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Structural optimization of fuzzy systems' rules base and aggregation models

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Abstract

Purpose – The purpose of this paper is to propose a general method to simplify the structure of fuzzy controllers' rule base using integrated methodology for reducing the number of fuzzy rules based on modelling and simulation.

Design/methodology/approach – The paper considers the problem of developing effective methods and algorithms for optimization of fuzzy rules bases of Sugeno-type fuzzy controllers that can be applied to control of dynamic objects, including objects with non-stationary parameters. The proposed approach based on calculating the impact of each of the rule on the formation of control signals for different types of input signals provides optimization of a linguistic rules database by using exclusion mechanism for rules with negligible influence. The effectiveness of the proposed approach is investigated using a fuzzy PID controller for control of a non-stationary object of second order.

Findings – In this paper, the authors argued that different aggregation models can be used for structural optimization of fuzzy controllers and not all the rules are actually required in the fuzzy controllers' rule base. Eliminating some of the rules does not necessarily lead to a significant change in the fuzzy controller's output. The proposed integrated approach based on combination of different kinds of reference input signals for fuzzy controllers modelling and simulation is able to provide guidelines to the users which rules are required and which can be eliminated. The results obtained from the case studies demonstrate that the proposed integrated approach is able to reduce the number of rules required and, at the same time, to have the desired values of quality control indices.

Research limitations/implications – In order to demonstrate the feasibility of the proposed approach, only control object of second order with PID fuzzy controller of Sugeno-type is chosen. Future studies can advance this research by applying the proposed approach in different types of fuzzy systems.

Practical implications – The proposed integrated approach is able to simplify the structural optimization methodology and make it possible to be implemented in real processes of the fuzzy controllers' design.

Originality/value – The value of the current paper is on the proposal of an integrated approach for rule reduction to enhance the practical use of modelling and simulation in a design of fuzzy controllers.

Keywords Fuzzy logic, Simulation, Control systems, Optimization techniques, Fuzzy controller, Structure, Optimization, Rules base, Aggregation model

Paper type Research paper

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Introduction

Fuzzy sets theory and fuzzy logic have been widely introduced into research and design practice recently. From the first study of fuzzy sets (Zadeh, 1965) researches received the theoretical foundation introducing fuzzy sets for successful solving of various problems in uncertainty (Gil-Aluja, 1999; Gil Lafuente, 2004; Hampel *et al.*, 2000; Negoita, 2009; Padet, 1996).

Especially it is important and effective for control of such objects with non-stationary functioning conditions as ships, underwater robots, manipulated systems with moving base and others. So, fuzzy controllers are components of one of the most important class of the fuzzy systems (Oh and Pedrycz, 2002) and their optimization has a significant impact on the efficiency of control processes (Buckley, 1993).

Special attention should be paid to structural-parameter optimization of fuzzy systems for their applications in engineering where fuzzy controllers are components of embedded computer systems (Kovacic and Bogdan, 2006; Michels *et al.*, 2006).

A number of methods of fuzzy controllers's synthesis (Arkhangelsky *et al.*, 1997; Buckley, 1993; Kondratenko and Al Zu'bi, 2009; Mizumoto, 1995) have been developed to date. They provide the desired quality control in fuzzy systems by optimizing parameters of membership functions (Lee and Chou, 2001) of linguistic terms and by using different aggregation models (Piegat, 2001; Werners, 1988; Zimmermann and Zysno, 1980). As an objective function in the implementation of these methods an integral quadratic criterion or standard deviation of the real transition from desirable are usually used.

At the same time, rules, that determine the control strategy (Hu *et al.*, 2008; Ortega *et al.*, 2003; Pedrycz and Vukovich, 2000; Stefanuk and Zhozhikashvili, 2002), are based on expert assessments for all possible combinations of linguistic terms. The described above approach does not take into account the redundancy of complete database rules, which makes the structure of fuzzy controllers too complicated and does not use the ability of fuzzy logic systems for extrapolation. The genetic algorithm was developed in Ho *et al.* (2008) for generalizing a set of nearly optimal fuzzy rules in quality enhancement based on the extracted fuzzy association rules in a supply chain network. The problem of reducing the numbers of rules in the rule base of fuzzy systems are considered in Tay and Lim (2006), Korvin and Shipley (2005) and Hayajneh *et al.* (2006).

Thus, the development of algorithms to optimize the structure of fuzzy controllers is quite necessary (Jantsen, 1997; Oleynik and Subbotin, 2009; Piegat, 2001; Sanchez and Otero, 2007; Yager and Filev, 1994), as it will simultaneously improve the performance of fuzzy control devices by decreasing the number of computer operations and reduce the complexity of the synthesis process of fuzzy controllers by decreasing the number of optimization parameters in the tasks of nonlinear programming.

General problem statement

This paper offers the introduction stage of structural optimization to the procedures of forming the base of linguistic rules of fuzzy controllers based on integrated approach for modeling and simulation. This stage is based on the identification of the impact level of linguistic rules on the defuzzified output control signal and building the appropriate ranked series of rules according to this specified parameter. The obtained ranked series will allow deleting the rules, whose impact on the formation of controller output signal is negligible, from the linguistic base. The correctness of excluding certain rules must be confirmed by comparing the quality of fuzzy control systems for two options: the complete and optimized knowledge bases of rules.

To test the proposed approach, the solution to the structural optimization problem of fuzzy PID controller (Mizumoto, 1995) for non-stationary control objects will be analyzed. This fuzzy controller is based on the fuzzy inference engine of Sugeno-type (Takagi and Sugeno, 1985) with linear functions of input signals in the consequents of linguistic rules. The output component of each rule is a PID-law control variable which was formed by parametric optimization within the gradient method according to the input signal vector of fuzzy controller, which looks like:

$$X = \{x_1(t), x_2(t), x_3(t)\} = \left\{\varepsilon(t), \int \varepsilon(t)\ dt, \frac{d\varepsilon}{dt}\right\},$$

where ε is the error of fuzzy control system. The integral quadratic criterion of the control quality plays the role of the objective function during parametric optimization. For fuzzyfication of each input signal we will use three linguistic terms with Gaussian form of membership function (Pedrycz, 1993; Piegat, 2001), which uniformly cover the range of possible values of corresponding input signals. Thus, the full linguistic knowledge base of the considered fuzzy controller consists of 27 linguistic rules such as:

$$\begin{aligned} i:\quad & \text{IF } x_1(t) \in \mu_{1,[(i-1)\, div\, 9]+1} && \text{AND} \quad x_2(t) \in \mu_{2,[((i-1)\, div\, 3) \bmod 3]+1} \\ & \text{AND} \quad x_3(t) \in \mu_{3,[(i-1) \bmod 3]+1} && \text{THEN} \quad u = k_{i,1}x_1 + k_{i,2}x_2 + k_{i,3}x_3, \end{aligned}$$

where i is number of rules, $i = 1\ldots27$; *div* and *mod* are operations of integer division and taking remainder of the division, respectively; $x_j\ (t)$ is component of input signal vector of fuzzy controller, $j = 1, 2, 3$. For example, for rules 5, 16 and 24 we can write:

$$\begin{aligned} i = 5:\quad & \text{IF} \quad x_1(t) \in \mu_{1,1} \quad \text{AND} \quad x_2(t) \in \mu_{2,2} \quad \text{AND} \quad x_3(t) \in \mu_{3,2} \\ & \text{THEN} \quad u = k_{5,1}x_1 + k_{5,2}x_2 + k_{5,3}x_3, \\ i = 16:\quad & \text{IF} \quad x_1(t) \in \mu_{1,2} \quad \text{AND} \quad x_2(t) \in \mu_{2,3} \quad \text{AND} \quad x_3(t) \in \mu_{3,1} \\ & \text{THEN} \quad u = k_{16,1}x_1 + k_{16,2}x_2 + k_{16,3}x_3, \\ i = 24:\quad & \text{IF} \quad x_1(t) \in \mu_{1,3} \quad \text{AND} \quad x_2(t) \in \mu_{2,3} \quad \text{AND} \quad x_3(t) \in \mu_{3,3} \\ & \text{THEN} \quad u = k_{24,1}x_1 + k_{24,2}x_2 + k_{24,3}x_3. \end{aligned}$$

Analysis of the impact of the reduced rule base on the effectiveness of control system

The information in a fuzzy controller during the process of forming the output signal is undergoing a number of successive stages of transformation, such as fuzzyfication, aggregation, activation, accumulation, and defuzzyfication (Jantsen, 1997; Kondratenko and Al Zu'bi, 2009; Pedrycz, 1993; Piegat, 2001). In fuzzy Sugeno-type controllers the output control signal is calculated as the position of the centre of material points masses located on the abscissa axis. The coordinates of these material points describe the output signal values formed at the output of each rule according to PID-law control, and points mass describes the degree of truth of the corresponding rule, calculated at the stage of aggregation. It is obvious that the smaller the weight of a point, the smaller its impact on the overall centre of mass and, consequently, on the value of the control signal. Thus, assessing (on the stage of designing fuzzy controllers) the change of the rules' truth degree in the control process enables to rank the rules according to their influence on the value of output control signal and henceforth to optimize the fuzzy linguistic database by deleting those rules, whose influence is too low. Changing the degree of truth of ith rule in the control process with corresponding reference signal is expressed by the following function of model time, t:

$$\mu_i^R(t) = \mathop{U}_{j=1}^{m} \mu_j^i(x_j(t)) = \inf_{j=1}^{m} \mu_j^i(x_j(t)), \tag{1}$$

where $\mu_i^R(t)$ is the degree of truth of ith rule in time moment t; x_j (t) is jth input fuzzy controller signal, $j = 1\ldots m$, $m = 3$; μ_j^i is the result of fuzzyfication of jth input signal x_j (t) by the corresponding linguistic term of ith rule.

The nature of transients in fuzzy control systems greatly depends on the type of reference signal and disturbing influence. Therefore, to ensure comparability of simulation conditions and real conditions of control system functioning it is advisable to conduct model experiments, in which the most common types of reference and disturbing inputs (Table I) are combined (control input: step, harmonic, linear-rising; disturbing input: step, linear-rising, harmonic, pulse, stochastic).

Figures 1-6 show the calculated by expression (1) dynamic dependences of the rules validity degrees in the control process at the output of a single step reference signal with permanent disturbance. As shown in Figures 2-6, the truth value of the rules set:

$$\mathbf{R}_1 = \{1, 2, 4, 5, 6, 7, 8, 9, 10, 11, 15, 16, 17, 18, 20, 21, 23, 25, 26\}$$

does not exceed $\mu = 0, 1$, and for the rules set $\mathbf{R}_2 = \{3, 12, 23, 27\}$ the truth throughout the transient process is about zero (Figure 6). Thus, the impact of rules, that are members of sets $\mathbf{R}_1$ and $\mathbf{R}_2$, is lower than that of other rules.

The next step is forming a ranked series of rules. It is necessary to choose such evaluative function $G[\mu_i^R(t)]$, the input for which is dependence $\mu_i^R(t)$of ith rule influence in time moment t on the control signal and the output is scalar value G_i, which represents a generalized characteristic of the rule impact on the control signal formation during the entire transient process.

One of the possible ways of building an assessment functional $G[\mu_i^R(t)]$ is the integration of expression (1) with subsequent averaging of functional values obtained

Table I. Combined reference-disturbance inputs for different versions of simulation f fuzzy controllers within the control system

Type of input signal	Number of modelling experiment 1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Control step input	+			+	+	+	+							
2. Control harmonic input		+	+					+	+	+	+	+	+	+
3. Control linear-rising input			+								+	+	+	+
4. Disturbing step input				+				+			+			
5. Disturbing linear-rising input												+		
6. Disturbing harmonic input					+									
7. Disturbing pulse input							+		+				+	
8. Disturbing stochastic input						+				+				+

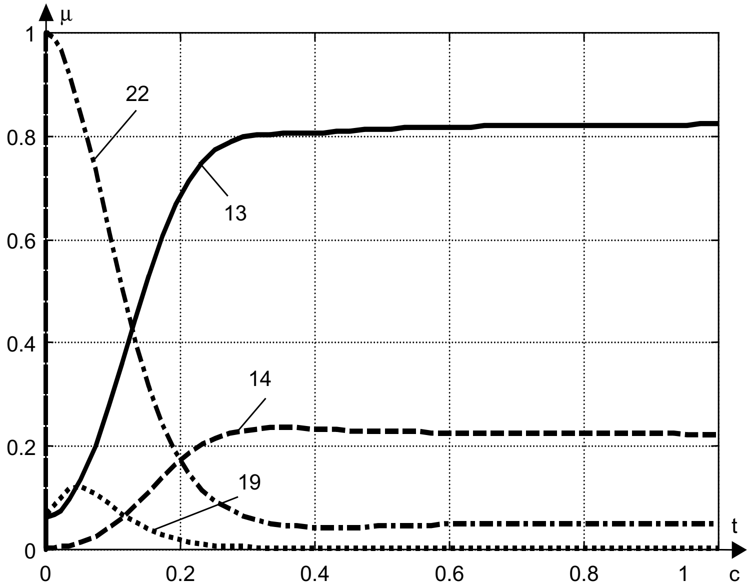


Figure 1.
Dependence $\mu_i^R(t)$ of the rules {13, 14, 19, 22} impact on the control signal (u) value

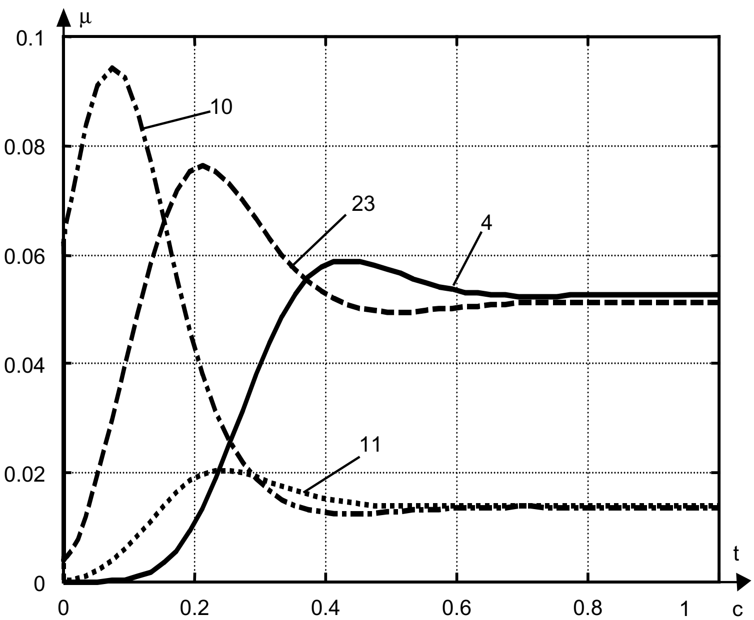


Figure 2.
$\mu_i^R(t)$ for the rules {4, 10, 11, 23}

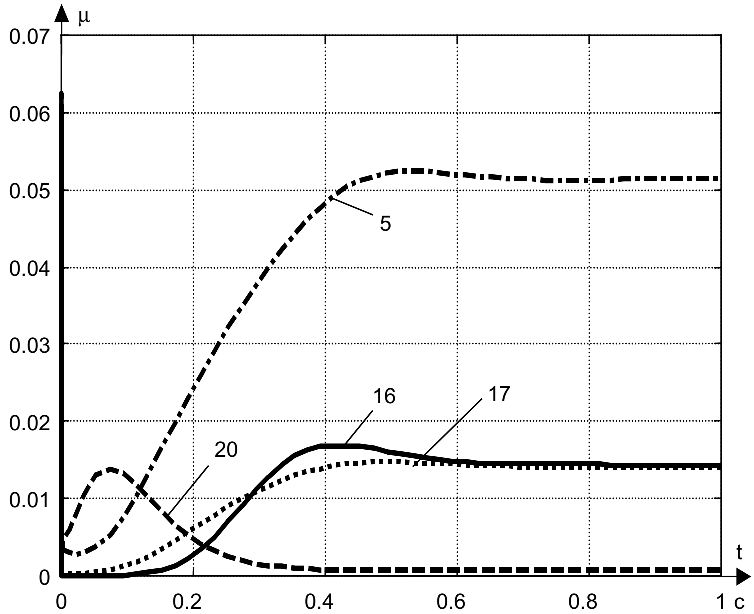


Figure 3.
$\mu_i^R(t)$ for the rules {5, 16, 17, 20}

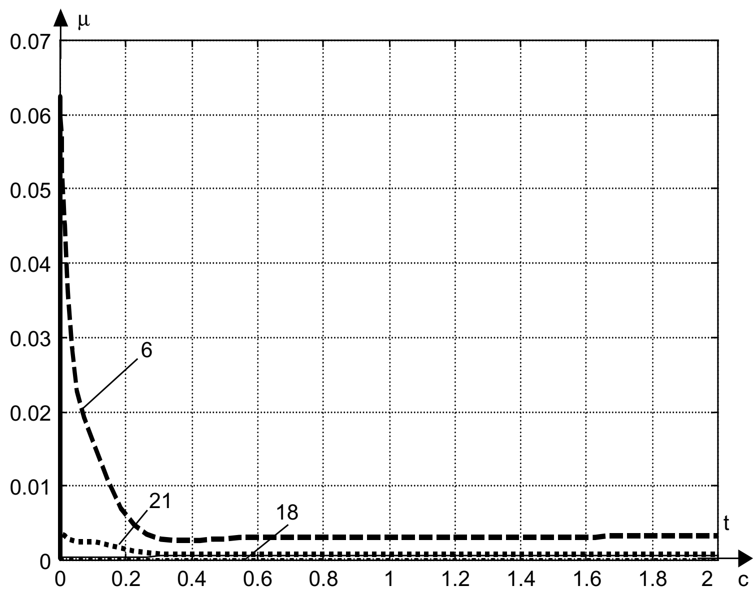


Figure 4.
$\mu_i^R(t)$ for the rules {6, 18, 21}

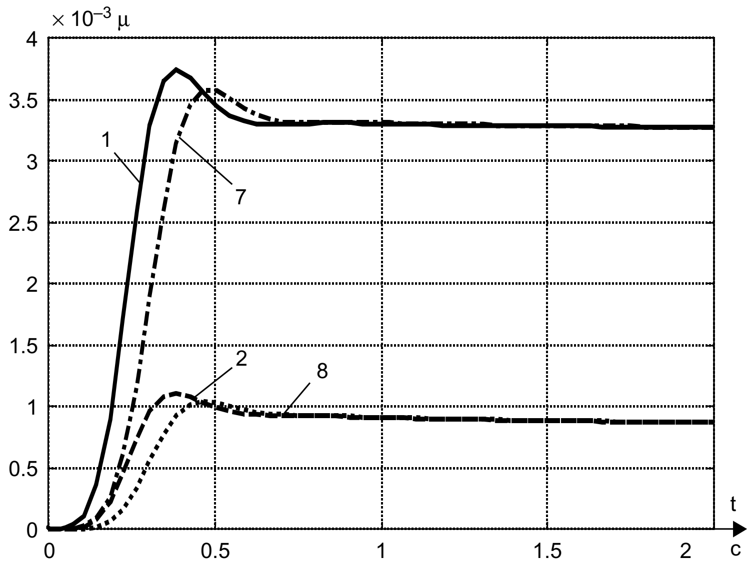


Figure 5.
$\mu_i^R(t)$ for the rules {1, 2, 7, 8}

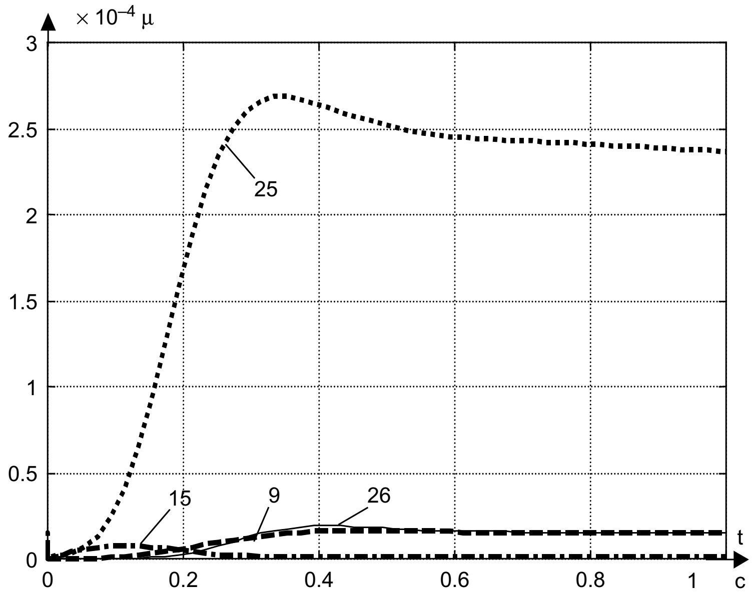


Figure 6.
$\mu_i^R(t)$ for the rules {9, 15, 25, 26}

in different conditions of the transient flow. The analytical representation of the proposed estimated functional is:

$$G_i\left[\mu_i^R(t)\right] = \frac{1}{T_{\max}} \int_0^{T_{\max}} \mu_i^R(t)\ dt = \frac{1}{T_{\max}} \int_0^{T_{\max}} \inf_{j=1}^{m} \mu_j^i(x_i(t))\ dt, \tag{2}$$

where G_i is the evaluation function value for ith rule; $T_{\max}$ is the duration of the transient process.

It is suggested that prior to ranking rules the values of the assessment functional, obtained in different simulation conditions (Table I), and should be averaged according to the algorithm:

$$G_i^{av}\left[\mu_{i,1}^R(t), \mu_{i,2}^R(t), \ldots \mu_{i,s}^R(t)\right] = \frac{1}{s}\sum_{k=1}^{s} G_{i,k}\left[\mu_{i,k}^R(t)\right], \tag{3}$$

For illustration of proposed integrated approach the average values of functional (3) for all 27-linguistic rules of the investigated fuzzy PID-controller are presented in the diagram (Figure 7).

The series formed by the ranking rules in descending order of their degree of influence on the control signal, is the following:

$$\mathrm{R} = \{13, 22, 14, 19, 4, 23, 10, 11, 5, 16, 20, 17, 1, 7, 2, 8, 6, 21, 25, 26, 9, 15, 18, 3, 27, 24, 12\}. \tag{4}$$

Later, it is possible to determine the critical (minimum) number of rules from equation (4), for which the index value of control quality will remain within acceptable limits. The task can be solved by simulation and analysis of transients in the fuzzy control system, starting with minimal linguistic database – a single rule with the highest rank, in particular rule 13. In this case, the fuzzy Sugeno-type controller functionally

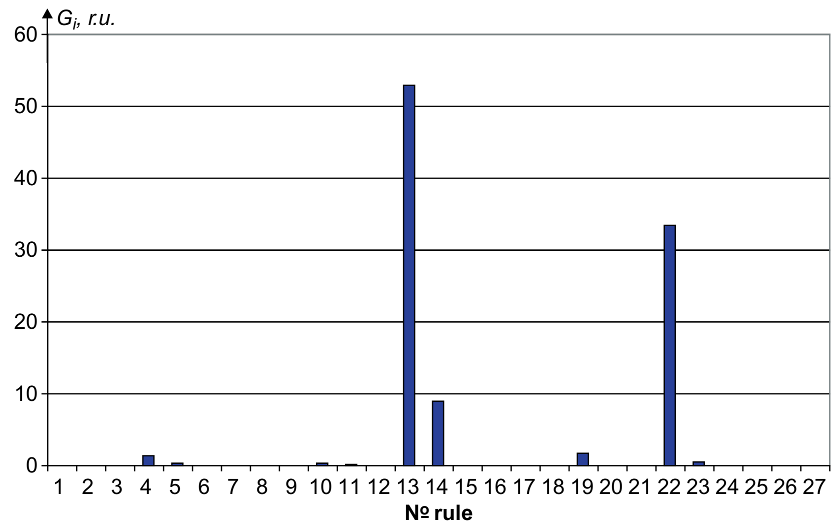
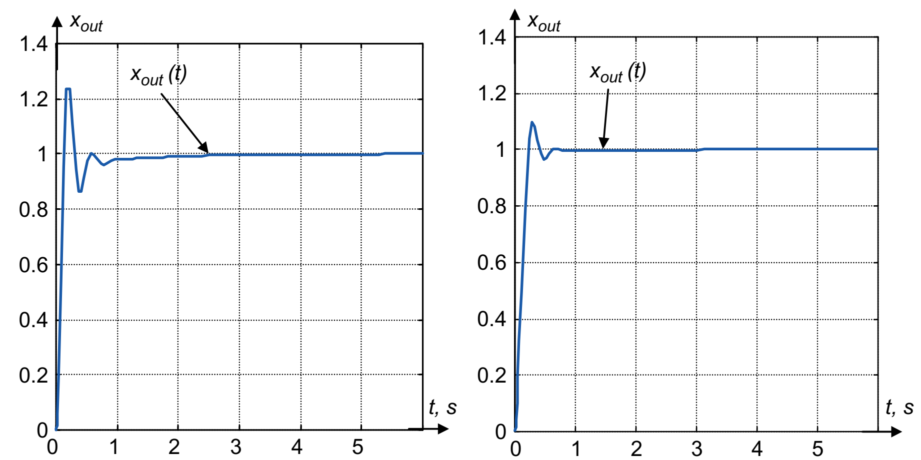


Figure 7.
Averaged evaluation functional $G_i\left[\mu_i^R(t)\right]$ for the Sugeno-controller base of rules

transforms into the traditional PID-regulator. Modelling process is repeated, the gradually adding rules to the linguistic knowledge base of fuzzy Sugeno-type controller in the order determined by the ranked series (4) until the control quality indices are within the limits determined by technical requirements.

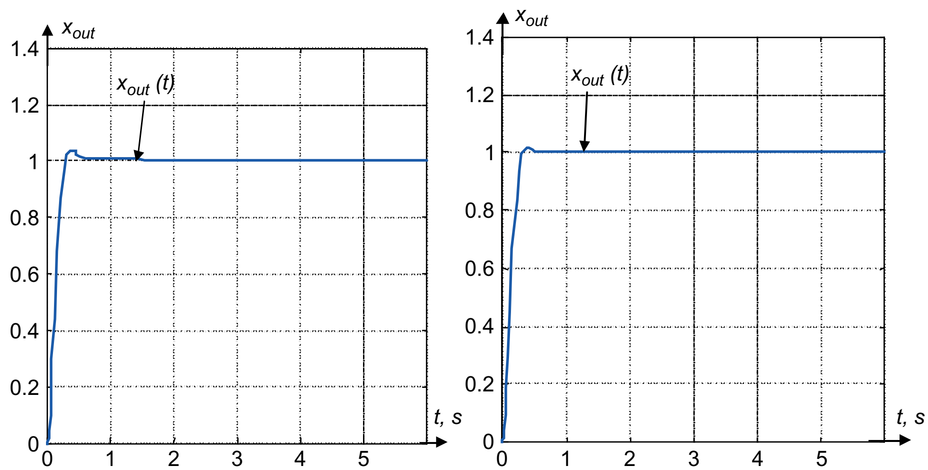
The described procedure was used for all above mentioned combinations of reference inputs and disturbing influences. The simulation enabled to determine the nature of the transient characteristics changes of fuzzy control systems with increasing number of rules (Figures 8 and 9). Thus, analyzing Figures 8 and 9, one can conclude that after the inclusion of the first seven rules of ranked series (4) to an optimized



(a) Knowledge base with one rule

(b) Knowledge base with two rules

Figure 8. Transient processes in fuzzy control system with one and two rules



(a) Knowledge base with four rules

(b) Knowledge base with seven rules

Figure 9. Transient processes in fuzzy control system with four and seven rules

knowledge database, its further expansion does not significantly affect the improvement of control quality. Based on the proposed conception of fuzzy controllers' structural optimization it is possible to formalize the following algorithm to reduce the amount of linguistic rules in knowledge database:

- *Step 1.* Calculating according to the expression (1) the functions of truth changes $\mu_i^R(t)$ for all the rules during control process.
- *Step 2.* Calculating evaluation $G_i\left[\mu_i^R(t)\right]$ with expression (2) and their averaging according to equation (3) for different modes of simulation.
- *Step 3.* Ranking the base of linguistic rules of fuzzy controller based on their impact on the control signal according to the value of evaluation functional $G_i\left[\mu_i^R(t)\right]$.
- *Step 4.* The formation of an optimized rules database by gradually adding rules to it (as defined in ranked series) with permanent monitoring of quality control indices.

The aggregation models and other directions for structural optimisation

It is necessary to make the structural optimization of fuzzy controllers by the consecutive or combined changes in the structure of the fuzzy controllers' information processing algorithms if the required parameters of fuzzy systems quality are not satisfied after realization of parametrical optimization of fuzzy controllers.

One of the variants for structural optimization of fuzzy controllers (before Rule Base reducing) is a choice of the most effective algorithms for the aggregation processes in the framework of the given structure of fuzzy control systems.

The algorithms, which are based on the published in Jantsen (1997) approach, use min-max gravity method. During the realization of this method the following fuzzy information processing algorithms are applied:

$$\mu_A \cap \mu_B = \min\ (\mu_A, \mu_B),$$
$$\mu_A \cup \mu_B = \max\ (\mu_A, \mu_B).$$

Another product-sum gravity method is on the basis of algorithms (Piegat, 2001):

$$\mu_A \cap \mu_B = \mu_A \cdot \mu_B,$$
$$\mu_A \cup \mu_B = \mu_A + \mu_B.$$

The structural optimization of fuzzy controllers may be carried out on the basis of application of analogues probabilistic processings of the fuzzy information (Piegat, 2001) as follows:

$$\mu_A \cap \mu_B = \mu_A \cdot \mu_B;$$
$$\mu_A \cup \mu_B = \mu_A + \mu_B - \mu_A \cdot \mu_B.$$

Special attention should be paid to the algorithms "fuzzy AND" and "fuzzy OR" (Werners, 1988):

$$\mu_A \cap \mu_B = \gamma \min\ (\mu_A, \mu_B) + (1 - \gamma)\frac{(\mu_A + \mu_B)}{2},$$

$$\mu_A \cup \mu_B = \gamma \max(\mu_A, \mu_B) + (1-\gamma)\frac{(\mu_A + \mu_B)}{2},$$

as well as compensation algorithms (Zimmermann and Zysno, 1980):

$$\mu_A \cap \mu_B = (\mu_A + \mu_B - \mu_A \cdot \mu_B)^{(1-\gamma)}(\mu_A \cdot \mu_B)^{\gamma};$$

$$\mu_A \cup \mu_{B_B} = (\mu_A \cdot \mu_B)^{(1-\gamma)}(\mu_A + \mu_B - \mu_A \cdot \mu_B)^{\gamma},$$

where γ is a compensation parameter.

Other ways for realization of fuzzy controllers' structural optimization (Kondratenko and Al Zu'bi, 2009; Lee and Chou, 2001) are related:

- with changing of chosen membership function's forms; and
- with changing of the quantity of linguistic terms $L_{X_i} = \left\{L^1_{X_i}, L^2_{X_i}, \ldots, L^k_{X_i}, \ldots, L^{K-1}_{X_i}, L^K_{X_i}\right\}$ for input signals X_i and linguistic terms $L_u = \left\{L^1_u, L^2_u, \ldots, L^h_u, \ldots, L^{H-1}_u, L^H_u\right\}$ of output signal u, where K and H are total numbers of corresponding linguistic terms.

Before each following step of fuzzy controllers' structural optimization it is expedient to carry out parametrical optimization for the parameters of membership functions and also by γ parameter of fuzzy information processing algorithms on the aggregation stage.

Conclusions

The concept and algorithm for optimization of fuzzy linguistic rules database of fuzzy controllers was tested on a fuzzy PID controller for control of a non-stationary object of second order. As a result of the optimization the total number of rules in the linguistic base was successfully reduced from 27 to seven without compromising the quality of the fuzzy control system, which confirms the effectiveness of the proposed approach. It is possible to expand such research onto the development of optimized linguistic rules database for different types of fuzzy information processing algorithms.

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