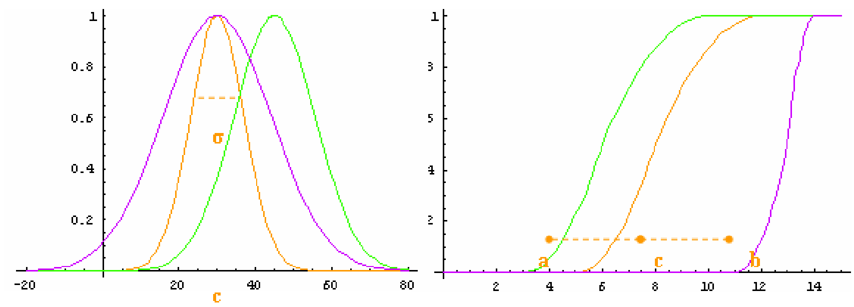


Fig. 1. Membership function charts: a) Gaussian for various parameters $c$ and $a$, b) the class $s$ function for different parameters $a$, $b$, $c$

Rys. 1. Funkcja przynależności: a) Gaussowska dla parametrów $c$ and $a$, b) klasy $s$ dla parametrów $a$, $b$, $c$

Table 1

Selected characteristics

| No. | Variable | Min | Max | Unit |
|---|---|---|---|---|
| 1 | r | -1.525 | 1.525 | meters |
| 2 | v | -6.1 | 6.1 | $\frac{\text{meters}}{\text{seconds}}$ |
| 3 | $\varphi$ | -45 | 45 | degree |
| 4 | $\omega$ | -200 | 200 | $\frac{\text{degree}}{\text{seconds}}$ |
| 5 | h | -1.078 | 1.078 | meters |

The values given in the Table 1 were transformed in an appropriate way to describe linguistic modification depending on the values of the formula (4) as follows:

"too little":

$$\mu_A^m(x) = \begin{cases} 1 & \text{for } x < a, \\ \frac{\left(\frac{x-a}{c-a}\right)^2}{2} & \text{for } a \leqslant x \leqslant b, \\ 1 - \frac{\left(\frac{x-c}{c-b}\right)^2}{2} & \text{for } b \leqslant x \leqslant c, \\ 0 & \text{for } x > c, \end{cases} \tag{5}$$

"too much":

$$\mu_A^m(x) = \begin{cases} 0 & \text{for } x < d, \\ \frac{\left(\frac{x-d}{e-d}\right)^2}{2} & \text{for } d \leqslant x \leqslant e, \\ 1 - \frac{\left(\frac{x-f}{e-f}\right)^2}{2} & \text{for } e \leqslant x \leqslant f, \\ 1 & \text{for } x > f, \end{cases} \tag{6}$$

where the following symbols mean $b$ – the middle of left compartment, $a$ – distance to the left of center $b$, $c$ – distance to the right of center $b$, $e$ – the middle of right compartment, $d$ – distance to the left of center $e$, $f$ – distance to the right of center $e$. Substituting appropriate values for $Min$ and $Max$ set in Table 1 we get variables describing the linguistic features shown in Figure 2.

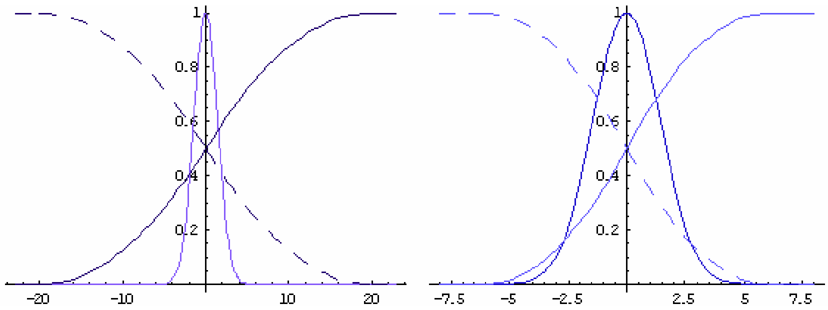


Fig. 2. Charts function describing a) distance $r$ and b) velocity $v$ according to the values described in Table 1

Rys. 2. Wykresy opisujące a) odległość $r$ oraz b) prędkość $v$ dla wartości opisanych w Tabeli 1

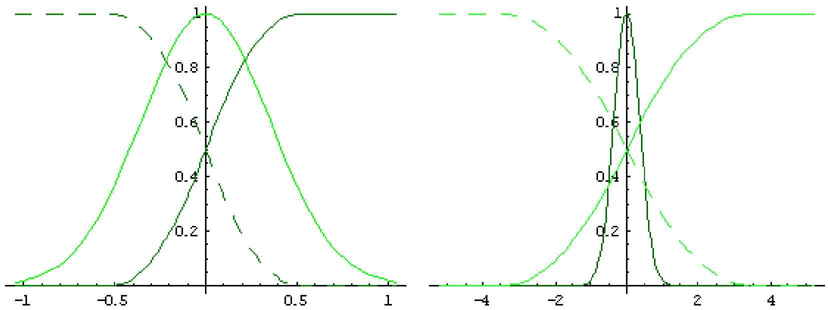


Fig. 3. Charts function describing a) the angle $\varphi$ and b) the angular velocity $\omega$ according to the values described in Table 1

Rys. 3. Wykresy opisujące a) kąt $\varphi$ oraz b) prędkość kątową $\omega$ dla wartości opisanych w Tabeli 1

On the basis of membership functions we can build a system of inference. Fuzzy rules help to control the presented system:

1. If the distance $r$ is "too much" or "too small" and the velocity $v$ is "too big" or "too small" and the angle $\varphi$ is "too small" or "too big" and the angular

velocity $\omega$ is "too large" or "too small" and the height $h$ is "too big" or "too small" then to balance the beam change the force $u$.

2. If the distance $r$ is the "correct" and the velocity $v$ is the "correct" and the angle $\varphi$ is the "correct" and the angular velocity $\omega$ is the "correct" and the height $h$ is the "correct" then to balance the beam do not change the force $u$.

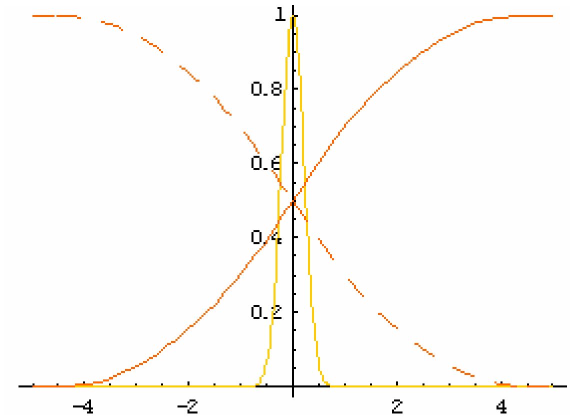


Fig. 4. Graph of the function describing the height $h$ according to the values described in Table 1
Rys. 4. Wykres opisujący wysokość $h$ dla wartości opisanych w Tabeli 1

Built in this way control system can be further improved by introducing a linear control equation. Linear control equation for distance from center of the system $|r| < 20$ and deviation angle from the balance $|\varphi| < \frac{\pi}{6}$ and also $|h| < 4.5$:

$$u = -0.0418 \cdot r - 0.1851 \cdot \frac{dr}{dt} + 6.4679 \cdot \varphi + 3.7331 \cdot \frac{d\varphi}{dt}. \tag{7}$$

## 3. Neural network design

The decision support system can also be designed based on the neural network. In this case, the computer will need the knowledge to describe the state space in the most accurate way. To build a state space description of the system was applied GA. As a result of GA characteristics of the simulated values were obtained points of the state space, described in a similar way by the authors [1]. Prepared in this way knowledge is processed in learning. Learning process itself is carried out according to the equation method of back propagation (BP) described by the following equation

$$w_{ij}^{k}(n+1) = w_{ij}^{k}(n) + \eta \cdot \left(-\nabla_{ij}^{k}(n)\right), \tag{8}$$

where the symbols mean: $w_{ij}^{k}$ – value of the coefficient matrix of connection weights for the $k$-th layer in the $n$-th epoch of the learning process for the connection between the $i$-th and $j$-th neuron, $\eta$ – factor in the process of teaching adopted by BP network learning, $\nabla_{ij}^{k}(n)$ – gradient value of the error function, which corrects the interlayer connection weights during the learning process calculated for the $k$-th layer and the $n$-th epoch.

Network learning process takes place during the $n$ periods in which the network forms knowledge of space events. The criterion for completion of the learning process is to achieve a specified level of network error

$$B(n) = \sum_{T} \epsilon^{2}(x), \tag{9}$$

where the symbols mean $T = \{x, y(x)\}$ – set trainee, $\epsilon(x)$ – residual function, which in part is a nonlinear: $\epsilon_{i}^{k} = d_{i}^{k}(n) - y_{i}^{k}(n)$.

Residual function is understood as the difference between the value returned by the network as $y_{i}^{k}(n)$ and approximated function (expected) by the network as $d_{i}^{k}(n)$. Learning process of the proposed neural network was presented in the illustrations, showing examples of the process of learning.

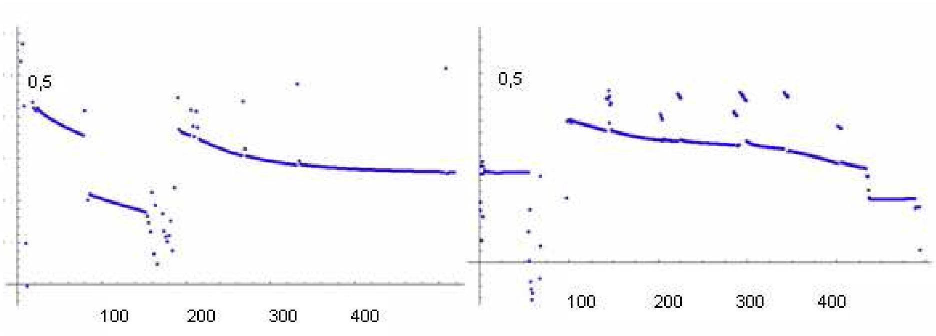


Fig. 5. Graphs of the learning process as a function of the error
Rys. 5. Wykres funkcji błędu w procesie nauczania

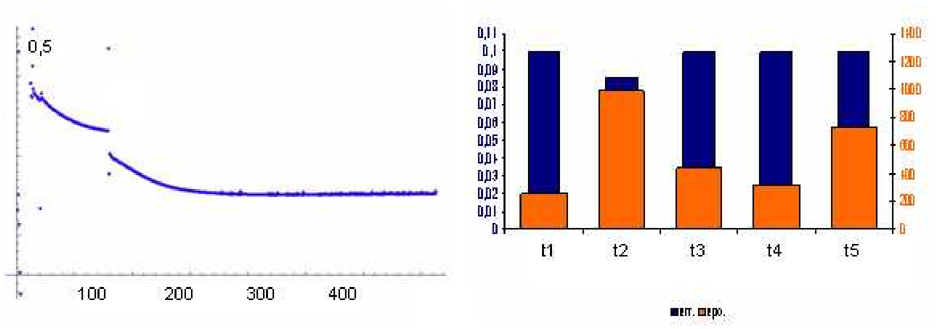


Fig. 6. Charts of learning process a) the error function in the individual epochs of the learning process, b) values of individual neurons at the and of the learning
Rys. 6. Wykresy opisujące proces nauczania: a) wartości funkcji błędu w kolejnych epokach procesu uczenia, b) wartości na wyjściu sieci na koniec procesu uczenia

Therefore, as knowledge of best quality was selected, the following system of matrixes was formulated. A matrix $A$ of connection weights in the neural network is shown in (10):

$$A = \begin{bmatrix} 0.192749 & 0.718096 & -0.657197 & 0.982485 \\ -0.784534 & -0.569059 & 0.913427 & 0.921139 \\ 0.308426 & 0.738595 & 0.00525528 & 0.561448 \\ 0.638206 & 0.820588 & 0.528583 & -0.243037 \\ 0.398055 & -0.639838 & 0.427844 & 0.308628 \\ 0.680163 & -0.672255 & -0.0645069 & 0.339789 \end{bmatrix}. \tag{10}$$

A matrix $B$ of connection weights in the neural network is shown in (11):

$$B = \begin{bmatrix} -0.512585 & -0.390351 & -0.40731 \\ 0.357304 & -0.728051 & -0.821293 \\ -0.320737 & 0.436164 & -0.0364768 \\ -0.559888 & 0.674007 & 0.874716 \end{bmatrix}. \tag{11}$$

# 4. Conclusions

Actions that are described in the work show the possibility of designing a decision support system by constructing an appropriate fuzzy inference system or by designing an appropriate neural network. Designing fuzzy decision support system is based mostly on setting rules and mathematical description of the object characteristics. The network can not examine the value of the test in a "continuous" as is the case for the fuzzy inference system. Neural network determines the value of "points" based solely on their knowledge. This means that if the learning process for a network space points will be sufficiently accurate depiction of the network may take the wrong decision. In the case of fuzzy inference system, the decision is based on linguistic values which are represented by continuous functions belonging. It follows that such a system is capable of making the correct decision at any point in the present study of the state space.

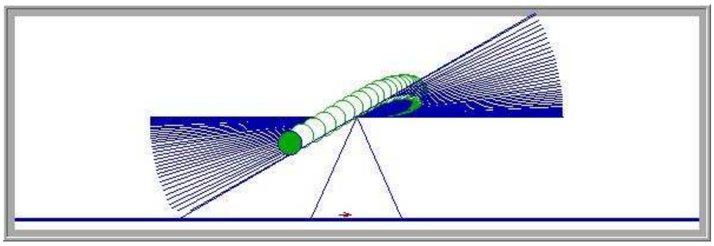

Fig. 7. Control simulation of the object
Rys. 7. Symulacja kontroli ruchu belki po równoważni

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## Omówienie

W artykule przedstawiono modelowanie systemu wspomagania decyzji. System wspomagania podejmowania decyzji jest ważnym elementem, który może efektywnie wspierać operatora urządzeń technicznych w trakcie pracy. W przedstawionym artykule omówione zostały dwie możliwości zbudowania efektywnych systemów wspomagania decyzji. Opracowane systemy wspomagające mogą usprawniać kontrolę ruchu kulki po równoważni. Pierwszym jest system rozmyty, a drugim neuronowy. Przedstawiona praca pokazuje w jaki sposób można zbudować efektywne systemy wspomagania kontroli wykorzystując do tego celu metody i techniki sztucznej inteligencji. Oba przedstawione rozwiązania mogą wspomagać kontrolę ruchu kulki po równoważni w czasie rzeczywistym.