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Thermal parameter control based on time series adaptive PID control

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Abstract. For the problem that optimal parameters is difficult to determine in the progress of ADRC(Active disturbance rejection controller), a ADRC parameter adjustment algorithm based on the estimation of sampling probability distribution is proposed. Firstly, parameter optimization controller is established in the linear ADRC process, and the ITAE result is used as a sub item on system dynamic performance for evaluation; then, for NP hard optimization problem in the parameters of ADRC controller, construct estimation of probability distribution of sampling probability based on Gibbs sampling probability model, improve the universality of the population in the estimation of distribution, and construct individual sampling structure for excellent learning samples, which improves the optimization performance of the algorithm; finally, reach standard test functions of the sampling probability distribution estimation to verify the validity of the proposed control algorithm, and use proposed control algorithm to establish overheated steam temperature of boiler control system model. The result shows that the optimized control system has good control performance and robustness.

Key words. ADRC optimization, Sampling probability, Distribution estimation, Parameter adjustment.

1. Introduction

The ADRC proposed by scholar Han Jingqing is a nonlinear type controller [1, 2]. It considers the different forms of disturbance existing in the inner and outer parts of the model as the total disturbance, and uses the extended type observer to realize the compensation and estimation of the total disturbance. Therefore, the ADRC controller can be used to solve the system uncertain control object [3, 4] with nonlinear characteristics. In the ADRC control, the parameter setting determines the performance of its controller. There are many parameters involved in the opti-

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mization of active disturbance rejection control parameters. If we only rely on the designer's experience, ADRC parameter tuning is time-consuming, and it cannot ensure that the system has the best response. Therefore, the optimization of controller parameters in ADRC control is a hot issue in the research. The literature [8] based on active genetic algorithm (AGA) reaches the optimization of ADRC parameters, which can solve the multi-parameter tuning problem of ADRC controller; literature [9] uses the proposed cloud clonal chaos method to realize ADRC controller parameter tuning effectively, which can achieve good control performance; literature [10] uses the multi-target parameters optimization method to reach hybrid optimization ADRC controller, which can effectively achieve the linear parameters setting. The above algorithm has achieved certain results in improving the performance of ADRC control. Based on the above research, we consider the use of Estimation of distribution algorithm (EDAs) to further improve the performance of ADRC parameter optimization. The distribution estimation algorithm was first proposed by the literature [11], and then different versions of the improved algorithms, such as the literature [12], have been designed to improve the performance of the algorithm.

At present, the research results of distributed estimation algorithms are relatively few in domestic researchers. From the perspective of innovation, this paper considers the use of EDAs algorithm as an optimization tool for ADRC controller parameters tuning. Considering to use Gibbs sampling in distribution estimation algorithm to improve algorithm, and construct probability condition distribution of Markov chain, we can effectively obtain approximate asymptotic joint distribution probability, realize the sample learning to enhance the quality, and thus enhance the estimation of distribution process results. The proposed algorithm for Gibbs sampling algorithm is based on probability distribution (Gibbs sampling probability distribution estimation, SPEDA). Then the model of the boiler superheat temperature control system is established by using the proposed SPEDA control algorithm. The results show that the performance of the temperature control system can be improved effectively.

2. Linear ADRC optimal control

2.1. ADRC control

In the two order typical linear structure of the distributed estimation controller (as in Figure 1), y and r are the output signals and the input setting signals of the distributed estimation controller, respectively. U is the input of the control law of the distribution estimation, and the d is an additional unknown disturbance, and G_p is the control object of the distributed estimation system. The ESO module in the figure is the extended state observer for the control system.

In the block diagram of the linear two order ADRC control shown in Figure 1, the state extended observer ESO module can be represented as the following form :

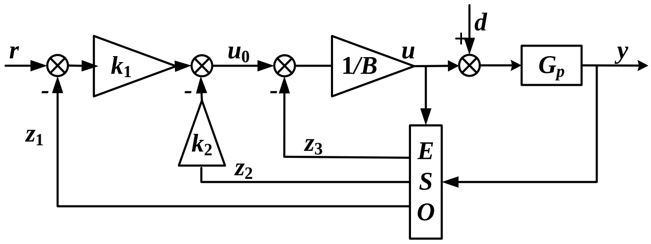


Fig. 1. Block diagram of linear two order ADRC control

$$\begin{cases} \dot{z}_1 = z_2 + \beta_1(y - z_1) \\ \dot{z}_2 = z_3 + \beta_2(y - z_1) + Bu \\ \dot{z}_3 = \beta_3(y - z_1) \end{cases} \tag{1}$$

In the formula, β_1, β_2 and β_3 are the optimization setting parameters of the ADRC system . The control object of the two order system can be expressed as:

$$\ddot{y} = f(t, y, \dot{y}, \omega) + Bu\,. \tag{2}$$

In the formula, f is ADRC gross error of system. y, $\dot{y}$ and $\ddot{y}$ are the real states of controlling the existence of the object., first order differential state and two order differential state. z_1, z_2 and z_3 severally are state observation value of y, $\dot{y}$ and f. $\omega(t)$ is uncertain disturbances existing in the ADRC system, f is expression of uncertain perturbation function, B is ADRC system controller parameter.

The linear two order control rate of the ADRC system can be expressed as the following function form:

$$\begin{aligned} u_0 &= k_1(r - z_1) - k_2 z_2 \\ u &= (u_0 - z_3)/B \end{aligned} \tag{3}$$

When adopting ESO template for getting $z_3 \approx f$, it can get closed loop expected transmission form as:

$$\frac{y(s)}{r(s)} = \frac{k_1}{s^2 + k_2 s + k_1}\,. \tag{4}$$

For the problem of multi parameter optimization in the linear optimal ADRC control, literary[13] decreases the setting parameters in the formula(4), from B, k_1, k_2, β_1, β_2 β_3 to B, k_1, k_2, w_0.

2.2. Evaluating indicator

The ITAE index is used to dynamically evaluate the performance of ADRC control system, that is to say, the absolute error value is multiplied by the integral form of time to build the evaluation performance index as:

$$J_{ITAE} = \int_0^\infty t\,|e(t)|dt\,. \tag{5}$$

In order to improve the performance of ADRC control system, we need to consider comprehensively the stability, rapidity and accuracy of the system operation. It is reflected in the evaluation performance index that the overshoot Sigma and the control rise time tr are considered in the control index. At the same time, if only the dynamic characteristics of the system as the pursuit of goals, need to transfer control signal is very strong, but it is in the system, the control object also has a certain saturation characteristic, control effect to difficult to achieve, it will cause a decline, the control performance of the proposed algorithm in this regard, in the performance evaluation in the comprehensive consideration of energy control u, the evaluation function can be rewritten as the following form

$$J = \lambda_3 tr + \int_0^{\infty} (\lambda_1 t\,|e(t)| + \lambda_2\,|u(t)| + \lambda_4\,|\sigma|)dt\,. \tag{6}$$

In the formula(6): λ_1, λ_2 and λ_3 separately are the equilibrium coefficient of the control index. For the optimization of the control index, the sampling probability distribution estimation algorithm is considered to be optimized, and the specific algorithm and its improved form will be described in the next section.

3. Sampling probability distribution estimation

3.1. Gibbs sampling description of the algorithm

The algorithm of EDAs is how to build the probability distribution model more efficiently and construct the method of sample and training for the corresponding model. But the standard form of EDAs algorithm has two obvious shortcomings: (1) the dimension constraint problem; the sample data with high dimension exist obvious high coupling situation; (2) unsupervised training has not ideal algorithm accuracy. To this end, we use the sampling probability model to build a new improved version of the EDAs algorithm.

If X is a given random high dimensional vector data, the joint probability density of the vector data can be expressed as $f_X(x)$. Because this probability density has some irregular random properties, it cannot be built directly. The way to solve the problem is to build a $f_{X_i|X^{(i)}}\left(x_i\,|x^{(i)}\right)$ model of probability distribution. Use Gibbs sampling method, establish probability conditional distribution model $f_{X_i|X^{(i)}}\left(x_i\,|x^{(i)}\right)$ featured Markov chain, and achieve the control effect of gradually approaching the joint probability distribution model $f_X(x)$.

The Gibbs algorithm is sampled for each variable, according to the probability distribution characteristics of the data and the current conditions of the population, the population by randomly to form new, using this method to build the Markov distribution chain sampling sequence, the probability distribution can be the steady probability of this sample sequence is based on the joint distribution of the time average approximation $\phi(X)$, statistic average approximation based on its mathematical description can be expressed as follows:

$$\lim \sum_{t=1}^{T} \phi\left(X\left(t\right)\right) \Big/ T = E\left\{\phi\left(X\right)\right\} . \tag{7}$$

In the formula (7), mathematical formulas can express the generated Markov chain sequence samples. The data sequence is the same as the samples sampled directly in the joint distribution model. The Gibbs sampling algorithm flow is, as described in the pseudo code 1 process.

1. Input data parameters: N, $P\left\{X_i \left| X^{(i)}\right.\right\}$;
2. Initialization sampling process.:
   $P = \emptyset, x\left(0\right) \sim Uniform\left(S\right)$;
3. Iterative execution process:
   for $t = 1 \sim \left(K_0 + N\right)$ ***do***
      for $i = 1 \sim D$ ***do***
         $x_i\left(t\right) \sim P\left(X_i \left| x_1\left(t\right), \cdots, x_{i-1}\left(t\right), x_{i+1}\left(t-1\right), \cdots, x_D\left(t-1\right)\right.\right)$;
      End for
   End for
4. Output result data:
   if $t > K_0$ ***then*** $P = P \cup \left\{x\left(t\right)\right\}$;

The purpose of selecting parameters $\Delta t = D$ in the Gibbs sampling procedure shown in pseudo code 1 is to ensure that the component of the algorithm has the Gibbs first sampling feature. The computational complexity of the above Gibbs sampling procedure algorithm can be expressed as $O\left(\left(D^2 + N\right) \cdot D\right)$.

3.2. Sample sequence training

According to the supervised training mode of the sample, the self-learning adjustment process of the execution parameters can be expressed as follows:

$$\mathcal{Q}_i = \left\{\left(x^{(i)}, x_i\right) | x \in P\right\} . \tag{8}$$

In the formula(8), do parameter estimation for probability conditional model $f_{X_i|X^{(i)}}\left(x_i \left| x^{(i)}\right.\right)$. $\left(x^{(i)}, x_i\right)$ represents the selected sequence of samples $x^{(i)}$ mean expectation is x_i. In order to simplify algorithm, assume X_i's value space is $X_i \in \{-1, 1\}$. So probability conditional model $f_{X_i|X^{(i)}}\left(x_i \left| x^{(i)}\right.\right)$'s estimation step can be expressed as:

Step1: The sample classifier is constructed with the sample sequence $\mathcal{Q}_i$ and the corresponding classification algorithm;

Step2: Estimation of parameter distribution of probability conditional model $f_{X_i|X^{(i)}}\left(x_i \left| x^{(i)}\right.\right)$ by using the constructed sample classifier

The form of the classified interface can be defined as follows:

$$g = \arg\min_{g \in \mathcal{G}} \left\{ \sum_{\mathcal{Q}} L\left(y, g\left(x\right)\right) \right\}. \tag{9}$$

In the formula (9), $\mathcal{Q} = \{(x, y)\}$ is a supervised sequential form for samples. $L\left(y, g\left(x\right)\right)$ set for the loss data of the sample data, $\mathcal{G}$ sets the function candidate and its function is shielding the output of the classification data from the undesirable data. The constructed classification interface can be expressed as a form. Then the probability condition estimation model can be expressed as:

$$\hat{P}\left(Y \left| X \right.\right) \sim \exp\left[-L\left(Y, g\left(X\right)\right)\right] \tag{10}$$

In the formula(10), based on the foregoing loss function and combining the maximum likelihood type function of the classification process, the equivalent model of the model (10) can be obtained, which is as follows:

$$g = \arg\max_{g \in \mathcal{G}} \left\{ \prod_{(x,y) \in \mathcal{Q}} \hat{P}\left(y \left| x \right.\right) \right\}. \tag{11}$$

3.3. Algorithm calculation process

Pseudo code 2: Sampling probability distribution estimation

1. Algorithm initialization:
   $P = \{x\left(i\right) \left| i = 1, \cdots, N \right.\}, x\left(i\right) \sim Uniform\left(S\right), P_{opt} = \emptyset;$
2. Executing iterative process:
   // Optimization
   for $ep = 1 : epoch$ do
   $x^* = \arg\max_{x \in P} \{eval\left(x\right)\}; \quad P_{opt} = P_{opt} \cup \{x^*\}; \quad P = P \backslash \{x^*\};$
   End for
   //study
   for $i = 1 : D$do
   $P_i = \left\{\left(x^{(i)}, x_i\right) \left| x \in P_{opt} \right.\right\}; \quad g_i = \arg\min_{g \in \mathcal{G}} \left\{ \sum_{\mathcal{Q}_i} L\left(y, g\left(x\right)\right) \right\};$
   $P\left(X_i \left| X^{(i)} \right.\right) \sim \exp\left(-L\left(X_i, g\left(X^{(i)}\right)\right)\right);$
   End for
   //sample
   $P_{new} = sample\left(N - N_0, \left\{\hat{P}\left(X_i \left| X^{(i)} \right.\right)\right\}\right);$
   //renewal
   $P = P_{new} \cup P_{opt}; \quad P_{opt} = \emptyset;$
3. Output algorithm :
   $x_{opt} = \arg\max_{x \in P} \{eval\left(x\right)\}; \quad fit_{opt} = eval\left(x_{opt}\right).$

Suppose $(x_{opt}, fit_{opt}) = IEDA\,(eval)$ is model expression form of EDAs algorithm, *eval* in the model expresses evaluation indicator, so improved EDAs algorithm calculation process as pseudo code states.

Based on the data cut-off method, a sequence updating form is constructed, then the fitness difference individuals are eliminated, and a new sample is constructed based on probability sampling model to achieve the replacement of fitness difference individuals. $(N - N_0)/N$ can be defined as the elimination ratio of the population of the population.

4. Experimental analysis

4.1. EDAs algorithm performance evaluation

Select the commonly used two standard test functions based on the comparative analysis of the experiment, the experiment software platform: the host system: Ultimate win7, test software: matlab2012a, selected host processor: i5-5440k CPU, RAM is selected as the host memory: 4G DDR3 1333. The experimental performance comparison method selects the classical EDAs algorithm and the environment recognition EDAs algorithm (EIEDA), which is described in the literature [12]. The selected standard test examples can be expressed as follows:

$$f_1\,(X) = \sum_{i=1}^{n} \left(100\,\left(x_{i+1} - x_i^2\right)^2 + (x_i - 1)^2\right). \tag{12}$$

$$f_2\,(X) = \left[\sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n} \cos\left(x_i \Big/ \sqrt{i}\right) + 1\right] \Bigg/ 4000\,. \tag{13}$$

The selection of experimental parameters: the algorithm termination algebra is set to 300, the termination threshold is set $\lg(f) = 10^{-7}$, the population size is set to 1024, and the population elimination rate is set to 0.5. The population size of the algorithm is set to 1024, mainly because the data dimension of the sub problems involved in this experiment is $n_i \leq 6$, in other words, the size of the problem subspace is $m \leq 64$, and the scale of 1024 species meets the requirements of dimension degradation. Based on the above parameter setting, the interval coverage of the EDAs algorithm is approximately $100 \times 1024 \approx 10^5$. We use the test function (12) to carry out experiments, and select two dimensions of data in two dimensions and three dimensions respectively to perform algorithm optimization and simulation, and make graphic presentation, as shown in Figure 2.

In the figure 2, For the test function (13) in the form of three dimensional $(n = 3)$, using the proposed EDAs to improve the distribution estimation of the population optimal individual evolution. It is the data evolution of SPEDA algorithm, which is based on the current optimal value of interval algebra. Based on the three dimensional evolutionary image schematic diagram, the SPEDA algorithm can avoid the local merit point effectively and gradually converge to the global best value point.

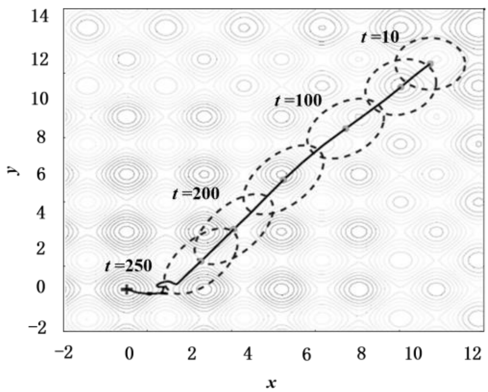
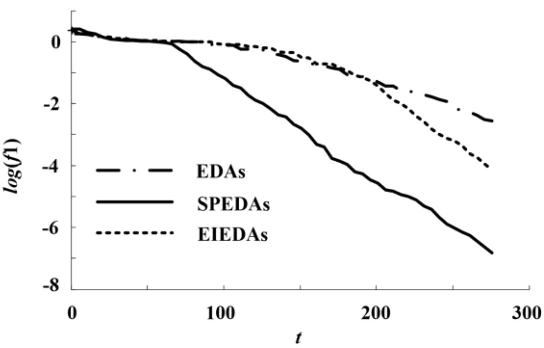
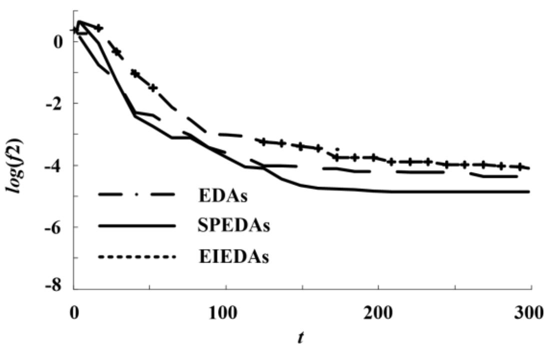


Fig. 2. Three dimensional evolution

Figure 3 (a$\sim$b) shows that the contrastive contrast of the three contrast algorithms, which are EIEDAsEDAs and SPEDA, on the standard test function (11$\sim$12). It is assumed that the initial search interval of the algorithm in the process of experiment is $x \in [0, 1]$, $y \in [0, 1]$, $n = 10$.



(a) Test function(11)



(b) Test function(12)

Fig. 3. Algorithm convergence contrast

From figure 3a we can know, the proposed SPEDAs algorithm compared with EIEDAs algorithm and EDAs has significant performance advantages, when the SPEDAs algorithm to the 283rd step, the algorithm reaches the set threshold $\lg(f) = 10^{-7}$, the iterative evolution accuracy of EIEDAs algorithm is only $\lg(f) \approx 10^{-4}$, and the iterative evolution accuracy of EDAs algorithm is $\lg(f) \approx 10^{-2}$, which reflects the convergence rate of SPEDAs method. From Figure 3B, we can see that three contrasting methods such as EIEDAs, EDAs and SPEDAs will produce premature phenomenon on a precision value, and they do not converge to the termination threshold $\lg(f) = 10^{-7}$. They all stop iterating at the 300 place of final value algebra. But the convergence accuracy of SPEDAs algorithm is approximately $\lg(f) \approx 10^{-5}$, and the convergence accuracy of EDAs and EIEDAs iterative optimization is about $\lg(f) \approx 10^{-4}$. In general, EDAs algorithm is better than EDAs algorithm. The experimental data verify the performance effectiveness of the proposed SPEDAs algorithm in computational accuracy and computational efficiency.

4.2. Optimization of boiler temperature control process

Experimental setup: According to the experimental comparison of boiler temperature control process optimization mentioned in document [14], the setting of control load is 75%, and the ADRC control system adopts cascade control, assuming that the proportion of secondary control loop is set to 100. First, the effective reduced order reduction of the control loop is realized based on two point crossover, and the first order approximate lagging object is obtained:

$$G(s) = \frac{1.195}{138.183s + 1} e^{-159.051s} . \tag{14}$$

According to the literature[14], the H infinite PID robust controller is used to control, the H infinite PID control parameters obtained is: $K_I = 0.0043$, $K_P = 0.908$, $K_D = 45$

Objective optimization experiment: The zero order coefficient of the molecule in the expression of the control object in its transmission model is 1.195. According to the method described in document [15], the PID control parameters are correspondingly rewritten as ADRC control parameter form, and four initial values of pending parameters are obtained. Then, the SPEDAs algorithm is used to optimize the transformed ADRC control parameters. The contrast algorithm still selects two algorithms, EIEDAs and EDAs. The iterative evolution process of the optimized target J is shown in Figure 4 contrast curve.

According to the figure 4, as the iterative evolution process of the algorithm continues, the SPEDAs algorithm has a faster convergence rate than the two contrast algorithms. And compared with the two algorithms of EIEDAs and EDAs, the SPEDAs algorithm has a higher convergence accuracy.

Step response simulation: On the basis of the above control parameters optimization, we use the three optimized algorithms to control the parameters of ADRC controller to compare the step signal control effect in the control process. The optimal control parameters of the three algorithms are shown in Table 1.

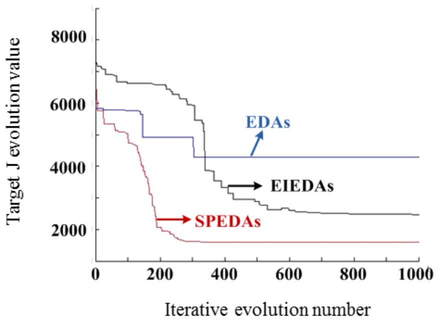


Fig. 4. Target J optimization curve

Table 1. ADRC step response parameters

algorithm	B	w_0	k_1	k_2
EDAs	0.1422	1.0544	0.0017	0.3266
EIEDAs	0.1292	0.9874	0.0024	0.3269
SPEDAs	6.5113e-4	0.0138	0.0026	3.4049e-4

Using the ADRC controller shown in Table 1, we control the step signal in the control process, and the control curves of the three algorithms of SPEDAs, EDAs and EIEDAs are shown in Figure 5.

According to the control curve shown in Figure 5, using ADRC SPEDAs optimization controller is designed in this paper, for the control of ADRC linear system response speed and overshoot compared to the best, the overshoot is smaller EDAs and EIEDAs, helps to improve the stability of the control system, has better control effect.

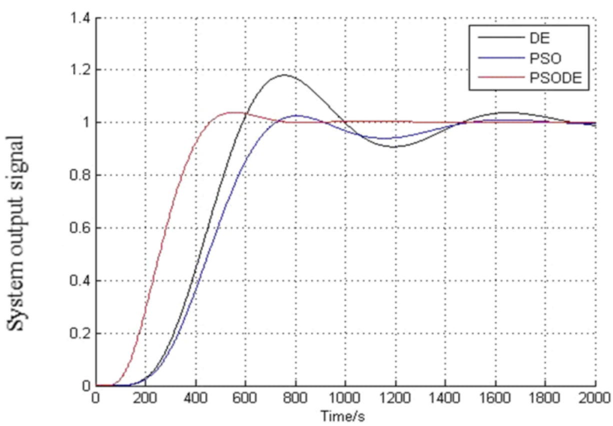


Fig. 5. System output signal under step corresponding

Robust stability analysis:In the actual boiler temperature control, the situation of control parameter ca not be determined. Here we use stochastic Monte-Carlo to construct control robustness performance evaluation of ADRC linear system. The ADRC control parameters are changed in $\pm 10\%$, and the control indexes of t_r and sigma $\sigma\%$ are compared. The experiment process of the Monte-Carlo is repeated 100 times, and the experimental results are shown in Figure 8.

The sigma $\sigma\%$ is used as the abscissa, and t_r is used as the ordinate. The point distribution shown in Figure 6 is a group of two dimensional data combinations. The better the degree of concentration of the data points shows, the stronger the robust control of the algorithm. According to the data shown in Figure 6, we can see that the data distribution of ADRC system based on SPEDAs algorithm is the most concentrated, which indicates that the ADRC system based on SPEDAs algorithm is more robust.

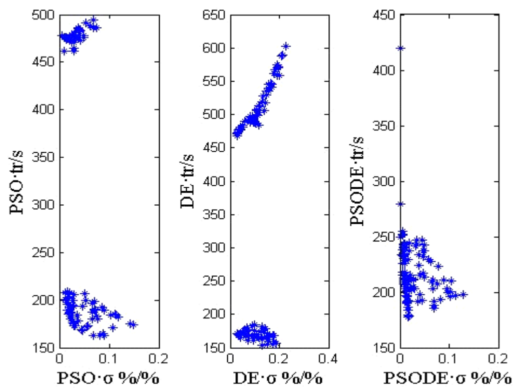


Fig. 6. Robust stability comparison

5. Conclusion

A series of experiments are carried out to evaluate the performance of time-delay systems with ADRC controller. The purpose is that test the applicability of PSODE algorithm to automatically optimize ADRC parameters. The simulation results verify the effectiveness of the proposed algorithm, and prove that the algorithm proposed in this paper, which enhances the robustness of the control system and improves the control ability of the control system.

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