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DESIGN ASPECTS OF OPTIMAL PI CONTROLLERS WITH REDUCED SENSITIVITY FOR A CLASS OF SERVO SYSTEMS USING PSO ALGORITHMS

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Abstract. *The paper investigates some implementation aspects concerning the design of optimal PI controllers with reduced sensitivity by means of Particle Swarm Optimization (PSO) algorithms. Second order controlled processes with an integral component are considered. The reduced sensitivity results from solving the optimization problems supported by the definition of four integral objective functions. The objective functions are based on the sum of the squared control error, the squared output sensitivity functions with respect to the parametric variations of the controlled process and eventually the squared derivatives of the control error. The effects of the modifications of some parameters specific to the PSO algorithms are analyzed and highlighted by digital simulation results considering several weighting parameters and dynamical regimes of the optimal control systems.*

Key words: *digital simulation, PI controllers, PSO algorithms, sensitivity*

1. INTRODUCTION

The design of optimal control systems based on reduced sensitivity is of great interest [1]–[6]. Frequency domain approaches and time domain approaches are very popular in this context.

This paper considers the sensitivity analysis with respect to the parametric variations of the controlled process, and the sensitivity models (with respect to time) of the control system are defined [7]. The output sensitivities are then added to the integral objective functions and new objective functions in the framework of adequate optimization

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problems are defined. However solving these optimization problems is not simple because of their difficult formulation as functions of the tuning parameters of the controller. Numerical problems are suggested in [7] and PSO algorithms in [8] with focus on second order servo systems with an integral component.

The main contributions of this paper with respect to [8] concern:

- the definition of new optimization problems based on continuous-time integral objective functions,
- the analysis of the effects of other parameters in the PSO algorithms on the results of the optimization, therefore useful design aspects are offered.

The paper treats the following topics. The definition of the optimization problems and their solving by PSO algorithms are presented in the next section. A case study is considered in Section 3. The results of the analysis are organized in terms of illustrative tables. Digital simulation results are included. The conclusions are outlined in Section 4.

2. DEFINITION AND SOLVING OF OPTIMIZATION PROBLEMS BY PSO ALGORITHMS

Many controlled processes for servo systems can be characterized by the simplified linearized mathematical model in terms of the transfer function

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

where k_P is the gain and T_Σ is the small time constant or the sum of parasitic time constants, variable with respect to the considered operating point (of linearization). Similar models to (1) are used in many applications [9]–[19].

Acceptable performance with respect to the reference and disturbance inputs can be obtained using the structure presented in Fig. 1 [8], where: r – reference input, y – controlled output, $e = r_1 - y$ – control error, u – control signal, r_1 – filtered reference input, d_1, d_2, d_3, d_4– classes of disturbance inputs.

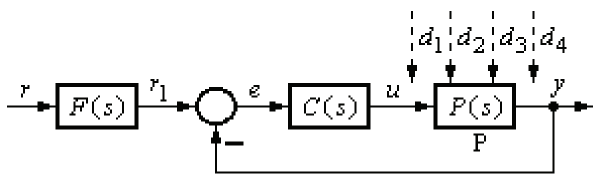

Fig. 1 Control system structure

Considering the disturbance input d_1 the following state-space mathematical model of P is defined:

$$\begin{aligned} \dot{x}_1 &= x_2, \\ \dot{x}_2 &= -(1/T_\Sigma)x_2 + (k_P/T_\Sigma)u + (k_P/T_\Sigma)d_1, \\ y &= x_1, \end{aligned} \tag{2}$$

The transfer function of the PI controller which can offer acceptable control system performance is

$$C(s) = k_c(1+sT_i)/s = k_C[1+1/(sT_i)],\ k_C = T_i k_c, \tag{3}$$

where: k_C (k_c) – gain, T_i – integral time constant, and the transfer function of the reference input filter is

$$F(s) = 1/(1+T_i s)\,. \tag{4}$$

The choice of the design parameter β specific to the ESO method [19] in the domain $1 < \beta < 20$ guarantees a compromise to the imposed control system performance indices (overshoot, settling time and phase margin). The performance indices can be modified according to the designer's option. The PI tuning conditions are

$$k_c = 1/(\beta\sqrt{\beta}T_\Sigma^2 k_P),\ T_i = \beta T_\Sigma\,. \tag{5}$$

The state variables in the presented models are: x_1 representing the controlled output (in case of d_1, d_2 and d_3) or the output of the integral component (in case of d_4), and x_2 standing for the output of the first-order delay component (in case of d_1, d_2 and d_4) or the output of the integral component (in case of d_3). Assuming that the state variable x_3 is the output of the integral component in the parallel construction of the PI controller for the nominal parameters of the controlled process $\{k_{p0}, T_{\Sigma 0}\}$ (with the subscript 0) the state-space mathematical model of the PI controller is

$$\begin{aligned} \dot{x}_3 &= [(1/\beta T_{\Sigma 0})]e, \\ u &= [1/(\sqrt{\beta}k_{P0}T_{\Sigma 0})](x_3 + e). \end{aligned} \tag{6}$$

The relations (2) and (6) lead to the state-space mathematical model of the control system

$$\begin{aligned} \dot{x}_1 &= x_2, \\ \dot{x}_2 &= -[k_P/(\sqrt{\beta}k_{P0}T_{\Sigma 0}T_\Sigma)]x_1 - (1/T_\Sigma)x_2 + [k_P/(\sqrt{\beta}k_{P0}T_{\Sigma 0}T_\Sigma)]x_3 \\ &\quad + [k_P/(\sqrt{\beta}k_{P0}T_{\Sigma 0}T_\Sigma)]r + (k_P/T_\Sigma)d_1, \\ \dot{x}_3 &= -[1/(\beta T_{\Sigma 0})]x_1 + [1/(\beta T_{\Sigma 0})]r, \\ y &= x_1. \end{aligned} \tag{7}$$

The sensitivity functions $\{\lambda_1, \lambda_2, \lambda_3\}$ and the output sensitivity function σ are defined next for (7):

$$\lambda_j = [\partial x_j/\partial\alpha]_{\alpha 0},\ \sigma = [\partial y/\partial\alpha]_{\alpha 0},\ \mathrm{j} = \overline{1,3}\,, \tag{8}$$

with the notation $\alpha \in \{k_p, T_\Sigma\}$. The calculation of the partial derivatives based on (7) and (8) leads to two sensitivity models of the control system for the dynamical regime characterized by the step modification of the set-point r of magnitude r_0 for d_1=0:

– the sensitivity model with respect to the modification of k_p:

$$
\begin{aligned}
&\dot{\lambda}_1 = \lambda_2, \\
&\dot{\lambda}_2 = -[1/(\sqrt{\beta}T_{\Sigma 0}^2)]\lambda_1 - (1/T_{\Sigma 0})\lambda_2 + \\
&\quad + [1/(\sqrt{\beta}T_{\Sigma 0}^2)]\lambda_3 - [1/(\sqrt{\beta}k_{P0}T_{\Sigma 0}^2)]x_{10} + \\
&\quad + [1/(\sqrt{\beta}k_{P0}T_{\Sigma 0}^2)]x_{30} + [1/(\sqrt{\beta}k_{P0}T_{\Sigma 0}^2)]r_0, \\
&\dot{\lambda}_3 = -[1/(\beta T_{\Sigma 0})]\lambda_1, \\
&\sigma_{kP} = \lambda_1,
\end{aligned}
\qquad (9)
$$

- the sensitivity model with respect to the modification of T_Σ:

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

The following objective functions are defined to achieve the good dynamical behavior of the control systems and reduced sensitivity:

$$
\begin{aligned}
I_{2e}^{kP}(\beta) &= \int_0^\infty [e^2(t) + \gamma_{kP}^2 \sigma_{kP}^2(t)]dt, \\
I_{2e}^{T\Sigma}(\beta) &= \int_0^\infty [e^2(t) + \gamma_{T\Sigma}^2 \sigma_{T\Sigma}^2(t)]dt,
\end{aligned}
\qquad (11)
$$

$$
\begin{aligned}
I_{2g}^{kP}(\beta) &= \int_0^\infty [e^2(t) + \tau_{kP}^2 \dot{e}^2(t) + \gamma_{kP}^2 \sigma_{kP}^2(t)]dt, \\
I_{2g}^{T\Sigma}(\beta) &= \int_0^\infty [e^2(t) + \tau_{T\Sigma}^2 \dot{e}^2(t) + \gamma_{T\Sigma}^2 \sigma_{T\Sigma}^2(t)]dt,
\end{aligned}
\qquad (12)
$$

where γ_{kP}, $\gamma_{T\Sigma}$, τ_{kP} and $\tau_{T\Sigma}$ are the weighting parameters. They result in the following optimization problems, which ensure the optimal design of the PI controllers:

$$
\beta^* = \arg\min_{\beta>1} I_{2e}^{kP}(\beta), \ \beta^* = \arg\min_{\beta>1} I_{2e}^{T\Sigma}(\beta), \qquad (13)
$$

$$
\beta^* = \arg\min_{\beta>1} I_{2g}^{kP}(\beta), \ \beta^* = \arg\min_{\beta>1} I_{2g}^{T\Sigma}(\beta), \qquad (14)
$$

where β^* is the optimal design parameter, and the inequality constraint is necessary because of the stability conditions imposed to the control systems.

Solving the optimization problems defined in (13) and (14) yields optimal control systems with reduced sensitivity. Since this is not a trivial task, a convenient way is to employ PSO algorithms as follows.

The PSO algorithms are evolutionary algorithms, which start with a random generation of candidate solutions and then search for the optimal solution [20], [21]. With this regard, agents are used, and they are evolving in a D-dimensional search space $\Re^D$ with randomly chosen velocities and positions knowing their best values so far and the positions in the search space. A swarm particle can be represented by two D-dimensional vectors $X_i = [x_{i1} \quad x_{i2} \quad \cdots \quad x_{iD}]^T \in \Re^D$ indicating the particle position and the particle velocity $V_i = [v_{i1} \quad v_{i2} \quad \cdots \quad v_{iD}]^T$. Let $P_{i,Best} = [p_{i1} \quad p_{i2} \quad \cdots \quad p_{iD}]^T$ be the best position of a specific particle and $P_{g,Best} = [p_{g1} \quad p_{g2} \quad \cdots \quad p_{gD}]^T$ be the best position of the swarm.

The particle velocity and position updating rules can be expressed in terms of the discrete-time state-space mathematical model [22]

$$V_i^{k+1} = wV_i^k + c_1 r_1 (P_{g,Best} - X_i^k) + c_2 r_2 (P_{i,Best} - X_i^k) \ , \tag{15}$$

$$X_i^{k+1} = X_i^k + V_i^{k+1} \ , \tag{16}$$

where: r_1, r_2 – random variables with a uniform distribution in (0, 1), i, $i = 1, n$ – index of the current particle in the swarm, n – number of particles in the swarm, k, $k = 1, j_{\max}$ – index of the current iteration, $j_{\max}$ – maximum number of iterations, and w – inertia weight showing the effect of the previous velocity vector on the new one. $V_{\max}$ is the upper limit placed on the velocity in all the dimensions preventing the particle from moving to rapidly in the search space.

The parameters c_1 and c_2 in (15) are the weighting factors of the stochastic accelerations pulling the particles towards their final positions. Adopting too low values of these weights will allow particles to roam far from the target regions before being tugged back. On the other hand, too high values will result in abrupt movements towards, or overshooting, the target regions.

The unified flowchart of the PSO algorithms is presented in Fig. 2 [8], [20]–[22].

4. CASE STUDY. DIGITAL SIMULATION RESULTS

The case study is focused on solving the four optimization problems defined in (13) and (14) with the objective functions according to (11) and (12). The controlled process in (1) is supposed to have the parameters $k_p = 1$ and $T_\Sigma = 1$s for the sake of simplicity. The analysis of the effects of several parameters of the PSO algorithms will be performed as follows. They will be associated with the presentation of samples of digital simulation results.

The conclusions can be different for other parameters of the controlled process [23], [24]. Additional nonlinearities lead to the necessity of real-time experimental results because the model (1) can be not enough to capture entirely all specific features of the controlled process.

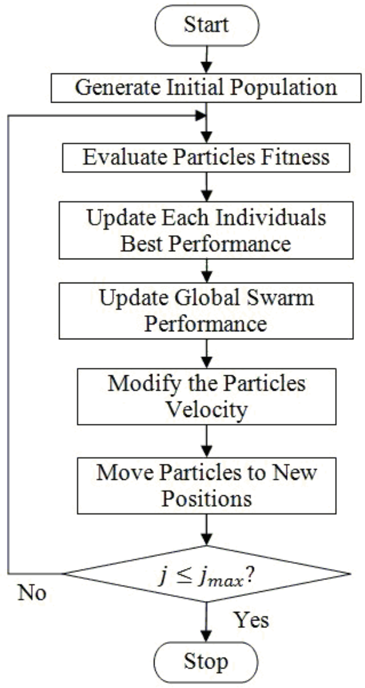

Fig. 2 Unified flowchart of PSO algorithms

As described in the previous section, the optimization problems (13) and (14) are reduced to finding the optimal value β^* of the design parameter β. That is expressed in terms of the solution search space with only one dimension, $D = 1$.

The evaluation of the population and the calculation of the local best $P_{i,Best}$ and global best $P_{g,Best}$ related to the fitness functions $I_{2e}^{kP}(\beta)$ and $I_{2e}^{T\Sigma}(\beta)$ for the optimization problems defined in (13) and to the fitness functions $c_1 = 0.3$ and $I_{2g}^{T\Sigma}(\beta)$ for the optimization problems defined in (14). The local and global best are calculated by repeated digital simulations of the control system behavior with respect to the unit step modification of the reference input accepting the presence of the reference input filter.

The values of the weighting parameters used in the minimization of $I_{2e}^{kP}(\beta)$ and $I_{2e}^{T\Sigma}(\beta)$ were chosen to be $\gamma_{kP}^2 = 0.7$ and $\gamma_{T\Sigma}^2 = 0.13$, and the parameter values of the corresponding PSO algorithms were set to $c_1 = 0.3$ and $c_2 = 0.3$. Considering the optimization problems defined in (13) the analysis of the effects of the number of particles n and of the maximum number of iterations $j_{\max}$ on the optimal controller parameters (k_C^* and T_i^*) and on the minimum values of the objective functions ($I_{2e\min}^{kP}$ and $I_{2e\min}^{T\Sigma}$) is presented in Table 1 for $I_{2e}^{kP}(\beta)$ and in Table 2 for $I_{2e}^{T\Sigma}(\beta)$.

Table 1 Results of the analysis of the effects of the number of particles and of the maximum number of iterations on the optimal controller parameters and on the minimum value of the objective function I_{2e}^{kP}

n	$j_{\max}$	β^*	k_C^*	T_i^* (s)	$I_{2e\min}^{kP}$
3	10	4.3032	0.4821	4.3032	7.1839
3	25	2.6263	0.6171	2.6263	5.4286
3	50	2.6262	0.6171	2.6262	5.4286
5	10	2.6783	0.6110	2.6783	5.4320
5	25	2.6264	0.6170	2.6264	5.4286
5	50	2.6262	0.6171	2.6262	5.4286
10	10	2.6482	0.6145	2.6482	5.4292
10	25	2.6260	0.6171	2.6260	5.4286
10	50	2.6262	0.6171	2.6262	5.4286

Table 2 Results of the analysis of the effects of the number of particles and of the maximum number of iterations on the optimal controller parameters and on the minimum value of the objective function $I_{2e}^{T\Sigma}$

n	$j_{\max}$	β^*	k_C^*	T_i^* (s)	$I_{2e\min}^{T\Sigma}$
3	10	2.7309	0.6051	2.7309	4.4050
3	25	4.2353	0.4859	4.2353	6.7337
3	50	2.1346	0.6844	2.1346	4.0155
5	10	4.1257	0.4923	4.1257	6.5292
5	25	2.1343	0.6845	2.1343	4.0155
5	50	2.1346	0.6844	2.1346	4.0155
10	10	2.1134	0.6879	2.1134	4.0163
10	25	2.1349	0.6844	2.1349	4.0155
10	50	2.1346	0.6844	2.1346	4.0155

For the optimization problem defined in (14) the values of the parameters used in the minimization of $I_{2g}^{kP}(\beta)$ and $I_{2g}^{T\Sigma}(\beta)$ were chosen to be $\gamma_{kP}^2 = 0.7$ and $\tau_{kP}^2 = 20000$ for $I_{2g}^{kP}(\beta)$, and $\gamma_{T\Sigma}^2 = 0.13$ and $\tau_{T\Sigma}^2 = 30000$ for $I_{2g}^{T\Sigma}(\beta)$.The analysis of the effects of the number of particles and of the maximum number of iterations on the optimal controller parameters and on the minimum values of the objective functions is presented in Table 3 for $I_{2g}^{kP}(\beta)$ and in Table 4 for $I_{2g}^{T\Sigma}(\beta)$.

The results presented here are a representative sample of the total set of simulations performed for these objective functions. The optimal choice of particles and iteration steps represents the main challenge when tuning the PSO algorithms in order to obtain the computational efficiency.

As it can be observed in Tables 1 to 4, choosing a small number of particles may give us smaller execution times. However the algorithms can easily get trapped into local minima as it happened for the case in which we chose to operate with only three particles.

Raising the number of particles to five showed some improvement, but the algorithm still got trapped occasionally. The solution to overcome this problem without adding new particles into the algorithms was to increase the number of iterations, thus allowing the particles to reach the global minimum.

Table 3 Results of the analysis of the effects of the number of particles and of the maximum number of iterations on the optimal controller parameters and on the minimum value of the objective function I_{2g}^{kP}

n	$j_{\max}$	β^*	k_C^*	T_i^* (s)	$I_{2g\min}^{kP}$
3	10	5.6483	0.4208	5.6483	9.6811
3	25	3.4943	0.5350	3.4943	6.0937
3	50	3.3263	0.5483	3.3263	5.9378
5	10	3.3852	0.5435	3.3852	6.0422
5	25	2.6573	0.6134	2.6573	5.4318
5	50	2.6577	0.6134	2.6577	5.4318
10	10	4.6705	0.4627	4.6705	7.8185
10	25	2.6573	0.6134	2.6573	5.4318
10	50	2.6577	0.6134	2.6577	5.4318

Table 4 Results of the analysis of the effects of the number of particles and of the maximum number of iterations on the optimal controller parameters and on the minimum value of the objective function $I_{2g}^{T\Sigma}$

n	$j_{\max}$	β^*	k_C^*	T_i^* (s)	$I_{2g\min}^{T\Sigma}$
3	10	4.6942	0.4615	4.6942	7.6492
3	25	5.6566	0.4205	5.6566	9.7277
3	50	2.1288	0.6854	2.1288	4.0169
5	10	4.6774	0.4624	4.6774	7.6060
5	25	2.1290	0.6853	2.1290	4.0169
5	50	2.1288	0.6854	2.1288	4.0169
10	10	4.0136	0.4992	4.0136	6.3439
10	25	2.2445	0.6675	2.2445	4.0356
10	50	2.1288	0.6854	2.1288	4.0169

The numerous simulations performed with these algorithms show a small sensitivity with respect to the initial conditions of both the algorithm and the control system behavior. The operation of the PSO algorithms with different numbers of particles increases the influence of the initial conditions by limiting the algorithms' capability to overcome local minima situations.

Two digital simulation results are presented as follows to illustrate the behavior of PSO-based optimal control systems. The behavior of the optimal control system with the parameters $k_C^* = 0.5350$ and $T_i^* = 3.4943\text{s}$, which correspond to the second line in Table 3, is presented in Fig. 3. The behavior of the optimal control system with the parameters $k_C^* = 0.4205$ and $T_i^* = 5.6566\text{s}$, which correspond to the second line in Table 4, is presented in Fig. 3. The results presented in Fig. 3 and Fig. 4 were obtained for the unit step modification of r followed by the 0.5 step modification of d_1.

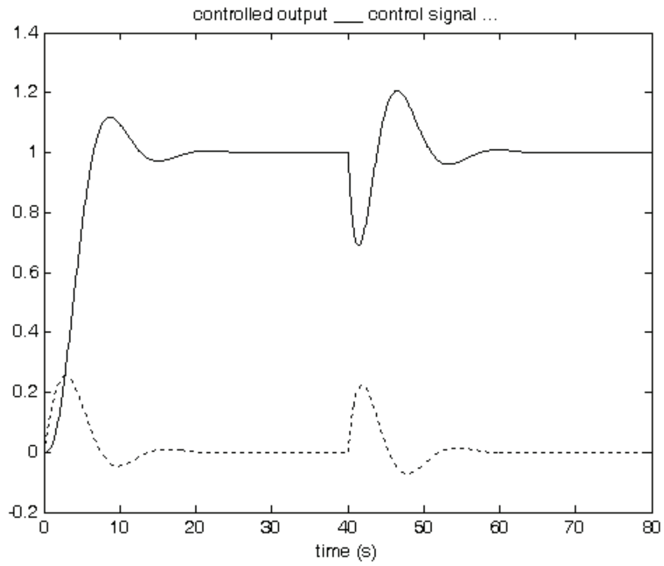

Fig. 3 Digital simulation results concerning the optimal control system with the parameters $k_C^* = 0.5350$ and $T_i^* = 3.4943$s

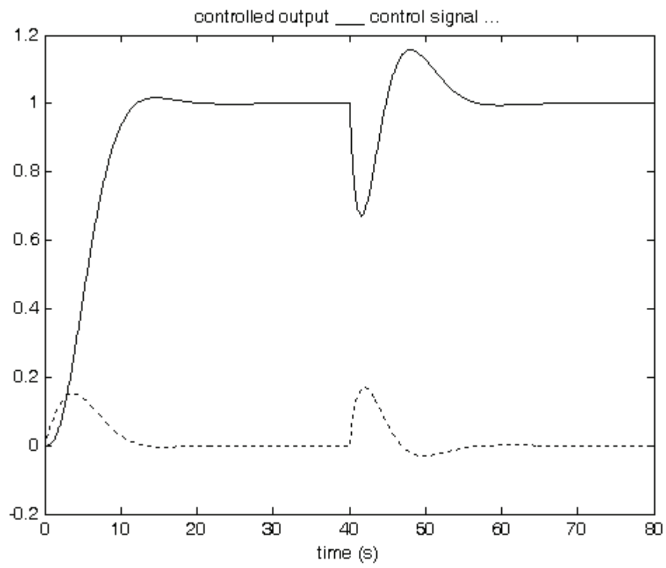

Fig. 4 Digital simulation results concerning the optimal control system with the parameters $k_C^* = 0.4205$ and $T_i^* = 5.6566$s

5. CONCLUSIONS

This paper presents several engineering aspects concerning the optimal design of PI controllers with reduced sensitivity with respect to the parametric variations of the controlled process considering a class of controlled processes. The integration of the PSO algorithms into the optimal design of the PI controllers raises new issues concerning the computational efficiency and convergence.

Simulations were conducted in order to illustrate the behavior of the optimal control systems in the dynamic regimes characterized by the step modifications of the reference and disturbance inputs. They show very good control system performance indices although the empirical optimization indices (overshoot, settling time, etc.) were not considered in the objective functions which were minimized. With this regard the introduction of the empirical optimization indices in the objective function will represent a direction of future research to be applied in various control systems applications [25]–[33].

The main limitation of the PSO algorithms regards the degrees of freedom resulted from the compromise to the computational efficiency and maximum accepted error. Therefore another direction of future research will include an adaptive method to tune the parameters of the PSO algorithms themselves. Extensive tests conducted for many real-world applications [34]–[41] are necessary in order to validate the new approach.

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ASPEKTI PROJEKTOVANJA OPTIMALNIH PI REGULATORA SMANJENE OSETLJIVOSTI ZA KLASU SERVO SISTEMA POMOĆU PSO ALGORITAMA

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Ovaj rad istražuje neke aspekte implementacije u vezi sa projektovanjem optimalnih PI regulatora smanjene osetljivosti pomoću PSO algoritama. Razmatrani su regulisani procesi drugog reda sa integralnom komponentom. Smanjena osetljivost se javlja kao rezultat rešavanja problema optimizacije na osnovu definicije četiri integralne objektivne funkcije. Objektivne funkcije su zasnovane na zbiru kvadrata greške upravljanja, kvadrata funkcija osetljivosti izlaza na promene parametara regulisanog procesa i, na kraju, kvadrata izvoda greške upravljanja. Efekti modifikacije nekih parametara specifičnih za PSO algoritme su analizirani i potvrđeni rezultatima digitalne simulacije u vezi sa nekoliko težinskih parametara i dinamičkih režima optimalnih sistema upravljanja.

Ključne reči: *digitalna simulacija, PI regulatori, PSO algoritmi, osetljivost*