論 文
52D-1-2

새로운 축소 모델을 이용한 Smith-Predictor 제어기 설계

Smith-Predictor Controller Design Using New Reduction Model

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Abstract - To improve the performance of PID controller of high order systems by model reduction, we proposed two model reduction methods. One, Original model with two point ($\angle G(jw) = -\pi/2, -\pi$)in Nyquist curve used gradient base method and genetic algorithm. The other, Original model without two point($\angle G(jw) = -\pi/2, -\pi$)in Nyquist curve used to add very small dead time. This method has annexed very small dead time on the base model for reduction, and we remove it after getting the reduced model, and , we improved Smith-predictor for a dead-time compensator using genetic algorithms. This method considered four points($\angle G(jw) = 0, -\pi/2, -\pi, -3\pi/2$) in the Nyquist curve to reduce steady state error between original and reduced model. It is shown that the proposed methods have more performance than the conventional method.

Key Words : Model reduction, PID Controller, Smith-Predictor Controller, Genetic Algorithm.

1. Introduction

Proportional-plus-integral-plus-derivative(PID) controllers are widely used in the process control industry. The main reason is its relatively simple structure, which can be easily understood and implemented in practice. They are thus more acceptable than advanced controllers in practical applications unless evidence shows that they are insufficient to meet specifications. Owing to their popularity in the industrial field, many approaches have been developed to determine PID controller parameters for single input. single output (SISO) systems. Among the well-known formulas there are the Ziegler-Nichols rule, the Cohen-Coon method, and internal model control. However, most of the tuning methods are derived for particular, situations, and therefore applied well only to their own limited areas. Therefore the PID tuning algorithm which can be applied generally to processes with varies dynamic characteristics has been studied. Among them, one of the popular approaches used model reduction. Wang has shown that for the case of process model with $\angle G(jw) = -\pi/2$ and $-\pi$ point in the Nyquist curve, second-order plus dead time model make from original model. But it exists error between original model and reduction model into time domain and frequency domain, and it cant applied process model without $\angle G(jw) = -\pi/2$ and $-\pi$ point in the Nyquist curve.

In this paper, to overcome these problems, we propose a new model reduction algorithm for SISO continuous-time systems considering four points in the Nyquist curve. The optimal parameters of reduction model are computed through gradient base method and genetic algorithm. And for high order systems without dead time that it have not two point $\angle G(jw) = -\pi/2, -\pi$ in Nyquist curve, we proposed a method to add very small dead time. This method has annexed very small dead time on the base model for reduction, and we remove it after getting the reduced model. The initial value of parameters of the reduced model is calculated to coincide four points ($0, -\pi/2, -\pi, -3\pi/2$) on the Nyquist curve. The GA is a probabilistic search procedure based on the mechanics of natural selection and natural genetics. Controller design methods using reduction model unite to cancel the poles of the model using GA and Smith predictor for dead time compensator. The rest of the paper is organized as following. Section II and III proposed the model reduction and controller design, respectively. Section IV present our simulation and results. Conclusions are in Section V.

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接受日字 : 2002年 6月 19日
最終完了 : 2002年 11月 6日

2. The model reduction algorithm

2.1 Model reduction for original model have two point $\angle G(jw) = -\pi/2,\ -\pi$ in Nyquist curve

It is à common and well-accepted practice to approximate high-order processes by low-order plus dead time models. Although first-order models are widely used for low-order modeling, they carry only real poles. Hence they are unable to generate peaks in the frequency response of oscillatory processes. We consider the second-order plus dead time model, and it is obtained optimal parameters of reduced model through calculation by three steps. The initial value of parameters of the reduced model is calculated to coincide four point (0, $-\pi/2, -\pi, -3\pi/2$)in the Nyquist curve.

Step 1) Determination of the initial value of the reduction model.

Consider the fllowing high-order system transfer function be given by

$$G(s) = \frac{\beta_0 s^m + \beta_1 s^{m-1} + \cdots\cdots + \beta_{m-1}s + \beta_m}{s^n + \alpha_1 s^{n-1} + \cdots\cdots + \alpha_{n-1}s + \alpha_n} \tag{1}$$

Let the strictly proper, second-order plus dead time reduction model $\widehat{G(s)}$ be given by

$$\widehat{G(s)} = \frac{e^{-Ls}}{as^2 + bs + c} \tag{2}$$

Where a, b, c and L are unknowns to be determined. To determine the four unknowns, four real equations are needed and can be constructed by fitting the process gain G(s) at four nonzero frequency point into eqn.(2). In this method, we pick the four point s=jwa , s=jwb , s=jwc, and s=jwd , where G(jwa)=0, G(jwb)=$-\pi/2$, G(jwc)=$-\pi$, and G(jwd)=$-3\pi/2$. Reduction model (eqn. (2)) can be rewritten as

$$\widehat{G(s)} \cong \frac{2-Ls}{Las^3 + (2a+bL)s^2 + (2b+Lc)s + 2c} \tag{3}$$

where $e^{-sL} \cong \dfrac{2-sL}{2+sL}$

Such that $G(jw_a) = \hat{G}(jw_a),\ G(jw_b) = \hat{G}(jw_b),\ G(jw_c) =,\ \hat{G}(jw_c),\ G(jw_d) = \hat{G}(jw_d)$It is followed that

$$2c - (2a+bL)w_a^2 + jw_a(2b + Lc - Law_a^2) = \frac{2 - jLw_a}{|G(jw_a)|} \tag{4}$$

$$2c - (2a+bL)w_b^2 + jw_b(2b + Lc - Law_b^2) = \frac{2 - jLw_b}{-j|G(jw_b)|} \tag{5}$$

$$2c - (2a+bL)w_c^2 + jw_c(2b + Lc - Law_c^2) = \frac{2 - jLw_c}{-|G(jw_a)|} \tag{6}$$

$$2c - (2a+bL)w_d^2 + jw_d(2b + Lc - Law_d^2) = \frac{2 - jLw_d}{j|G(jw_d)|} \tag{7}$$

From eqn. (5) and eqn. (6) the eqn.(8) is given as

$$(2a+Lb)(w_c^2 - w_b^2) = \frac{Lw_b}{|G(jw_b)|} + \frac{2}{|G(jw_c)|} \tag{8}$$

From eqn.(5) and eqn. (7) the eqn.(9) is given as

$$\frac{1}{L}(2a+Lb)(w_d^2 - w_b^2) = \frac{Lw_b}{|G(jw_b)|} + \frac{Lw_d}{|G(jw_d)|} \tag{9}$$

From eqn.(8) and eqn. (9) parameter L of reduction model is given as

$$L = \frac{(w_d^2 - w_b^2)|G(jw_c)|}{2(w_c^2 - w_b^2)} x_2 - \frac{w_b|G(jw_c)|}{2|G(jw_b)|} \tag{10}$$

where $x_1 = \dfrac{w_b}{|G(jw_b)|} + \dfrac{w_d}{|G(jw_d)|}$

From eqn. (8) and eqn.(6) parameter c of reduction model is given as

$$c = \frac{(x_1\ w_c^2)}{(w_c^2 - w_b^2)2} - \frac{1}{|G(jw_c)|} \tag{11}$$

where $x_1 = \dfrac{Lw_b}{|G(jw_b)|} + \dfrac{2}{|G(jw_c)|}$

From eqn. (6) and eqn. (8) parameter a of reduction model is given as

$$a = \frac{1}{4 + L^2 w_c^2}\left(\frac{2x_1}{(w_c^2 - w_b^2)} - \frac{L^2}{|G(jw_c)|} + L^2 c\right) \tag{12}$$

From eqn.(8) parameter b of reduction model is given as

$$b = \frac{1}{L}\left(\frac{x_1}{(w_c^2 - w_b^2)} - 2a\right) \tag{13}$$

Four complex equations must be contentment of four eqn.(4)~(7) to solve. The initial values of reduction model parameters is determined through above equations using four point of Nyquist curve.

Step 2) Determination of the optimal value of parameter c

Note that amplitude of reduction model determined only parameter c, where angle of Nyquist curve is zero.

Hence the optimal value of parameter c is easily obtained by gradient method, where other values of parameters of reduction model are held to initial values.

Step 3) Determination of the optimal parameters a, b, and L using genetic algorithm.

The GA is completely different from the conventional optimization procedures

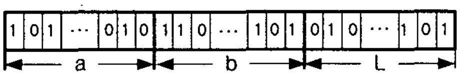
(1) The GA works with a coding of the parameter set, not the parameters themselves.
(2) The GA searches from a population of points, not a single input.
(3) The GA only uses information about the objective function, not derivatives or other auxiliary knowledge.
(4) The GA uses probabilistic transition rules, not deterministic rules.

These characteristics suggest that the GA is a global optimization procedure, i.e. it reduces the probability of being looked of the traditional optimization methods.

Before describing our algorithm, define the vector Õ to be

$$\tilde{O} = [a1,\ b1,\ L1,\ \cdots ak,\ bk,\ Lk] \qquad (14)$$

Each of the parameters (a, b, L) of reduction model in Õ is represented with a binary bit string of m bit and arranged into one string by using the concatenated, multi-parameter, mapped, fixed-point coding method as follows:



The genetic algorithm is described as follows.

①: Initiation) Generate an initial population of M binary bit strings for Õ randomly

②: Decoding) decode in binary bit strings into Õ

③: Fitness-value calculation) calculate the fitness values using eqn.(7) follows.

$$f=(|\angle G(jw_a)|-|\angle \hat{G}(jw_a)|)+(|\angle G(jw_b)|-|\angle \hat{G}(jw_b)|)+\ldots$$
$$(|\angle G(jw_c)|-|\angle \hat{G}(jw_c)|) \qquad (15)$$

where $jw_a=-\frac{\pi}{2},\ jw_b=-\pi,\ jw_c=-\frac{3\pi}{2}$

$$J=\frac{1}{f} \qquad (16)$$

④: Reproduction)In this paper the reproduction is implemented as linear search through roulette-wheel slots weighted in proportion to the fitness value of the individual string, i.e. each of individual strings is reproduced with the probability of J, Õ.

⑤: Crossover) Pick up two strings randomly and decide whether or not to cross them over according to the crossover probability Pc. if the crossover is required, exchange strings at a crossing position. The crossing position is chosen randomly. Pc is usually chosen greater than 60%.

⑥: Mutation) alter a bit of string (0 or 1) according to the mutation probability Pm. Pm is generally designed to be quite low, for example less than few percent.

⑦: Repetition) step ②~⑦ are repeated from generation to generation so that the best and average fitness value of the population increase until the termination criterion is satisfied. Finally, Õ is determined as the individual string with the best fitness value over all the past generation.

The follow chart of proposed algorithm I is described as figure1.

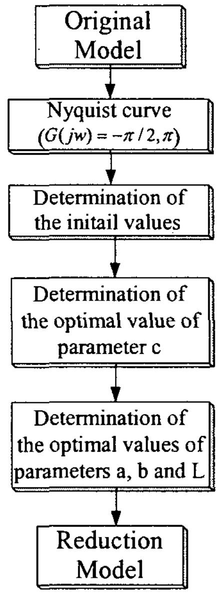


Fig. 1 Proposed algorithm I

2.2 Model reduction for original model have not two point ($\angle G(jw) = -\pi/2,\ -\pi$) in Nyquist curve.

Wangs method cannot be applied process model without $\angle G(jw) = -\pi/2$ and $-\pi$ point, i.e , process model without dead time, in the Nyquist curve . To overcome this problem, we proposed a method to add very small dead time to original model, and we remove it after getting the reduced model. High-order system transfer function to be add small deadtime given by

$$G(s) = \frac{\beta_0 s^m + \beta_1 s^{m-1} + \cdots\cdots + \beta_{m-1}s + \beta_m}{s^n + \alpha_1 s^{n-1} + \cdots\cdots + \alpha_{n-1}s + \alpha_n} e^{-\rho s} \qquad (17)$$

Where $e^{-\rho s}$is to annex very small dead time.

Let the strictly proper, second-order plus dead time reduction model $\hat{G}(s)$ be given by

$$\widehat{G(s)} = \frac{e^{-(L+\rho)s}}{as^2 + bs + c} \qquad (18)$$

Therefore reduction model be obtained remove to add very small dead time of eqn. (18).

The follow chart of proposed algorithm II is described as figure2.

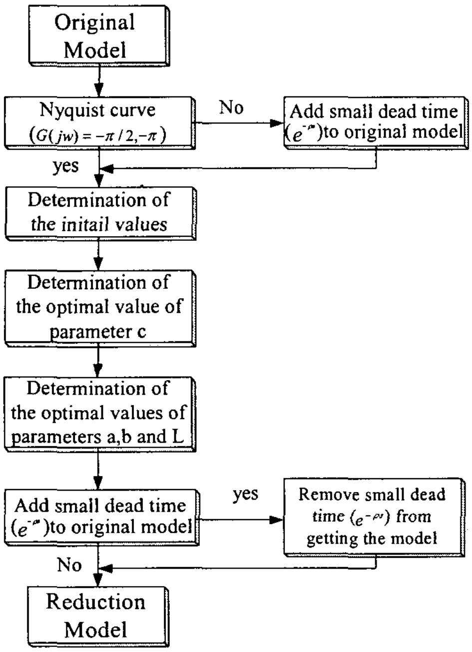


Fig. 2 Proposed algorithm II

3. The Smith Predictor Design Method Using Genetic Algorithm.

The Smith Predictor is well known as an effective dead time compensator for a stable process with large dead time. A block diagram of the Smith predictor is shown in Fig 3.

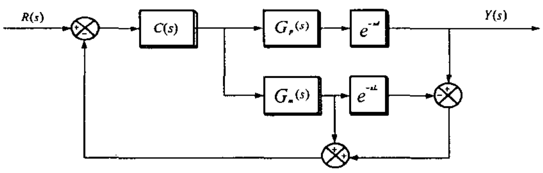


Fig. 3 The block diagram of the Smith predictor

The transfer function of the Smith predictor is defined as

$$\frac{Y(s)}{R(s)} = \frac{C(s)G_p(s)e^{-sd}}{1+C(s)G_m(s)+C(s)[G_p(s)e^{-sd}-G_m(s)e^{-sL}]} \quad (19)$$

Where R(s) is set point, Y(s) is output, C(s) is controller, $G_p(s)e^{-sd}$ is plant, $G_m(s)e^{-sL}$ is a reduced model.

We assumed that $G_p(s)e^{-sd} \cong G_m(s)e^{-sL}$ and then eqn.(19) can be rewritten as following

$$\frac{Y(s)}{R(s)} \simeq \frac{C(s)G_p(s)e^{-sd}}{1+C(s)G_m(s)} \quad (20)$$

We will find that time delay term of denominator of close-loop response is eliminated in equation (20).

The PID controller can be rewritten in the form

$$K(s)=k\left(\frac{As^2+Bs+C}{s}\right) \quad (21)$$

where, $A=(K_D/k)$, $B=(K_P/k)$, $C=(K_I/k)$

We choose zeros of the controller to cancel the model poles, i.e. $A=a, B=b, C=c$, where a, b, and c are the model parameters in eqn.(2) Then from eqn.(20) and eqn.(21) the resultant close-loop transfer function is approximated by

$$\frac{Y(s)}{R(s)} \simeq \frac{ke^{-sL}}{s+k} \quad (22)$$

As shown in eqn.(22), process output is depend on the value of k

We proposed a new method to obtain optimized parameter k using genetic algorithm.

Table 1 is shown values for genetic algorithm.

Table 1 Parameters of genetic algorithm.

Numberof generation	30
Population size	50
Crossover rate	60%
Mutation rate	10%
binary bit	10 bit

4. Simulation and result

In this section three examples are shown to illustrate our method.

For each example, we compare proposed reduction method with Wangs method, moreover show that proposed Smith predictor using a genetic algorithm make a favorable comparison with Wangs method.

Example 1> In case of nonoscillatory high order plus dead time process

$$G(s) = \frac{e^{-0.5s}}{(s+1)(s+5)^2} \quad (23)$$

The reduced model using Wangs method is

$$\widehat{G_1}(s) = \frac{e^{-0.606s}}{7.7724s^2+32.317s+25.220} \quad (24)$$

And PID controller of which parameters were tuned using Wangs method is

$$K_1(s)=26.995+\frac{21.067}{s}+6.452s \quad (25)$$

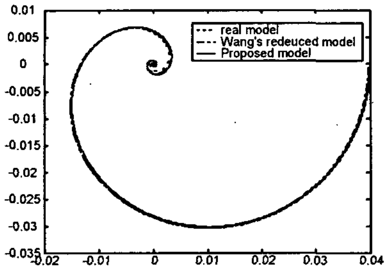
The reduced model using proposed algorithm is

$$\widehat{G_2}(s) = \frac{e^{-0.6072s}}{6.8622s^2+32.1506s+25.0632} \quad (26)$$

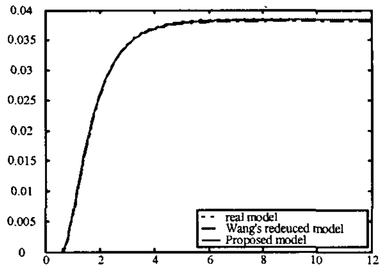
The parameters of PID controller can be obtained from reduced model. And it was determine the gain k=5.014 using genetic algorithm.

PID controller is

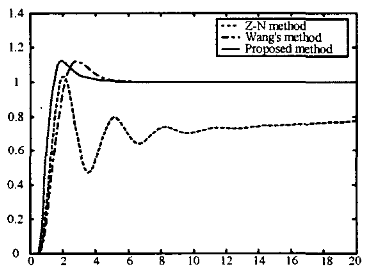
$$K_2(s) = 5.014\left(\frac{6.8622s^2 + 32.1506s + 25.0632}{s}\right) \quad (27)$$



(a) Frequency responses



(b)Step responses



(c) controller performance

Fig. 4 Process of example 1 $G(s) = e^{-0.5s}/(s+1)(s+5)^2$

The frequency response and step response of reduced models were shown in Fig 4(a), (b), respectively. And the step responses of the controllers are shown in Fig 4(c).

Wangs reduction method is quite close to ours and the responses are similar as in Fig 4(a), (b), because this example has a monotonic step response. But the performance of PID controller using proposed method is some more improved than Wangs PID controller. Moreover Ziegler-Nichols tuning method is not suitable for this process. As shown in Fig 4 (c)

Example 2> In case of high order plus dead time and heavily oscillatory process with multiple lag.

$$G(s) = \frac{e^{-0.1s}}{(s^2+s+1)(s+2)^2} \quad (28)$$

The reduced model using Wangs method is

$$\widehat{G}_1(s) = \frac{e^{-0.837s}}{5.648s^2 + 4.950s + 4.497} \quad (29)$$

And PID controller of which parameters were tuned using Wangs method is

$$K_1(s) = 1.503 + \frac{1.366}{s} + 1.715s \quad (30)$$

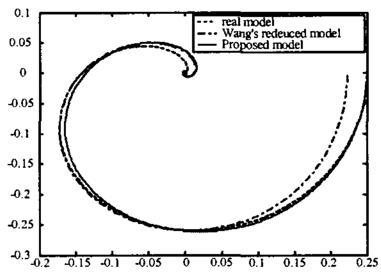
The reduced model using proposed algorithm is

$$\widehat{G}_2(s) = \frac{e^{-0.9836s}}{6.7159s^2 + 5.9684s + 4.01} \quad (31)$$

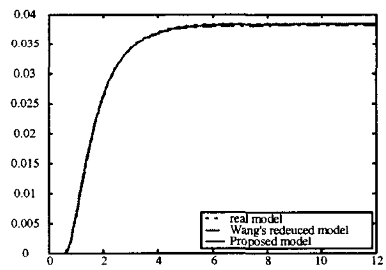
The parameters of PID controller can be obtained from reduced model. And it was determine the gain k=5.014 using genetic algorithm.

PID controller is

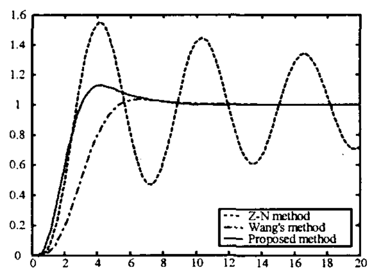
$$K_2(s) = 2.1088\left(\frac{6.7159s^2 + 5.9684s + 4.01}{s}\right) \quad (32)$$



(a) Frequency responses



(b)Step responses



(c) controller performance

Fig. 5 Process of example 2 $G(s) = e^{-0.1s}/(s^2+s+1)(s+2)^2$

The frequency response and step response of reduced models were shown in Fig. 5(a), (b), respectively. And the step responses of the controllers are given in Fig 5(c).

The proposed reduction method is more close to real process than Wangs method, and the proposed controller results in an improved response with smaller overshoot and shorter settling time as shown Fig 5 (c)

Example 3> Consider high order process

$$G(s) = \frac{(s+2)}{(s+3)(s+5)(0.5s+1)} \tag{33}$$

It cant applied wangs method because this process has no time delay. In this case, we added the optional time delay as describes in case (2) of section III

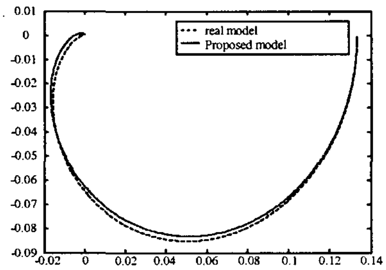
In this example, we add $e^{-0.1s}$

The reduced model using proposed method is

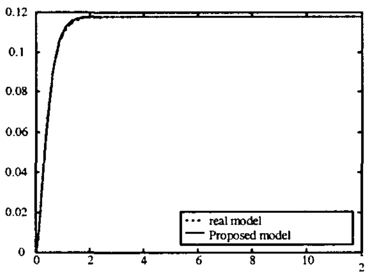
$$\widehat{G(s)} = \frac{e^{-0.0186s}}{0.3769s^2+3.9030s+7.500} \tag{34}$$

And the Smith predictor using genetic algorithm is

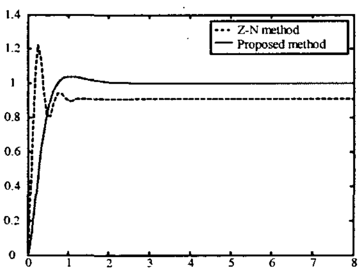
$$K(s) = 4.002\left(\frac{0.3769s^2+3.9030s+7.500}{s}\right) \tag{35}$$



(a) Frequency responses



(b)Step responses



(c) controller performance

Fig. 6 Process of example 3 $G(s) = (s+2)/(s+3)(s+5)(0.5s+1)$

Fig 6 (a) and (b) are shown the frequency responses and step responses of reduced model and real process. And Fig 6 (c) is shown the step responses of controller.

It is shown that in Fig 6(a) and (b) are similar as original model and reduction model. It cant compare to Wangs method because of process model without dead time. And Ziegler-Nichols tuning method has poor such as rise and steady state error, but proposed control method has satisfactory response as shown Fig 6 (c).

5. Conclusion

in Nyquist curve used gradient base method and genetic algorithm. The other, Original model without two pointMost of the tuning methods are derived for particular situations, and therefore applied well only to their own limited areas. Therefore the PID tuning algorithm which can be applied generally to processes with varies dynamic characteristics has been studied. Among them, one of the popular approaches used model reduction. Wang has shown that for the case of process model with $\angle G(jw) = -\pi/2$ and $-\pi$ point in the Nyquist curve, second-order plus dead time model make from original model. But it exists error between original model and reduction model into time domain and frequency domain, and it cant applied process model without $\angle G(jw) = -\pi/2$ and $-\pi$ point in the Nyquist curve. In this paper, to overcome these problems, One, Original model with two point ($\angle G(jw) = -\pi/2, -\pi$) in Nyquist curve used gradient base method and genetic algorithm. The other, Original model without two point($\angle G(jw) = -\pi/2, -\pi$) in Nyquist curve used to add very small dead time. This method has annexed very small dead time on the base model for reduction, and we remove it after getting the reduced model. Unit step and frequency response between original and reduction model is quite closed to wangs reduction method. But the Unit step response of PID controller using smith-predictor is some more improved than wangs method. As shown in Fig 4 (c) . And reduction model about original model is oscillatory is more improved than wangs method. As shown in Fig 5 (a, b, c) . Finally, the case of the model without point ($\angle G(jw) = -\pi/2, -\pi$) in Nyquist, and it cant applied wangs method, but the response of the proposed method was shown the high performance.

Put note

This paper was supported by Wonkwang University in 2002

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