Optimal Selection of Membership Functions Types for Fuzzy Control and Decision Making Systems

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Abstract

This paper proposes the advanced approach for optimal selection of linguistic terms membership functions (LTMF) types for fuzzy control and decision making systems based on bioinspired optimization techniques. The developed approach allows to effectively optimize membership functions for improvement the fuzzy system (FS) performance as well as for simplification the further procedure of its parametric optimization of linguistic terms by reducing the number of optimized parameters. In order to study and validate the efficiency of the presented approach the optimization of the LTMF types for the fuzzy control system of the clamping device for a mobile robot (MR) of vertical movement is carried out in this work. The obtained simulation results confirm the high efficiency of the developed approach for optimal selection of LTMF types, as well as the expediency of its application for structural optimization of fuzzy systems and devices of various types, configurations and purposes.

Keywords

Fuzzy system, membership functions, intelligent approach, bioinspired optimization techniques, fuzzy controller, mobile robot.

1. Introduction

Fuzzy logic is a popular and powerful tool for automation of control and decision-making processes, which has a great potential [1, 2]. Intelligent decision-making systems based on the theory of fuzzy sets and fuzzy logic are widely used in the following areas: transport logistics, medical and technical diagnostics, financial management, stock market forecasting, etc. [3-5]. Also, fuzzy inference devices are successfully developed and applied as controllers, observers, adaptive devices, identifiers, tactical control units and others in automation systems of complicated nonlinear and/or nonstationary plants, such as robotic production lines and warehouses, power plants and chemical reactors, mobile robots and drones, marine floating structures and ships, unmanned aerial and underwater vehicles, etc. [6-8].

An essential feature of fuzzy systems and devices is a large number of adjustable parameters and structure elements, which significantly affect their performance [9]. Namely, the following are the subjects for adjustment: the number of linguistic terms of input and output variables, as well as the types and parameters (vertices) of their membership functions, the antecedents and consequents of the rule base (RB), the number of RB fuzzy rules, the input normalizing coefficients, the types of aggregation, activation and accumulation procedures, as well as the defuzzification method [10, 11]. This allows to implement complex, flexible and most effective strategies of control and decision-making, however, significantly complicates the design procedures of these systems and devices. So, in a number of cases, FSs developed on the basis of expert knowledge and assessments do not provide a significant improvement in indicators compared to similar conventional systems and, at the same

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time, have a more complex software and hardware implementation [12]. Therefore, in recent years, one of the leading research directions of the modern theory of fuzzy systems is the development and approbation of highly efficient approaches, methods and information technologies for their design, which include certain procedures of structural-parametric optimization [13, 14].

2. Related works

At the moment, a fairly large number of works have been published on various aspects of the structural-parametric optimization of different types FSs [15-17]. Particularly, designing methods and information technologies based of parametric optimization of the LTMF and weight coefficients of RB are given in [18, 19]. Techniques of FSs structural optimization including the RB reduction and interpolation, as well as optimal choice of defuzzification procedures are presented in papers [20, 21]. In turn, the most recent studies show that bioinspired intelligent methods and information technologies are very promising for performing FSs design and optimization and have a number of advantages compared to conventional optimization techniques [22, 23]. Among them are: methods of ant colony optimization [24], biogeography based optimization [25], particle swarm optimization [26], genetic methods [27] and evolutionary strategies [28], methods of artificial immune systems [29], etc. The given bioinspired methods can be also effectively applied for solving the challenge of LTMF optimization, in particular optimal selection of their types, that will allow not only to improve the efficiency of the FS itself, but also to simplify the procedure for its parametric optimization by reducing the number of optimized parameters of terms.

Thus, the purpose of this paper is development and research of an advanced intelligent approach for optimal selection of membership functions types for fuzzy systems based on bioinspired optimization techniques.

3. Intelligent approach for optimal selection of LTMF types for fuzzy systems

It is advisable to implement optimization of the LTMF types for improvement the FS performance (quality indicators) and to simplify the subsequent optimization procedures of linguistic terms parameters. In turn, the proposed intelligent approach consists of the following stages.

Stage 1. Setting of operating ranges of input and output variables changing of the developed fuzzy system. At this stage, for each i-th ($i = 1, 2, \dots, n$) input and j-th ($j = 1, 2, \dots, m$) output FS variables, the operating ranges are set, within which these variables can change. For example, if the input variables are fed to the FS inputs in relative units from their maximum value, then it is advisable to set their operating ranges from –1 to 1, or from 0 to 1 [2].

Stage 2. Formation of a set of membership functions used in the optimization process. At this stage, a set of alternative LTMFs S_{MF} is created, at which the search for optimal membership functions will be carried out for all linguistic terms of each i-th input and j-th output variables of the developed FS. It is advisable to include in this set the most frequently used membership functions: triangular *TrFN*, trapezoidal *TrpFN*, bell-shaped *GbFN*, Gaussian 1st *Gs1FN* and 2nd *Gs2FN* types, π-shaped *PiFN*, S-shaped *SFN*, Z-shaped *ZFN* , sigmoid *SgFN*, double sigmoid difference function *DsgFN*, and product of two sigmoid functions *PsgFN* [4, 30]. The number of adjustable parameters k_{MF} [10, 11] of these membership functions are shown in Table 1.

Table 1
Number of adjustable parameters k_{MF} for LTMF

S_{MF}	*TrFN*	*TrpFN*	*GbFN*	*Gs1FN*	*Gs2FN*	*PiFN*	*SFN*	*ZFN*	*SgFN*	*DsgFN*	*PsgFN*
k_{MF}	3	4	3	2	4	4	2	2	2	4	4

Stage 3. Selection of the number of linguistic terms for the FS input and output. At this stage, the number of linguistic terms is selected τ_i ($i = 1, 2, \dots, n$) and τ_j ($j = 1, 2, \dots, m$) for each i-th input and j-th output variables of the FS. In real FS, the number of linguistic terms for input variables should be set in the range from 2 to 7 ($\tau_i = 2\dots7$) [10, 16], and for output variables – form 3 to 9 ($\tau_j = 3\dots9$) [18].

Stage 4. Setting of parameters initial values of the LTMF for the developed fuzzy system. At this stage, for all LTMFs included in the set formed at Stage 2 (Table 1), the values of their parameters are pre-set. In most cases, at the beginning of the optimization process, it is advisable to set the parameters of the membership functions in such a way, that linguistic terms for all input and output variables, depending on their number τ_i and τ_j, selected at Stage 3, are evenly distributed over their working ranges previously set at Stage 1.

Stage 5. Formation of the vector **S** *structure, which determines the set of LTMF for the developed FS.* The LTMF vector **S** for fuzzy systems of Mamdani [9] and Takagi-Sugeno [14] types can be represented by equations (1) and (2), respectively:

$$\begin{gathered}\mathbf{S}=\{S_{in}^{i}(q),S_{out}^{j}(k)\},q=(1,2,...,\tau_{i}),k=(1,2,...,\tau_{j}),i=(1,2,...,n),j=(1,2,...,m),\\ S_{in}^{i}(q)\in\{TrFN,TrpFN,GbFN,Gs1FN,Gs2FN,PiFN,SFN,ZFN,SgFN,DsgFN,PsgFN\},\\ S_{out}^{j}(k)\in\{TrFN,TrpFN,GbFN,Gs1FN,Gs2FN,PiFN,SFN,ZFN,SgFN,DsgFN,PsgFN\},\end{gathered} \tag{1}$$

$$\begin{gathered}\mathbf{S}=\{S_{in}^{i}(q)\},q=(1,2,...,\tau_{i}),i=(1,2,...,n),\\ S_{in}^{i}(q)\in\{TrFN,TrpFN,GbFN,Gs1FN,Gs2FN,PiFN,SFN,ZFN,SgFN,DsgFN,PsgFN\},\end{gathered} \tag{2}$$

where $S_{in}^{i}(q)$, $S_{out}^{j}(k)$ are variables that determine the types of membership functions of the *q*-th linguistic term of the *i*-th input variable and the *k*-th term of the *j*-th output variable, respectively.

Moreover, vector **S** may have certain restrictions. For instance, S-shaped *SFN* and sigmoid *SgFN* membership functions can be used only for rightmost linguistic terms ($q = \tau_i$, $k = \tau_j$), and Z-shaped *ZFN* – only for leftmost terms ($q = 1$, $k = 1$) for all FS variables.

Stage 6. Selection of the initial hypothesis of the vector **S**, *which determines the set of LTMF for the developed FS.* At this stage, in accordance with the number of terms selected at Stage 3 τ_i ($i = 1, 2, \dots, n$) and τ_j ($j = 1, 2, \dots, m$) the initial values of the components of the vector **S** are selected. These initial values can be selected on the basis of an expert approach or randomly. For example, if at the beginning of the optimization process in a MISO Mamdani-type FS (with parameters $n = 2$, $\tau_i = \{7, 5\}$, $m = 1$, $\tau_j = \{5\}$), Gaussian membership functions of the 2st type *Gs2FN* are selected for all linguistic terms of input variables, and triangular functions *TrFN* are selected for all terms of output variable, then the initial value of the vector $\mathbf{S}_0$ is determined by expression (3)

$$\begin{gathered}\mathbf{S}_{0}=\{S_{in}^{i}(q),S_{out}^{j}(k)\}=\{S_{in}^{1}(1),S_{in}^{1}(2),S_{in}^{1}(3),S_{in}^{1}(4),S_{in}^{1}(5),S_{in}^{1}(6),S_{in}^{1}(7),\\ S_{in}^{2}(1),S_{in}^{2}(2),S_{in}^{2}(3),S_{in}^{2}(4),S_{in}^{2}(5),S_{out}^{1}(1),S_{out}^{1}(2),S_{out}^{1}(3),S_{out}^{1}(4),S_{out}^{1}(5)\}=\\ =\{Gs2FN,Gs2FN,Gs2FN,Gs2FN,Gs2FN,Gs2FN,Gs2FN,\\ Gs2FN,Gs2FN,Gs2FN,Gs2FN,Gs2FN,TrFN,TrFN,TrFN,TrFN,TrFN\}.\end{gathered} \tag{3}$$

Stage 7. Formation of a complex objective function J_C for evaluating the effectiveness of the developed fuzzy system. At this stage, the type, parameters and optimal value of the complex objective function J_C, used to find the optimal types of membership functions, are determined. Since, the total number of linguistic terms parameters, that will be optimized at subsequent stages of FS design, depends on the LTMF types, then in the process of vector **S** optimization it is advisable to use criterion J_1, which evaluates the FS performance itself, and criterion J_2, which takes into account the degree of complexity of further parametric optimization of the system being developed. Therefore, the current value of the complex objective function J_C should be calculated based on the equation (4)

$$J_{C}=J_{1}+k_{J2}J_{2}, \tag{4}$$

where k_{J2} is the scaling factor for J_2, which determines its importance in the process of computational search.

For example, when designing a MISO fuzzy automatic control system, the criterion J_1 can be presented as the generalized integral deviation of the real transient response $Y_R(t, \mathbf{S})$ from the desired transient response of the reference model $Y_D(t)$ [9, 31, 32]:

$$J_{1}\left(t,\mathbf{S}\right)=\frac{1}{t_{\max}}\int_{0}^{t_{\max}}\left[(E_{Y})^{2}+k_{11}(\dot{E}_{Y})^{2}+k_{12}(\ddot{E}_{Y})^{2}\right]dt, \tag{5}$$

where E_Y is the deviation of $Y_R(t, \mathbf{S})$ from $Y_D(t)$, $E_Y = Y_D(t) - Y_R(t, \mathbf{S})$; t_{max} is the system's total transient time; k_{11}, k_{12} are the corresponding weights for the components $(\dot{E}_{Y})^{2}$ and $(\ddot{E}_{Y})^{2}$.

In turn, the values of the criterion J_2 can be calculated depending on the number of optimized parameters of linguistic terms for FS of Mamdani and Takagi-Sugeno types based on the following dependencies:

$$J_2 = \sum_{i=1}^{n} \sum_{q=1}^{\tau_i} k_{in}^{i}(q) + \sum_{j=1}^{m} \sum_{k=1}^{\tau_j} k_{out}^{j}(k); \tag{6}$$

$$J_2 = \sum_{i=1}^{n} \sum_{q=1}^{\tau_i} k_{in}^{i}(q), \tag{7}$$

where $k_{in}^{i}(q)$ and $k_{out}^{j}(k)$ are the numbers of optimized parameters of the q-th linguistic term for the i-th input variable and the k-th linguistic term for the j-th output variable, depending on their membership functions types (Table 1).

Stage 8. Conduction of an iterative global search for the optimal vector $\mathbf{S}_{\text{opt}}$ *of the membership functions types using bioinspired intelligent algorithms.* At this stage, the search for the global extremum of the objective function $J_{\text{C}} \rightarrow \min$ is carried out using one or several bioinspired algorithms of global optimization. In turn, the following algorithms can be used, which are well adapted to complex high-dimensional discrete optimization problems: genetic algorithms, ant colony optimization, biogeography based optimization, evolutionary strategies, algorithms of artificial immune systems. In this case, vector $\mathbf{S}$ is a vector of unknown parameters, the complex objective function J_{C} is a fitness function, iterative procedures are carried out based on the features of a specifically selected algorithm.

Stage 9. Analysis of the results obtained and selection of the best variant of the membership functions types vector. At this stage the obtained optimization results are analyzed and the best variant of the vector of LTMF types is then selected. After that, the FS parametric optimization and its software and hardware implementation can be carried out for further application [33, 34].

The efficiency research of the proposed intelligent approach is performed in this paper at optimization of the LTMF types for a fuzzy control system of the clamping device for a mobile robot of vertical movement [35, 36].

4. Optimal selection of LTMF types for fuzzy control system of the mobile robot clamping device

The considered mobile robot moves by means of wheeled or caterpillars propulsors and uses an electromagnetic clamping device to hold on vertical and inclined ferromagnetic surfaces when implementing different types technological operations (painting, welding, rust removal, inspection) [35, 37, 38]. The clamping device must provide a certain value of the clamping force F for safe and effective movement of the MR on various surfaces under the action of various external disturbances. The simplified mathematical model of the MR clamping device consists of the following equations [36]:

$$F = \frac{\Phi_\delta^2}{2\mu_0 s_\delta}; \tag{8}$$

$$\Phi_\delta = \frac{\mu_0 s_\delta I_{\text{m}} W_{\text{m}}}{\delta}; \tag{9}$$

$$L_{\text{m}} \frac{dI_{\text{m}}}{dt} + R_{\text{m}} I_{\text{m}} = u_{\text{m}}; \tag{10}$$

$$T_{\text{C}} \frac{du_{\text{m}}}{dt} + u_{\text{m}} = k_{\text{C}} u_{\text{F}}, \tag{11}$$

where Φ_δ is the magnetic flux of the clamping electromagnet; μ_0 is the magnetic permeability of the gap; s_δ is the gap cross-sectional area; I_{m} is the current of the clamping electromagnet; W_{m} is the number of turns of the electromagnet winding; δ is the gap length; L_{m} and R_{m} are the inductance and resistance of the electromagnet winding; u_{m} is the supply voltage of the electromagnet; T_{C} and k_{C} are the time constant and gain of the power converter; u_{F} is the clamping device control signal.

For automatic control of the MR clamping force it is advisable to use the sliding mode fuzzy controller that gives the opportunity to effectively automate complex nonlinear plants [39-41]. Since, the clamping device is a 2nd order nonlinear plant, the sliding surface s_F for its control has the form [39]

$$s_F = \dot{e}_F + k_s e_F, \qquad (12)$$

where e_F is the clamping force control error; k_s is the reference model coefficient.

The conventional sliding mode controller calculate the control signal u_F based on the sliding surface value s_F according to the expression (13) [39]

$$u_F = \begin{cases} +u_{Fmax}, & \text{at } s_F > 0; \\ 0, & \text{at } s_F = 0; \\ -u_{Fmax}, & \text{at } s_F < 0, \end{cases} \qquad (13)$$

where u_{Fmax} is the maximum value of the clamping device control signal.

In turn, the fuzzy sliding mode controller provides the implementation of the given above control law using fuzzy inference on the basis of the dependence $u_{FC} = f_{FC}(e_F;\ \dot{e}_F)$. This allows to obtain high quality control indicators, as well as to eliminate the chattering problem that is inherent in conventional sliding mode controllers [39, 40]. In this paper LTMF types optimization is carried out for the given fuzzy sliding mode controller in accordance with the main stages of the proposed advanced intelligent approach.

At the stage 1, the operating ranges for the fuzzy controller inputs e_F and $\dot{e}_F$ as well as for output u_{FC} are set from –1 to 1. Then, the set of alternative LTMFs S_{MF} is created at the stage 2, which include all membership functions presented in Table 1. At the third stage for the SMFC inputs e_F and $\dot{e}_F$ five linguistic terms are selected for each: BN – big negative; SN – small negative; Z – zero; SP – small positive; BP – big positive. As for output u_{FC} it has only 3 terms to implement the sliding mode control strategy: N – negative; Z – zero; P – positive. For all these linguistic terms at stage 4, the initial parameters (vertices) are set in such a way, that terms are evenly distributed over their working ranges. Further, at the fifth stage the vector **S** structure is formed as follows

$$\begin{aligned} \mathbf{S} = \{S_{in}^{i}(q), S_{out}^{j}(k)\} = \{S_{in}^{1}(1), S_{in}^{1}(2), S_{in}^{1}(3), S_{in}^{1}(4), S_{in}^{1}(5), \\ S_{in}^{2}(1), S_{in}^{2}(2), S_{in}^{2}(3), S_{in}^{2}(4), S_{in}^{2}(5), S_{out}^{1}(1), S_{out}^{1}(2), S_{out}^{1}(3)\}. \end{aligned} \qquad (14)$$

As the initial hypothesis of the vector **S** triangular membership functions are selected for all linguistic terms at the stage 6:

$$\begin{aligned} \mathbf{S} = \{S_{in}^{i}(q), S_{out}^{j}(k)\} = \{TrFN, TrFN, TrFN, TrFN, TrFN, \\ TrFN, TrFN, TrFN, TrFN, TrFN, TrFN, TrFN, TrFN\}. \end{aligned} \qquad (15)$$

In turn, the rule base for the developed SMFC is composed to implement the sliding mode control principle and presented in Table 2.

Table 2

SMFC rule base

e_F / $\dot{e}_F$	BN	SN	Z	SP	BP
BN	N	N	N	N	Z
SN	N	N	N	N	Z
Z	N	N	Z	P	P
SP	Z	P	P	P	P
BP	Z	P	P	P	P

At the stage 7 the complex objective function J_C is formed that is calculated according to equation (4). In turn, the criterions J_1 and J_2 are represented by the expressions (5) and (6) respectively. As the optimal values of the functions J_C, J_1 and J_2 the following values are selected: $J_{Copt} = 7 \cdot 10^5$; $J_{1opt} = 3{,}5 \cdot 10^5$; $J_{2opt} = 35$. The scaling factor k_{J2}, in this case, is equal to 10^4. Before implementation of the LTMF types optimization process, the objective functions J_C, J_1 and J_2 for the SMFC with RB presented in Table 2 and triangular membership functions (according to initial hypothesis of the vector **S**) had the following values: $J_C = 7{,}62 \cdot 10^5$; $J_1 = 3{,}72 \cdot 10^5$; $J_2 = 39$.

At the stage 8 the iterative global search for the optimal vector $\mathbf{S}_{opt}$ of the LTMF types is conducted by means of the following bioinspired intelligent algorithms (adapted to the specifics of this task): GA, BBO and AIS. At carrying out the procedure of searching for optimal membership functions using bioinspired algorithms, the main parameters of GA, BBO and AIS were selected experimentally for this specific problem. In particular, the initial population of 100 chromosomes was created for the genetic algorithm. Proportional selection was chosen as the selection operator, single-point crossover as the crossover operator, and simple mutation as the mutation operator [23, 27]. Moreover, the values of the probabilities of crossover P_C and mutation P_M are set: $P_C = 0{,}25$; $P_M = 0{,}1$. For the BBO algorithm the initial ecosystem of 100 habitats (islands) was created. The dependences of species migration on the number of species on the islands $\lambda(N)$ and $\nu(N)$ are linear, wherein $\lambda_{max} = \nu_{max} = 1$ [25]. Mutation operator coefficient $r = 0{,}1$, the maximum possible number of species on the island corresponding to the optimal value of the habitat suitability index f_{opt}, $N_{max} = 10$. In turn, the initial population of 100 immune cells was created for the artificial immune systems algorithm. The uniform clone operator is used as the clone operator [29]. Also, the number of memory cells $N_m = 10$, the number of cells in the population with the worst affinity $N_w = 50$, the clone operator parameter $N_c = 5$, the mutation operator parameter $r = 2$. For all used bioinspired algorithms, 100 iterations were performed. The Fig. 1 shows the curves of changes in the best values of the complex objective function J_C (convergence curves) in the process of searching for the optimal types of membership functions **S** at stage 8 based on the considered algorithms (GA, BBO, AIS).

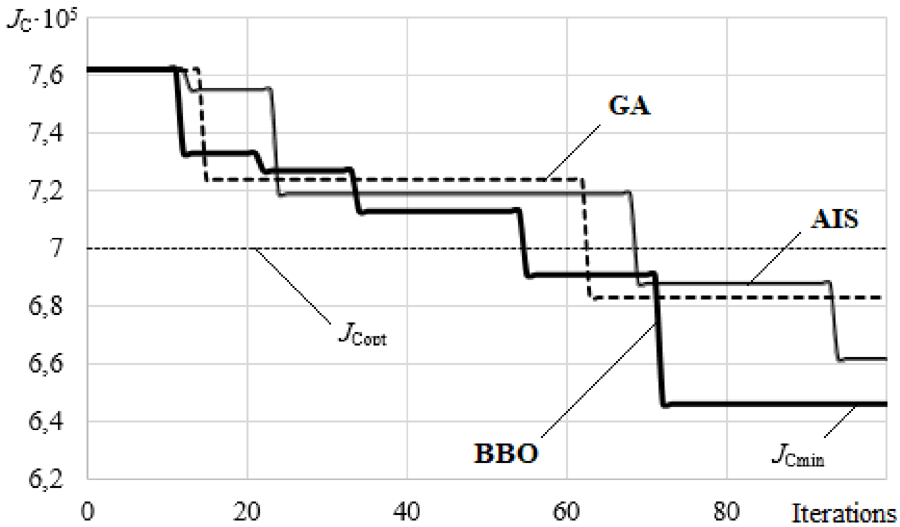

Figure 1: Convergence curves in the process of searching for the optimal LTMF types

At the final 9th stage the obtained results of the LTMF types optimization by means of the given above bioinspired algorithms are analyzed. In turn, the best value of the objective function J_C is attained by means of the BBO algorithm ($J_{Cmin} = 6{,}463 \cdot 10^5$) at the 72nd iteration. The found vector **S** that is correspondent to the given best value of the objective function J_{Cmin} is considered to be optimal optimal $\mathbf{S}_{opt}$ for this system and has the following form

$$\mathbf{S}_{opt} = \{ZFN, TrFN, Gs1FN, TrFN, SFN, \\ Gs1FN, TrFN, TrFN, Gs1FN, SgFN, TrFN, Gs1FN, TrFN\}. \quad (16)$$

Moreover, for this variant, separately taken components of the complex objective function J_1 and J_2 also have the best values ($J_{1min} = 3{,}263 \cdot 10^5$, $J_{2min} = 32$). Also, for this particular problem, the BBO algorithm showed the best convergence, since the optimal value of the complex objective function J_{Copt} was achieved with the lowest computational costs (for the least number of iterations – 55). In turn, genetic and AIS algorithms also showed satisfactory results, since they also made it possible to achieve the optimal value of the complex objective function J_C for an acceptable number of iterations (63 and 69), which in general confirms the expediency of their application in this approach.

To evaluate the results of optimization of the LTMF types by means of the proposed IIT, transient graphs for the control system of the MR clamping force are presented in Fig. 2 for two cases: 1 – for SMFC with triangular types LTMF (according to initial hypothesis $\mathbf{S}_0$); 2 – for SMFC with optimal types LTMF (according optimal vector $\mathbf{S}_{opt}$). In turn, for both cases, the simulation was carried out at a set value of clamping force F = 5000 N.

As can be seen from Fig. 2, the clamping force control system with optimized LTMF types of the SMFC has higher quality indicators in comparison with the same system, that has triangular LTMF of its SMFC. In particular, it has a lower static error value (ΔF = 0,52% for SMFC with optimal LTMF types; ΔF = 2,6% for SMFC with triangular LTMF types) with the same rise and transient time.

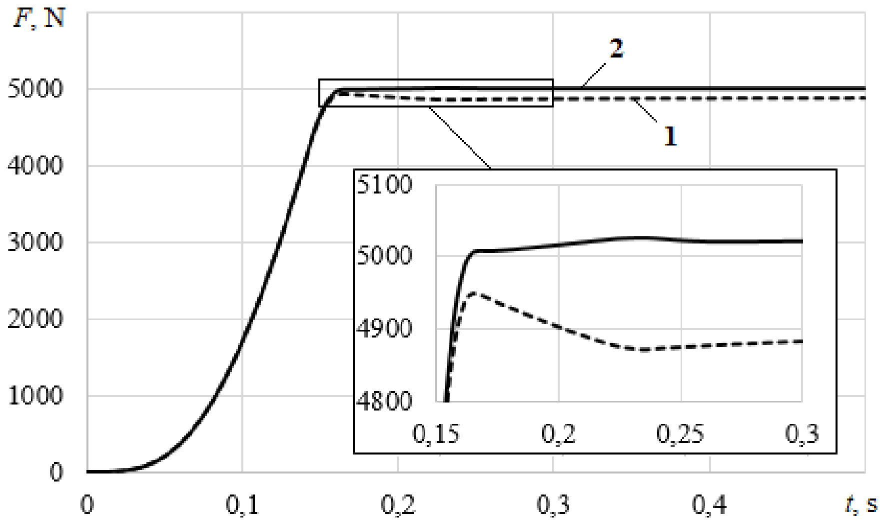

Figure 2: Transients for the control system of the MR clamping force

In addition to improved quality indicators of the control system, SMFC linguistic terms with optimal membership functions have fewer parameters that need to be optimized at further parametric optimization. Namely, the total number of parameters of linguistic terms was reduced by 7 parameters, which will significantly reduce the computational costs for their further parametric optimization. Also, to find the optimal LTMF vector $\mathbf{S}_{opt}$ for the given fuzzy controller using proposed intelligent approach did not require significant computational and time costs, which confirms its high efficiency.

5. Conclusions

The development and research of the advanced intelligent approach for optimal selection of membership functions types for fuzzy systems based on bioinspired optimization techniques is presented in this paper. The proposed IIT allows to effectively optimize LTMF types for improvement the FS performance as well as for simplification the further procedure of its parametric optimization by reducing the number of optimized parameters.

The efficiency research of the proposed approach is performed in this paper at optimization of the LTMF types for the sliding mode fuzzy controller of the clamping device control system for a mobile robot of vertical movement. In particular, at the implementation of this IIT, the iterative global search for the optimal vector $\mathbf{S}_{opt}$ of the LTMF types for SMFC is conducted by means of several bioinspired algorithms (GA, BBO and AIS) with further comparison of the obtained results. In this case, the BBO algorithm showed the best results, as it provided the fastest convergence ($J_C \le J_{Copt}$ at the 55th iteration) and the highest SMFC performance ($J_{Cmin} = 6{,}463 \cdot 10^5$ at the 72nd iteration). In turn, genetic and AIS algorithms also showed satisfactory results, since they also made it possible to attain the optimal value of the complex objective function J_{Copt} using acceptable computational costs (63 and 69 iterations), which in general confirms the expediency of their application in this intelligent approach. Moreover, the clamping force control system with optimized LTMF types (obtained by IIT based on

BBO algorithm) of the SMFC has higher quality indicators in comparison with the same system, that has triangular LTMF of its SMFC. In addition, the SMFC linguistic terms with optimal membership functions obtained by the presented IIT have fewer parameters that need to be optimized at further parametric optimization procedures.

Thus, the results obtained in this work confirm the high efficiency of the developed IIT for optimal selection of LTMF types, as well as the expediency of its application for structural optimization of fuzzy systems and devices of various types, configurations and purposes.

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