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Gravitational Search Algorithms in Fuzzy Control Systems Tuning

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Abstract: This paper suggests the use of Gravitational Search Algorithms (GSAs) in fuzzy control systems tuning. New GSAs are first offered on the basis of the modification of the depreciation equation of the gravitational constant with the iteration index and of an additional constraint regarding system's overshoot. The GSAs are next used in solving the optimization problems which minimize the discrete-time objective functions defined as the weighted sum of the squared control error and of the squared output sensitivity functions. The sensitivity functions are derived from the sensitivity models defined with respect to the parametric variations of the controlled plant such that to aim the parametric sensitivity reduction. The presentation focuses the representative case of Takagi-Sugeno PI-fuzzy controllers (PI-FCs) that controls a class of servo systems characterized by second-order linearized models with integral component. Discussions concerning the tuning of the PI-FC parameters in a case study are included.

Keywords: Gravitational Search Algorithm, fuzzy control systems, objective functions, performance specifications, servo systems.

1. INTRODUCTION

The design and tuning of fuzzy control systems is needed to be carried out systematically in order to guarantee the fulfilment of the performance specifications in a wide range of applications (Kruszewski et al., 2009; Precup et al., 2009; Lendek et al., 2010; Riid and Rüstern, 2010). The performance specifications of control systems can be expressed in terms of empirical control system performance indices (overshoot, settling time, phase margin and so on) or objective functions expressed as integral quadratic performance indices in the framework of appropriately defined optimization problems. The usual aim in order to fulfil the performance specifications is to minimize the objective functions (Grancharova et al., 2008; Wilamowski et al., 2008; Li and Chan, 2010).

The derivative-free optimization algorithms prove to be successful because their ability to cope with complicated and/or non-convex objective functions which can exhibit several local minima. Such algorithms include genetic algorithms, genetic programming, memetic computing, Particle Swarm Optimization (PSO), Simulated Annealing (SA), Ant Colony Optimization or cross-entropy (Mininno et al., 2008; Wolf et al., 2008; Ahmad et al., 2009; Botzheim et al., 2009; Haber et al., 2010; Vieira et al., 2010).

The sensitivity models with respect to the parametric variations of the controlled plants are necessary because the uncontrollable parametric variations of the controlled plants can lead to undesirable behaviours of the control systems. The use of sensitivity models in optimal control applications has been the subject of many recent papers (Precup and Preitl, 2004; Köppen, 2006; Zhou et al., 2008). The first objective of this paper is to suggest a new generation of Gravitational Search Algorithms (GSAs) to solve the optimization problems which minimize the discrete-time objective functions defined as the weighted sum of the squared control error and of the squared output sensitivity functions which can be viewed as the discrete-time counterparts of the extended continuous-time quadratic performance indices (Precup and Preitl, 2004). Since the variables of these objective functions are the tuning parameters of the fuzzy controllers, the second objective of this paper is to offer an original GSA-based tuning of the fuzzy control systems in order to ensure a reduced parametric sensitivity.

The GSAs are inspired by Newton's law of gravity and law of motion to solve the optimization problems with non-convex objective functions which eventually have several local minima (Rashedi et al., 2009, 2010). Our new GSAs are based on the modification of the depreciation equation of the gravitational constant with the iteration index and of an additional constraint regarding system's overshoot.

This paper is organized as follows. Section 2 defines the optimization problems which ensure the tuning of fuzzy control systems with reduced sensitivity by means of the new GSAs. In section 3 a case study is presented, which deals with the GSA-based tuning of the Takagi-Sugeno PI-fuzzy controllers (PI-FCs) for a class of servo systems characterized by second-order linearized models with integral component. Section 4 is dedicated to results and discussions, and the conclusions are highlighted in Section 5.

2. OPTIMIZATION PROBLEMS WITH A REDUCED SENSITIVITY BASED ON GRAVITATIONAL SEARCH ALGORITHMS

The fuzzy control system structure is presented in Fig. 1, where FC is the fuzzy controller, P is the controlled plant, r is the reference input, d_{inp} is the disturbance input, y is the controlled output, u is the control signal, and e is the control error defined as

$$e = r - y. \tag{1}$$

Fig. 1 points out the nonlinear blocks FC and P, and the controller and plant parameters which are grouped in the parameter vectors $\boldsymbol{\alpha}$ and $\boldsymbol{\rho}$; $\boldsymbol{\alpha} = [\alpha_1 \quad \alpha_2 \quad \dots \quad \alpha_m]^T \in R^m$ is the controlled plant parameter vector containing the parameters α_a, $a = 1...m$, of the controlled plant, and $\boldsymbol{\rho} = [\rho_1 \quad \rho_2 \quad \dots \quad \rho_q]^T \in R^q$ is the controller tuning parameter vector containing the tuning parameters of the controller, ρ_l, $l = 1...q$.

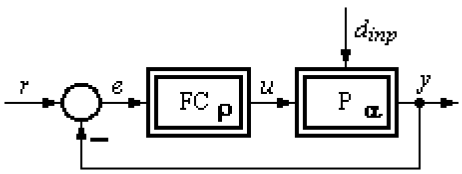

Fig. 1. Fuzzy control system structure.

Accepting that the controlled plant and the controller can be characterized by Single Input-Single Output (SISO) nonlinear state-space models, the state vector of the controlled plant $\mathbf{x}_P = [x_{P,1} \quad x_{P,2} \quad \dots \quad x_{P,n}]^T \in R^n$ and the state vector of the controller $\mathbf{x}_C = [x_{C,1} \quad x_{C,2} \quad \dots \quad x_{C,p}]^T \in R^p$ are grouped in the state vector of the control system $\mathbf{x}$

$$\mathbf{x} = \begin{bmatrix} \mathbf{x}_P \\ \mathbf{x}_C \end{bmatrix} = [x_1 \quad x_2 \quad \dots \quad x_{n+p}]^T \in R^{n+p},$$
$$x_b = \begin{cases} x_{P,i} & \text{if } b = 1...n \\ x_{C,i-n} & \text{otherwise} \end{cases}, \; b = 1...n+p, \tag{2}$$

where the superscript T indicates the matrix transposition.

Using the fuzzy control system structure (Fig. 1) the state-space model of the fuzzy control system is obtained in terms of connecting the state-space models of C and P. The class of control systems taken into consideration is constrained to accepting that the state-space model of the fuzzy control system is differentiable with respect to the parameter α_a, $a = 1...m$, of the controlled plant whose variation is of interested viz. the parameter which is subjected to the sensitivity analysis. In this context the state sensitivity functions $\lambda_b^{\alpha_a}$, $b = 1...n+p$, and the output sensitivity function σ^{α_a} are defined as follows:

$$\lambda_b^{\alpha_a} = \left[\frac{\partial x_b}{\partial \alpha_a}\right]_{\alpha_a,0}, \; \sigma^{\alpha_a} = \left[\frac{\partial y}{\partial \alpha_a}\right]_{\alpha_a,0}, \tag{3}$$
$$b = 1...n+p, \; a = 1...m,$$

where the subscript 0 indicates the nominal value of the parameter α_a, $a = 1...m$, which is subjected to variations and requires the sensitivity reduction.

The sensitivity reduction can be ensured if the following discrete-time objective functions:

$$I_{ISE}^{\alpha_a}(\boldsymbol{\rho}) = \sum_{t=0}^{\infty} \{e^2(t) + (\gamma^{\alpha_a})^2 [\sigma^{\alpha_a}(t)]^2\}, \; a = 1...m \tag{4}$$

are minimized in the framework of the optimization problems

$$\boldsymbol{\rho}^* = \arg \min_{\boldsymbol{\rho} \in Do} I_{ISE}^{\alpha_a}(\boldsymbol{\rho}), \; a = 1...m, \tag{5}$$

where t, $t \in N$, is the (discrete) time variable, γ^{α_a}, $a = 1...m$, are the weighting parameters, all variables in the sum depend on the vector $\boldsymbol{\rho}$, ISE points to the Integral of Squared Error (the first term of the sum in (5)), $\boldsymbol{\rho}^*$ is the optimal value of the vector $\boldsymbol{\rho}$ containing the optimal tuning parameters of the fuzzy controller, and Do is the feasible domain of $\boldsymbol{\rho}$. The stability of the fuzzy control system should be first taken into account when setting the domain Do but other technical constraints can be accounted for.

As mentioned in (Rashedi et al., 2009, 2010), GSAs make use of particles with performance measured by their masses. The gravity force attracts each other these particles leading to the global movement of all particles towards the particles with heavier masses. The heavy masses (which correspond to good solutions of the optimization problem, i.e., the solutions which are close to the optimum) move more slowly than the lighter ones.

The GSAs which solve the optimization problem defined in (5) consist of the following six steps:

Step 1. Initialize the q-dimensional search space and the number of agents (masses) N, and initialize randomly the agents' position vector $\mathbf{X}_i$

$$\mathbf{X}_i = [x_i^1 \quad \dots \quad x_i^d \quad \dots \quad x_i^q]^T, \; i = 1...N, \tag{6}$$

where x_i^d is the position of the i^{th} agent in the d^{th} dimension.

Step 2. Update the gravitational constant $g(k)$

$$g(k) = \delta\, k / k_{\max}, \tag{7}$$

where $k_{\max}$ is the maximum number of iterations, $\delta = \text{const}$, $\delta > 0$, is set such that to ensure the GSAs' convergence and to influence the search accuracy, and update the terms $b(k)$ (corresponding to the best agent), $w(k)$ (corresponding to the worst agent) and the masses $m_i(k)$ as well (Rashedi et al., 2009, 2010):

$$\begin{aligned} b(k) &= \min_{j=1,n} I_{ISE}^{\alpha_a}(\mathbf{X}_i), \\ w(k) &= \max_{j=1,n} I_{ISE}^{\alpha_a}(\mathbf{X}_i), \\ n_i(k) &= [I_{ISE}^{\alpha_a}(\mathbf{X}_i) - w(k)]/[b(k) - w(k)], \\ m_i(k) &= n_i(k) / \sum_{j=1}^{N} n_j(k). \end{aligned} \tag{8}$$

The step 2 involves the evaluation of the objective functions according to (8). That requires the simulation of the fuzzy control systems or the experiments conducted with the fuzzy control systems in the important operating regimes.

Step 3. Calculate the total force $F_i^d(k)$ in different directions i.e. the total force acting on the i^{th} agent in the d^{th} dimension, $i = 1...N$, $d = 1...q$:

$$\begin{aligned} r_{ij}(k) &= \| \mathbf{X}_i(k) - \mathbf{X}_j(k) \|, \\ F_{ij}^d(k) &= g(k) \frac{m_i(k) m_j(k)}{r_{ij}(k) + \varepsilon} [x_j^d(k) - x_i^d(k)], \\ F_i^d(k) &= \sum_{j=1, j\neq i}^{N} \rho_j F_{ij}^d(k), \end{aligned} \tag{9}$$

where $r_{ij}(k)$ is the Euclidian distance between the two agents i and j, $\varepsilon = \text{const}$, $\varepsilon > 0$, takes a small value, and ρ_j, $0 \le \rho_j \le 1$, is a random generated number.

Step 4. Calculate the accelerations $a_i^d(k)$ and the velocities $v_i^d(k+1)$ and update the agents' positions

$$\begin{aligned} a_i^d(k) &= F_i^d(k) / m_i(k), \\ v_i^d(k+1) &= \rho_i v_i^d(k) + a_i^d(k), \\ x_i^d(k+1) &= x_i^d(k) + v_i^d(k+1), \end{aligned} \tag{10}$$

where ρ_i, $0 \le \rho_i \le 1$, is a uniform random variable, and $i = 1...N$.

Step 5. Validate the obtained vector solution $\mathbf{X}_i(k)$ by checking the inequality-type constraint

$$| y(t_f) - r(t_f) | \le 0.001 \, | r(t_f) - r(0) |, \tag{11}$$

where t_f is the final time moment in the evaluation of the objective functions (theoretically ∞ according to (4)) after the transients of the fuzzy control system are finished. Our relation (11) validates the fuzzy control system with the controller tuning parameters at this iteration

$$\boldsymbol{\rho} = \mathbf{X}_i(k) \tag{12}$$

will have the desired behaviour for the current solution.

Step 6. Increment the iteration index k and go to step 2 until the maximum number of iterations is reached, i.e., $k = k_{\max}$.

The tuning procedure, which offers fuzzy control systems with a reduced parametric sensitivity with respect to the parameter α_a, $a = 1..m$, consists of the following tuning steps:

Step I. Derive the discrete-time sensitivity models of the controlled plant with respect to the parameter α_a, $a = 1..m$, of the controlled plant, and express the output sensitivity function σ^{α_a}, $a = 1...m$.

Step II. Set the weighting parameters γ^{α_a}, $a = 1...m$, in the objective function defined in (4) to meet the performance specifications imposed to the fuzzy control system.

Step III. Implement the six steps, 1 to 6, of the GSA presented before to solve the optimization problem defined in (5) which leads to the optimal controller tuning parameter vector $\boldsymbol{\rho}^*$.

3. CASE STUDY

The controlled plant with the following transfer function is considered to validate the new GSAs in solving the optimization problems (5) which ensure the optimal tuning of the fuzzy controllers with a reduced parametric sensitivity:

$$P(s) = k_P / [s(1 + T_\Sigma s)], \tag{13}$$

where k_P is the plant gain and T_Σ is the small time constant or the sum of parasitic time constants. The transfer function of the controlled plant presented in (13) includes the actuator and measuring element dynamics. Such transfer functions are simplified linearized models of servo systems in many applications (Ge et al., 2001; Boukezzoula et al., 2007; Ferreira and Ruano, 2009; Pizzileo et al., 2009). A set of parameters of the controlled plant in (13) which corresponds to a DC servo system with backlash laboratory equipment aiming the angular speed control are $k_P = 139.88$ and $T_\Sigma = 0.92$ s, and the sampling period is $T_s = 0.05$ s.

As shown in (Preitl and Precup, 1999), for the plant given in (13) the ESO method can be applied to tune the parameters of the PI controllers to guarantee a good trade-off to the desired / imposed control performance indices making use of a single tuning parameter β, $4 \le \beta \le 16$. Introducing the transfer function of the PI controller

$$C(s) = k_c (1 + sT_i)/s = k_C [1 + 1/(sT_i)], \; k_C = k_c T_i, \tag{14}$$

where with k_c (k_C) is the controller gain T_i is the integral time constant, the PI tuning conditions are

$$k_c = 1/(\beta\sqrt{\beta}T_\Sigma^2 k_P),\ T_i = \beta T_\Sigma, \tag{15}$$

and the parameter β will be an element of the vector $\boldsymbol{\rho}$, therefore it is tuned using GSAs. The control system performance indices can be improved if the reference filter with the following transfer function is used:

$$F(s) = 1/(1 + T_i s), \tag{16}$$

and the control system structures can be viewed as two-degree-of-freedom ones (Precup et al., 2009).

The Takagi-Sugeno PI-FCs (Fig. 2 (a) with $\Delta e(t)$ – the increment of control error, $\Delta u(t)$ – the increment of control signal, and q^{-1} – the backward shift operator) are designed and tuned to improve further the fuzzy control system performance indices. The fuzzification in the nonlinear Two Inputs-Single Output fuzzy controller (TISO-FC) block (the strictly speaking part of the PI-FC) is carried out using the membership functions presented in Fig. 2 (b).

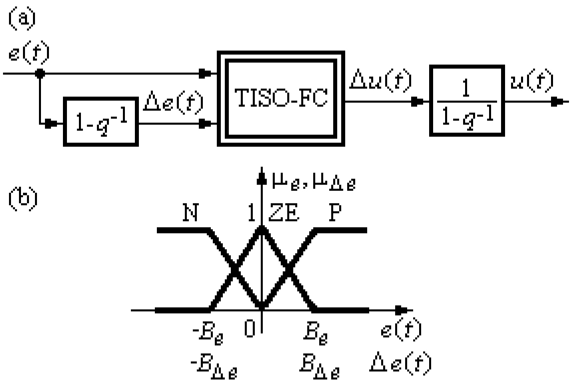

Fig. 2. Takagi-Sugeno PI-FC structure (a) and input membership functions of TISO-FC block (b).

The weighted average method is employed for defuzzification, and the SUM and PROD operators are used in the inference engine of the TISO-FC block. The decision table of the TISO-FC block is presented in Table 1 which consists of the rule consequents expressed as

$$f_1(t) = K_P[\Delta e(t) + \mu\, e(t)],\ f_2(t) = \eta\, f_1(t), \tag{17}$$

where the seven rule consequents $\Delta u(t) = f_1(t)$ correspond to the quasi-continuous digital PI controller obtained from (14), and the other two rule consequents $\Delta u(t) = f_2(t)$ are characterized by the additional parameter η, $0 < \eta < 1$, is inserted to reduce the overshoot which occurs for the same signs of $e(t)$ and $\Delta e(t)$.

Table 1. Decision table of TISO-FC block

$\Delta e(t)$	$e(t)$		
	N	ZE	P
P	$\Delta u(t) = f_1(t)$	$\Delta u(t) = f_1(t)$	$\Delta u(t) = f_2(t)$
ZE	$\Delta u(t) = f_1(t)$	$\Delta u(t) = f_1(t)$	$\Delta u(t) = f_1(t)$
N	$\Delta u(t) = f_2(t)$	$\Delta u(t) = f_1(t)$	$\Delta u(t) = f_1(t)$

The application of Tustin's method leads to the following relations between the parameters of the digital PI controller and those of the continuous-time PI one:

$$K_P = k_c\,(T_i - T_s/2),\ \mu = 2T_s/(2T_i - T_s). \tag{18}$$

Fig. 2 (b), Table 1 and the relations (14) and (17) highlight the tuning parameters of the PI-FC, B_e, $B_{\Delta e}$, η and β. The number of parameters is reduced because the modal equivalence principle results in the useful tuning condition

$$B_{\Delta e} = \mu\, B_e. \tag{19}$$

Concluding, the controller tuning parameter vector $\boldsymbol{\rho}$ ($q = 3$) and the parameter vector of the controlled plant $\boldsymbol{\alpha}$ ($m = 2$) obtain the following expressions for the accepted case study:

$$\begin{aligned}\boldsymbol{\rho} &= [\rho_1 = B_e \quad \rho_2 = \beta \quad \rho_3 = \eta]^T \in R^3,\\ \boldsymbol{\alpha} &= [\alpha_1 = k_P \quad \alpha_2 = T_\Sigma]^T \in R^2.\end{aligned} \tag{20}$$

The parameter vector presented in (20) shows that only three parameters of the accepted Takagi-Sugeno PI-FC must be tuned. In addition, the accepted Takagi-Sugeno PI-FC structure and operating mechanism outlines the advantage of using the GSA, because it is not required to have differentiable objective functions.

4. RESULTS AND DISCUSSIONS

Two GSAs were implemented according to the six steps presented in Section 2 to solve the two optimization problems in (4) for the case study defined in Section 3. The two objective functions which were minimized are $I_{ISE}^{k_P}$ and $I_{ISE}^{T_\Sigma}$, thus ensuring the reduced sensitivity of the fuzzy control systems with respect to the parameters k_P and T_Σ, respectively.

The evaluation of the agents (masses) and the update of the worst and best masses are conducted using the digital simulation of the fuzzy control system behaviour with respect to the step-type modification of the reference and disturbance inputs. The GSAs were implemented by means of N masses generated randomly, $N \in \{10,20,50\}$. The weighting parameter values were set to

$$\begin{aligned}&(\gamma^{k_P})^2 \in \{0,1000,10000,100000\},\\ &(\gamma^{T_\Sigma})^2 \in \{0,0.05,0.5,5\}.\end{aligned} \tag{21}$$

Each particle is a $q = 3$-dimensional vector, and each dimension is initialized in terms of the following constraints which define the domain Do:

$$22.5 \le B_e \le 40,\ 0.55 \le \eta \le 1,\ 4 \le \beta \le 16, \tag{22}$$

but other constraints resulting from the stability analysis of the fuzzy control systems can also be accounted for including Linear Matrix Inequality-type stability conditions.

The values of the two parameters defined in (7) were set to

$$k_{\max} \in \{75,100,150\},\ \delta = 0.5, \tag{23}$$

to ensure acceptable GSAs' convergence and search accuracy.

For the sake of simplicity only a part of the results concerning the Takagi-Sugeno PI-FC tuning to minimize the objective function $I_{ISE}^{k_P}$ are presented as follows. The continuous-time sensitivity model of the fuzzy control system with respect to k_P, which was discretized, is

$$\begin{aligned}
\dot{\lambda}_1^{T_\Sigma} &= \lambda_2^{T_\Sigma}, \\
\dot{\lambda}_2^{T_\Sigma} &= -[1/(\sqrt{\beta}T_{\Sigma 0}^2)]\lambda_1^{T_\Sigma} - (1/T_{\Sigma 0})\lambda_2^{T_\Sigma} \\
&\quad + [1/(\sqrt{\beta}T_{\Sigma 0}^2)]\lambda_3^{T_\Sigma} + [1/(\sqrt{\beta}T_{\Sigma 0}^3)]x_{10} + (1/T_{\Sigma 0}^2)x_{20} \\
&\quad - [1/(\sqrt{\beta}T_{\Sigma 0}^3)]x_{30} - [1/(\sqrt{\beta}T_{\Sigma 0}^3)]r_0, \\
\dot{\lambda}_3^{T_\Sigma} &= -[1/(\beta T_{\Sigma 0})]\lambda_1^{T_\Sigma}, \\
\sigma^{T_\Sigma} &= \lambda_1^{T_\Sigma}.
\end{aligned} \qquad (24)$$

This sensitivity model incorporates the sensitivity model of the PI controller instead of the Takagi-Sugeno PI-FC because the structure of the Takagi-Sugeno PI-FC determines that its sensitivity model cannot be calculated. However, the modal equivalence principle can justify the use of the state-space model of the PI controller, instead of that of the fuzzy one in the calculation of the sensitivity model.

A part of the results is synthesized in Table 2, where superscript * highlights the optimum value of a certain parameter. The performance index $StDev(I_{ISE}^{k_P})\%$ evaluates the convergence of the GSA, and it is defined as the percentage represented by the standard deviation $StDev(I_{ISE}^{k_P})$ compared to the average value $Avg(I_{ISE}^{k_P})$ of the objective function obtained after all simulations of the fuzzy control system behaviour.

Table 2. Parameters and objective function $I_{ISE}^{k_P}$ for $N = 50$ and $k_{\max} = 100$

$(\gamma^{k_P})^2$	B_e^*	β^*	η^*
0	34.95422	7.333734	0.270214
1000	32.14256	7.301204	0.252184
10000	31.11246	6.806004	0.26495
100000	34.15234	6.680212	0.299149
$(\gamma^{k_P})^2$	k_C^*	T_i^*	$I_{ISE}^{k_P}$
0	0.002897	6.747032	9118.426
1000	0.002904	6.717108	9753.51
10000	0.003021	6.261524	17682.04
100000	0.003062	6.145796	97726.66
$(\gamma^{k_P})^2$	$Avg(I_{ISE}^{k_P})$	$StDev(I_{ISE}^{k_P})$	$StDev(I_{ISE}^{k_P})\%$
0	9118.426	306.2352	3.358422
1000	9753.51	136.4733	1.399222
10000	17682.04	624.9955	3.534634
100000	97726.66	2274.794	2.327711

One sample of the digital simulation results with the control system obtained after the application of the GSA is presented in Fig. 3. The results are expressed as the evolution of the controlled output y versus time accepting the simulation scenario characterized by the $r = 40$ rad step modification of the reference input followed by the $d_{inp} = -0.5$ step modification of the disturbance input applied after 50 s.

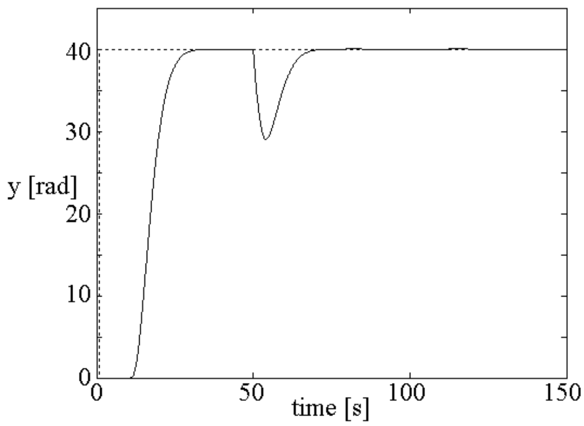

Fig. 3. Controlled output y versus time for fuzzy control system after GSA-based tuning.

The differences between GSA and other derivative-free optimization algorithms in the optimal tuning of controller parameters including PSO and SA come from the strategies applied to find the optimal solution. The movement strategy used in case of GSA is contained in the computation of the overall force that takes into consideration the position of all other agents. In PSO the agents' position update is calculated based on the local best and global best of the swarm. In SA the current solution is constantly altered in order to obtain a performance improvement. These differences result in other emergent topics and their combination can lead to algorithms' performance enhancement.

5. CONCLUSIONS

The paper has suggested the GSA-based optimal tuning of fuzzy control systems. The advantage of our approach concerns its generality, because it is addressed to a large class of controlled plants and controllers and the quick improvement of the control system performance indices.

One shortcoming of the GSA-based optimal tuning of fuzzy control systems is that the global minimum cannot be guaranteed. However, the fast convergence of the objective function as shown in the example from Fig. 4 is sufficient, as our goal was to present a fuzzy control system with reduced parametric sensitivity, and not with minimum sensitivity.

The limitation of the area of application of our new approach results from the necessity to differentiate the state-space model of the controller (and of the controlled plant) with respect to the controlled plant parameter which is subjected to variations and requires thus the parametric sensitivity reduction. This was solved, according to the discussion in the previous section, by using the linear (PI) controller instead of the fuzzy one in the calculation of the sensitivity model of the fuzzy control system.

The future research will be focused on classes of fuzzy controllers which should ensure the calculation of the sensitivity models while keeping reasonable implementation costs. Additional constraints resulted from the stability analysis of the fuzzy control systems, will be taken into consideration in more convincing applications.

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