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EXPERIMENTS IN FUZZY CONTROLLER TUNING BASED ON AN ADAPTIVE GRAVITATIONAL SEARCH ALGORITHM

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This paper presents aspects concerning the implementation of an adaptive Gravitational Search Algorithm (GSA) in the optimal tuning of fuzzy controllers. Takagi-Sugeno-Kang proportional-integral fuzzy controllers (TSK PI-FCs) are designed and tuned for a class of nonlinear servo systems. The adaptive GSA is based on five stages to solve the optimization problems with objective functions which depend on output sensitivity functions. TSK PI-FCs with a reduced process parametric sensitivity are thus offered. A set of illustrative experiments is given to validate the fuzzy controller tuning in a laboratory servo system application.

Key words: experiments, fuzzy controllers, Gravitational Search Algorithm, sensitivity, tuning.

1. INTRODUCTION

Fuzzy control has successfully been used in many applications [1–8] as a convenient and relatively easily understandable nonlinear control strategy for processes with nonlinear or ill-defined models. The systematic design and tuning of fuzzy controllers can employ stability, robustness, sensitivity analysis and optimization. Some recent approaches to the optimal tuning of fuzzy controllers based on evolutionary algorithms include genetic algorithms [9–11], Particle Swarm Optimization (PSO) [9, 12–14], Ant Colony Optimization [13, 15–17], Simulated Annealing [18–21], and Gravitational Search Algorithms [22–25].

Building upon authors' results on adaptive evolutionary algorithms [26, 27], an adaptive Gravitational Search Algorithm (GSA) has been proposed in [28]. The adaptive GSA consists of five stages as in the structure of adaptive staged PSO algorithms [29], and it exploits the modification of the parameters with beneficial effects on the search process, viz. it uses two depreciation laws of the gravitational constant and it adapts a parameter in the weighted sum of all forces exerted from the other agents to the iteration index.

This paper offers implementation details and experimental results concerning a new application of the adaptive GSA suggested in [28] to the optimal tuning of the parameters of Takagi-Sugeno-Kang proportional-integral fuzzy controllers (TSK PI-FCs). The presentation is focused on a class of nonlinear servo systems which consist of second-order models with an integral component in the linear part plus a saturation and dead zone static nonlinearity. The adaptive GSA solves optimization problems which aim the minimization of objective functions which depend on the output sensitivity functions. The output sensitivity functions are derived from the sensitivity models with respect to the parametric variations of the process. Therefore the tuning of TSK PI-FCs which exhibit both control system performance enhancement and a reduced process parametric sensitivity is proposed.

The paper is organized as follows: the adaptive GSA is discussed in the next Section. Section 3 presents an adaptive GSA-based tuning approach for TSK PI-FCs for the considered class of nonlinear servo systems. A case study which deals with the TSK PI-FC tuning meant for the position control of a laboratory direct current (DC) servo system is treated in Section 4. A set of experimental results is included. Some concluding remarks are highlighted in Section 5.

2. ADAPTIVE GRAVITATIONAL SEARCH ALGORITHM

The operating mechanism of the standard GSA [30, 31] is centred on the movement of agents (i.e. particles), based on Newtonian law of motion and an alternate version of gravitational law [32]. The depreciation of the gravitational constant with the advance of GSA's iterations is modelled by one of the following two laws:

$$g(k)=\psi(1-k/k_{\max})g_0 \ , \tag{1}$$

$$g(k)=g_0\exp(-\zeta\, k/k_{\max}) \ , \tag{2}$$

where $g(k)$ is the gravitational constant at the current iteration index k, $g_0=g(0)$, the parameters $\psi>0$ and $\zeta>0$ influence GSA's convergence and search accuracy, and $k_{\max}$ is the maximum number of iterations.

Considering N agents and a q-dimensional search space, the position of i^{th} agent is the vector

$$\mathbf{X}_i=\left[x_i^1 \cdots x_i^d \cdots x_i^q\right]^{\mathrm{T}} \in \mathbb{R}^q, \quad i=1\cdots N, \tag{3}$$

where x_i^d is the position of i^{th} agent in d^{th} dimension, $d=1...q$, and T indicates the matrix transposition. The total force $F_i^d(k)$ acting on i^{th} agent in d^{th} dimension is

$$F_i^d(k)=\sum_{j=1, j\neq i}^{N}\sigma_j F_{ij}^d(k), \tag{4}$$

where σ_j, $0\le\sigma_j\le 1$, is a random generated number and $F_{ij}^d(k)$ is the force acting on i^{th} agent from j^{th} agent:

$$F_{ij}^d(k)=g(k)m_{Pi}(k)m_{Aj}(k)[x_j^d(k)-x_i^d(k)]/[r_{ij}(k)+\varepsilon], \tag{5}$$

$m_{Pi}(k)$ is the active gravitational mass of i^{th} agent, $m_{Aj}(k)$ is the passive gravitational mass of j^{th} agent, $\varepsilon>0$ is a relatively small constant, and $r_{ij}(k)$ is the Euclidian distance between i^{th} and j^{th} agents:

$$r_{ij}(k)=\|\mathbf{X}_i(k)-\mathbf{X}_j(k)\|. \tag{6}$$

The acceleration $a_i^d(k)$ of i^{th} agent at the iteration index k in d^{th} dimension is

$$a_i^d(k)=F_i^d(k)/m_{Ii}(k), \tag{7}$$

where $m_{Ii}(t)$ is the inertia mass related to i^{th} agent. The expressions of agent's masses are

$$n_i(k)=[f_i(k)-w(k)]/[b(k)-w(k)],\ m_i(k)=n_i(k)/[\sum_{j=1}^{N}n_j(k)],\ m_{Ai}=m_{Ii}=m_i, \tag{8}$$

where $f_i(k)$ is the fitness value of i^{th} agent, and the terms $b(k)$ (corresponding to the best agent) and $w(k)$ (corresponding to the worst agent) are obtained as

$$b(k)=\min_{j=1...n} f_j(k),\ w(k)=\max_{j=1...n} f_j(k). \tag{9}$$

The next velocity of an agent, $v_i^d(k+1)$, and the next position of an agent, $x_i^d(k+1)$, are obtained in terms of the state-space equations

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

where ρ_i, $0\le\rho_i\le 1$, is a uniform random variable.

The five stages of the adaptive GSA are presented in Fig. 1. The exploration (stage II) is conducted for the first 15% iterations, i.e., runs, in the search process using the depreciation law (1) of the gravitational constant. The explanation (stage III) is conducted for the next 45% iterations using the depreciation law (2). The last gravitational constant value of previous stage is used as initial value for this stage, and ε is reduced starting with the preset value $\varepsilon_0 > 0$ in terms of the law

$$\varepsilon = \varepsilon_0 (k_{\max} - k)/(0.85 k_{\max}) . \tag{11}$$

The elaboration (stage IV) is conducted for the next 40% runs with the reduced value of ε according to (11); the worst fitness and position values are reset to the best values after each iteration. The evaluation (stage V) applies the tuned parameters to the TSK PI-FC in the real-world process, and experiments are conducted to evaluate the fuzzy control system behaviour. The other stages are backed up by simulations using accurate fuzzy control system models because of the large number of algorithm's runs.

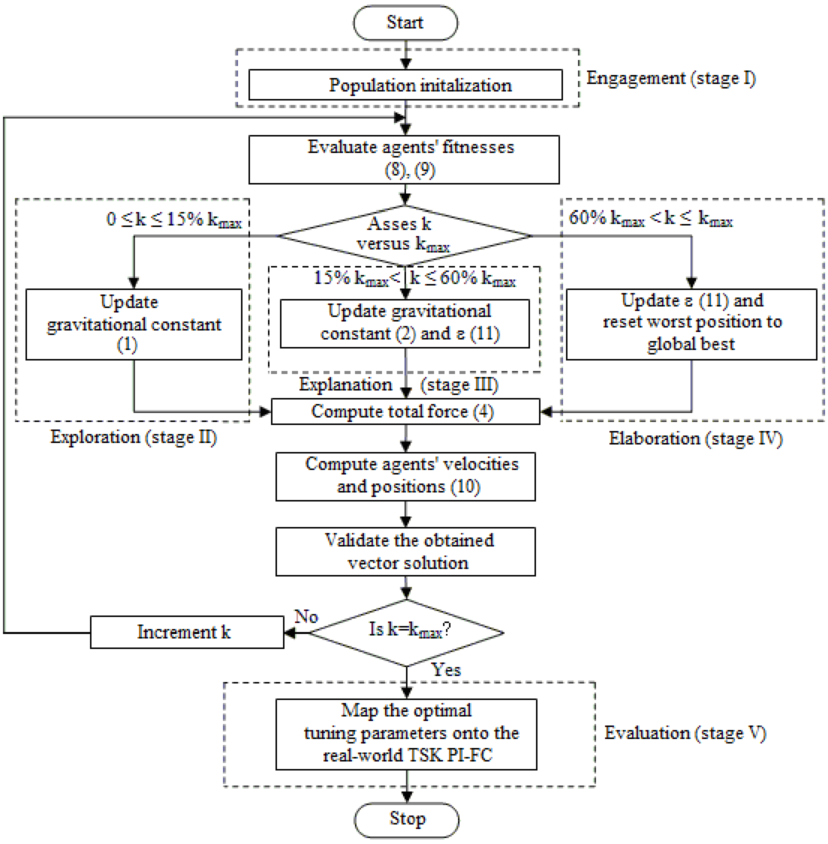

Fig. 1 – Flowchart of adaptive GSA.

3. TUNING APPROACH FOR TAKAGI-SUGENO-KANG PI-FUZZY CONTROLLERS

The optimization problem solved by the adaptive GSA presented in the previous section is defined as

$$\boldsymbol{\rho}^* = \arg\min_{\boldsymbol{\rho} \in D_{\boldsymbol{\rho}}} I(\boldsymbol{\rho}), \;\; I(\boldsymbol{\rho}) = \sum_{t=0}^{\infty} [\,| e(t) | + \gamma^2 \sigma^2 (t)] , \tag{12}$$

where $\boldsymbol{\rho}^*$ is the optimal value of the parameter vector $\boldsymbol{\rho}$ of TSK PI-FC, $D_{\boldsymbol{\rho}}$ is the feasible domain of $\boldsymbol{\rho}$, $I(\boldsymbol{\rho})$ is the objective function whose minimization leads to TSK PI-FCs with a reduced process parametric sensitivity, *e* is the control error, σ is the output sensitivity function, γ is the weighting parameter, *t*, $t \in \mathbb{N}$, is the discrete time argument, and the variables *e* and σ also depend on $\boldsymbol{\rho}$.

The process belongs to servo systems modelled by the following discrete-time state-space models which consist of second-order linear systems with an integral component plus a saturation and dead zone static nonlinearity:

$$
\begin{aligned}
& m(t) = \begin{cases} 0, & \text{if } |u(t)| \le u_a, \\ k_{u,m}[u(t) - u_a \operatorname{sgn}(u(t))], & \text{if } u_a < |u(t)| < u_b, \\ k_{u,m}(u_b - u_a)\operatorname{sgn}(u(t)), & \text{if } |u(t)| \ge u_b, \end{cases} \\
& x_{P,1}(t+1) = x_{P,1}(t) + T_\Sigma[1 - \exp(-T_s / T_\Sigma)]x_{P,2}(t) + k_{P1}[T_s + T_\Sigma \exp(-T_s / T_\Sigma) - T_\Sigma]m(t) + T_s d_{inp}(t), \\
& x_{P,2}(t+1) = [\exp(-T_s / T_\Sigma)]x_{P,2}(t) + k_{P1}[1 - \exp(-T_s / T_\Sigma)]m(t), \\
& y(t) = x_{P,1}(t),
\end{aligned}
\tag{13}
$$

where u is the control signal, i.e. a pulse width modulated duty cycle, d_{inp} is the disturbance input, y is the controlled output, m is the output of the nonlinearity with the parameters $k_{u,m}$ u_a, u_b, $k_{u,m} > 0$, $0 < u_a < u_b$, $x_{P,1}(t) = \alpha(t)$ is the first state variable that represents the (angular) position, $x_{P,2}(t) = \omega(t)$ is the second state variable that represents the (angular) speed, and T_s is the sampling period. The following simplified model of the process is expressed as the transfer function $P(s)$ and used in the controller design and tuning:

$$P(s) = k_P / [s(1 + T_\Sigma s)], \tag{14}$$

where k_P is the process gain, $k_P = k_{u,m} k_{P1}$, and T_Σ is the small time constant.

The models (13) and (14) can be employed as simplified process models in servo systems in many applications [33–42] accepting that the parameters k_P and T_Σ depend on the operating point. Therefore the sensitivity analysis with respect to the parametric variations of these two parameters and the design and tuning of controllers with a reduced parametric sensitivity are justified.

As shown in [43] in the linear case and in [44, 45] in the fuzzy case, PI controllers and PI-fuzzy controllers can cope with the process (14) in the framework of two-degree-of-freedom (2-DOF) control system structures presented in Fig. 2 in the fuzzy case, where F is the reference input filter, P is the process, r is the reference input, and r_1 is the filtered reference input. The Two Inputs-Single Output fuzzy controller (TISO-FC) block pointed out in Fig. 2 operates on the basis of the weighted average defuzzification method and of the SUM and PROD operators in the inference engine.

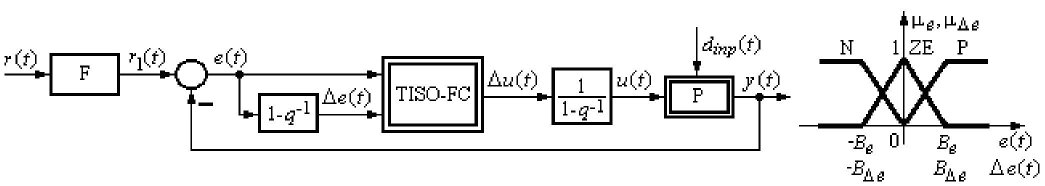

Fig. 2 – Structure of fuzzy control system and input membership functions.

The complete rule base of TSK PI-FC is expressed as nine rules which can be reduced to only two:

$$
\begin{aligned}
& \text{Rule 1: IF } (e(t) \text{ IS N AND } \Delta e(t) \text{ IS ZE OR P) OR } (e(t) \text{ IS ZE) OR} \\
& \qquad (e(t) \text{ IS P AND } \Delta e(t) \text{ IS N OR ZE) THEN } \Delta u(t) = K_P[\Delta e(t) + \mu\, e(t)], \\
& \text{Rule 2: IF } (e(t) \text{ IS N AND } \Delta e(t) \text{ IS N) OR } (e(t) \text{ IS P AND } \Delta e(t) \text{ IS P)} \\
& \qquad \text{THEN } \Delta u(t) = \eta\, K_P[\Delta e(t) + \mu\, e(t)],
\end{aligned}
\tag{15}
$$

where the parameter η, $0 < \eta \le 1$, aims the alleviation of the overshoot of the fuzzy control system when $e(t)$ and $\Delta e(t)$ have the same signs. The expression in the consequent of rule 1 is the incremental discrete-time form (by Tustin's method) of the continuous-time linear PI controller with the transfer function

$$C(s) = k_c(1 + sT_i)/s = k_C[1 + 1/(sT_i)],\ k_C = k_c T_i, \tag{16}$$

where k_c is the controller gain, T_i is the integral time constant, and the discrete-time parameters are

$$K_P = k_c\,(T_i - T_s/2),\ \mu = 2T_s/(2T_i - T_s)\,. \tag{17}$$

The TSK PI-FC with the rule base given in (15) exhibits like a bumpless interpolator between two separately designed PI controllers. The PI tuning conditions specific to the Extended Symmetrical Optimum (ESO) method are [43]

$$k_c = 1/(\beta\sqrt{\beta}\,T_\Sigma^2\,k_P),\ T_i = \beta\,T_\Sigma\,, \tag{18}$$

and the transfer function of the linear F is

$$F(s) = 1/(1+\beta\,T_\Sigma s)\,, \tag{19}$$

where β, $1 < \beta \le 20$, is the single design parameter.

The adaptive GSA-based tuning approach for TSK PI-FCs consists of the following steps:

- Set the sampling period T_s according to the requirements of quasi-continuous digital control, derive the sensitivity models [21, 22, 28], and set the weighting parameter γ in (12) to meet the performance specifications of the fuzzy control systems.
- Apply the adaptive GSA presented in the previous section in order to solve the optimization problem (12) and to obtain the optimal value of the parameter vector

$$\boldsymbol{\rho} = [\rho_1\quad \rho_2\quad \rho_3]^T,\ \rho_1 = \beta,\ \rho_2 = B_e,\ \rho_3 = \eta\,. \tag{20}$$

The adaptive GSA is mapped onto the optimization problem (12) by the relationships

$$f_j(k) = I(\boldsymbol{\rho}),\ j = 1...N,\ \mathbf{X}_i = \boldsymbol{\rho},\ i = 1,...,N\,, \tag{21}$$

and the following inequality is inserted to validate the obtained vector solution by the guarantee of the convergence of the objective function:

$$|\,y(t_f) - r(t_f)\,| \le \varepsilon_y\,|\,r(t_f) - r(t_0)\,|\,, \tag{22}$$

where t_0 is the initial time moment, t_f is the final time moment, and $\varepsilon_y = 0.001$ for a 2% settling time. Theoretically $t_f \to \infty$ as in (12), but t_f is finite to capture all system transients.

- Apply the modal equivalence principle to obtain the parameter $B_{\Delta e}$

$$B_{\Delta e} = \mu\,B_e = 2T_s B_e/(2\,\beta\,T_\Sigma - T_s)\,. \tag{23}$$

4. CASE STUDY AND EXPERIMENTS

The tuning approach is applied to the tuning of a TSK PI-FC for the angular position control of the INTECO DC nonlinear servo system laboratory equipment. The values of process parameters are [23, 24, 28]: $k_{P1} = 121.6956$, $T_\Sigma = 0.9198$ s, $k_{u,m} = 1.149$, $u_a = 0.13$, $u_b = 1$ and $k_P = k_{u,m}k_{P1} = 139.88$. The sampling period was set to $T_s = 0.01$ s and the weighting parameter was set to $\gamma^2 = 112.95$ in order to ensure a ratio of 0.1 between the first and second terms resulted from the sum in (12). The parameters of the adaptive GSA and of the non-adaptive GSA (for the sake of comparison) were set to $N = 20$, $k_{\max} = 100$, $\zeta = 30$, $\varepsilon_0 = 0.01$ and $g_0 = 100$, in order to ensure a good convergence of both algorithms.

Considering as in [28] the sensitivity reduction with respect to the process parameter T_Σ, the domain $D_{\boldsymbol{\rho}}$ is $D_{\boldsymbol{\rho}} = \{\beta\,|\,3 \le \beta \le 17\} \times \{B_e\,|\,20 \le B_e \le 40\} \times \{\eta\,|\,0.25 \le \eta \le 0.75\}$. Accepting the dynamic regimes characterized by the $r = 40$ rad step type modification and zero disturbance input, the adaptive GSA leads to the parameter values $\beta = 3.52585$, $B_e = 40$, $\eta = 0.75$, $B_{\Delta e} = 0.123503$, to the objective function $I = 52{,}536.5$

and to the average number of 1899.8 evaluations of the objective function for the best five runs of the algorithm. The parameters of the non-adaptive GSA are $\beta = 3.57934$, $B_e = 40$, $\eta = 0.75$, $B_{\Delta e} = 0.121655$, the objective function $I = 52,585.6$ and the average number of 258.4 evaluations in the same conditions. These results show that the adaptive GSA leads to an improved optimal value of I compared to the non-adaptive GSA. The increased number of evaluations of the objective function carried out by the adaptive GSA indicates improved exploration and exploitation capabilities resulting in the overall superior search accuracy.

The experimental results which correspond to the control systems with the linear PI controller and with the fuzzy controller are presented in Fig. 3 and in Fig. 4, respectively. The controllers are also tested against a process parametric disturbance, i.e., the approximate 10% increase of T_Σ, from 0.9198 s to 1 s. These results are presented in Fig. 5 and in Fig. 6 for the linear control system and for the fuzzy control system, respectively. The objective function measured for the control system with PI controller is $I = 53{,}021.3$, and the objective function measured for the fuzzy control system with TSK PI-FC is $I = 53{,}096.4$.

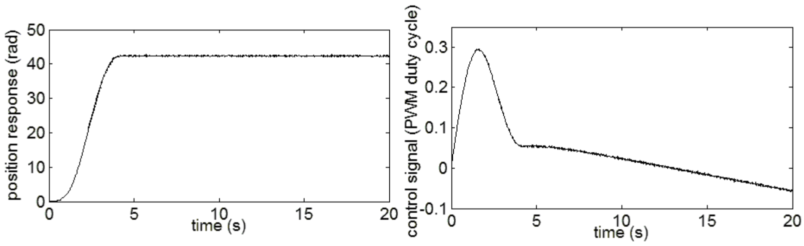

Fig. 3 – Real-time experimental results of the control system with PI controller.

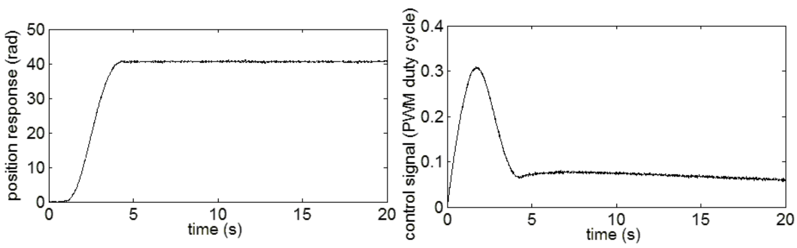

Fig. 4 – Real-time experimental results of the fuzzy control system with TSK PI-FC.

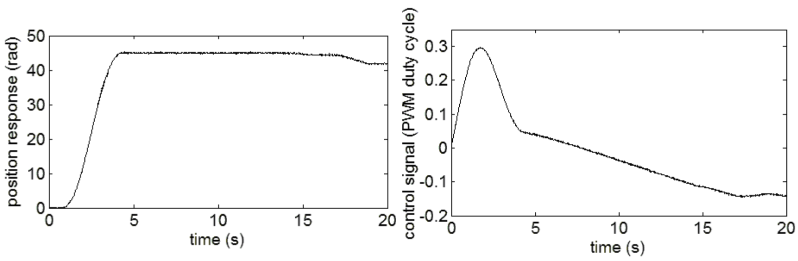

Fig. 5 – Real-time experimental results of the control system with PI controller and process with parametric disturbance.

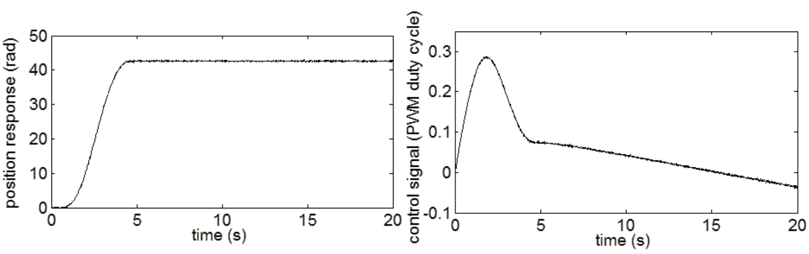

Fig. 6 – Real-time experimental results of the fuzzy control system with TSK PI-FC and process with parametric disturbance.

5. CONCLUSIONS

This paper has discussed aspects concerning the implementation of the adaptive GSA suggested in [28] in the optimal tuning of TSK PI-FCs. Figs. 3 to 6 highlight the performance improvement offered by this tuning approach in the angular position control of a laboratory servo system application.

Future research will target the introduction of experiment-based gradient information, the sensitivity reduction with respect to the random parameters in the algorithm, and the introduction of fuzzy logic [26, 27, 46] in the adaptation in order to obtain further performance improvements.

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