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A tuning strategy for multivariable PI and PID controllers using differential evolution combined with chaotic Zaslavskii map

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ABSTRACT

A technique for tuning of decoupled proportional-integral (PI) and proportional-integral-derivative (PID) multivariable controllers based on a chaotic differential evolution (DE) approach is presented in this paper. Due to the simple concept, easy implementation and quick convergence, nowadays DE has gained much attention and wide application in solving continuous non-linear optimization problems. However, the performance of DE greatly depends on its control parameters and it often suffers from being trapped in local optimum. The application of chaotic sequences based on chaotic Zaslavskii map instead of random sequences in DE is a powerful strategy to diversify the population and improve the DE's performance in preventing premature convergence to local optima. The optimized PD and PID controllers shows good closed-loop responses in control of the binary Wood–Berry distillation column, a multivariable process with strong interactions between input and output pairs. Some comparison results of PD and PID tuning using chaotic DE, classical DE and genetic algorithm are presented and discussed.

1. Introduction

The proportional-integral-derivative (PID) controller has remained, by far, as the most commonly used controller in practically all industrial control applications. More than 90% of all control loops are PID, with a wide range of applications: process control, motor drives, magnetic memories, automotive, flight control, among others (Åström & Hägglund, 2001). The reason is that it has a simple structure which is easy to be understood by the engineers. In the past decades, different tuning methodologies of PI and PID controllers have been proposed in the literature such as autotuning, self-tuning, pattern recognition, and computational intelligence (Åström & Hägglund, 1995, 2001; Cominos & Munro, 2002).

Unfortunately, it has been quite difficult to tune properly the gains of PID controllers because many industrial plants are often burdened with problems such as high order, time delays, poorly damped, nonlinearities, and time-varying dynamics.

Over the years, several authors have proposed the tuning of PID to control monovariable processes by optimization methods, such as genetic algorithms (Altınten, Ketevanlioğlu, Erdoğan, Hapoğlu, & Alpbaz, 2008; Huang & Chen, 1997; Hwang & Thompson, 1993; Jan, Tseng, & Liu, 2008; Krohling & Rey, 2001; Li, Jan, & Shieh, 2003; Takahashi, Peres, & Ferreira, 1997; Wang & Kwok, 1993; Zhang, Zhuang, Du, & Wang, 2009), particle swarm optimization (Chang, 2009; Kim, Maruta, & Sugie, 2008), tribes algorithm (Coelho & Bernert, 2009a), harmony search (Coelho & Bernert, 2009b), evolution strategy (Coelho & Coelho, 1999), ant colony (Duan, Wang, & Yu, 2006), among others (Bianchi, Mantz, & Christiansen, 2008; Toscano, 2005; Toscano & Lyonnet, 2009; Xu, Li, Qi, & Cai, 2005). Moreover, there is literature about the tuning of multivariable PI and PID controllers using genetic algorithms (see details in Zuo (2005), Vlachos, Williams, and Gomm (2002), Chang (2007), Herreros, Baeyens, and Perán (2002)).

Recently, a new evolutionary computation technique, called differential evolution (DE) algorithm, has been proposed in Storn and Price (2005, 1997). The DE has three main advantages: it can find near optimal solution regardless the initial parameter values, its convergence is fast and it uses few number of control parameters. In addition, DE is simple in coding, easy to use and it can handle integer and discrete optimization (Storn & Price, 2005). Due to the good features of DE algorithm, nowadays it has been emerged as a new and attractive optimizer and applied in variety of research fields.

This paper presents a hybrid optimization approach given by combination of DE (Storn & Price, 1997, 2005) with chaotic Zaslavskii map (Zaslavskii, 1978) (DECZ) to determine PID control gains in a multiloop control scheme. The main benefits of DECZ over traditional DE approaches are allowing the diversity maintenance and aids in slowing premature convergence and exploring the search space. A lack of diversity in a population corresponds to sample solutions being very similar with respect to the distance metric. Conversely, when samples are not very similar then the degree of

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diversity is high. In this context, the chaotic Zaslavskii map can be useful in mutation factor tuning in DECZ approach.

The feasibility of the proposed PI and PID schemes based on DECZ tuning is demonstrated on a simulated binary distillation column. Additionally, the simulation results are compared to those obtained using classical tuning based on DE and genetic algorithm with floating point representation.

The remainder of this paper is structured as follows. In Section 2, a description of binary distillation column is provided. Section 3 presents the fundamentals of PI and PID controllers. Section 4 explains the DE algorithm combined with chaotic Zaslavskii map. Simulation results are presented and discussed in Section 5. Finally, Section 6 outlines a brief conclusion about this study.

2. Case study: a distillation column model

Distillation columns are very commonly used separation equipment in chemical and process industries. The Wood–Berry model is a 2×2 (two inputs and two outputs) transfer function model of a pilot plant distillation column that separates methanol and water (Wood & Berry, 1973). The Wood–Berry model is highly coupled and attracts much attention in the literature. This methanol-water column model has been used for several controller studies, including advanced control algorithms (Aceves-López & Aguilar-Martin, 2006; Deshpande & Ash, 1988; Edgar, Postlethwaite, & Gormandy, 2000; Jain & Lakshminarayanan, 2007; Lee & Yu, 1994; Luyben, 1986; Mantz & De Battista, 2002; Shridhar & Cooper, 1997; Wang, Zou, Lee, & Qiang, 1997; Zeng, Chen, & Gao, 2009). The composition of the top and bottom products expressed in weight% of methanol are the controlled variables. The reflux and the reboiler steam flow rates are the manipulated inputs expressed in l b/min. The distillation column is the binary with eight plates, reported by Wood and Berry (1973) that is shown in Fig. 1. The transfer function of distillation column has first order dynamics and significant time delays and it has a strong interaction between inputs and outputs. The linear Wood–Berry model is given by

$$\begin{bmatrix} y_1(s) \\ y_2(s) \end{bmatrix} = \begin{bmatrix} \frac{12.8e^{-s}}{16.7s+1} & \frac{-18.9e^{-3s}}{21.0s+1} \\ \frac{6.6e^{-7s}}{10.9s+1} & \frac{-19.4e^{-3s}}{14.4s+1} \end{bmatrix} \cdot \begin{bmatrix} u_1(s) \\ u_2(s) \end{bmatrix} + \begin{bmatrix} \frac{3.8e^{-8.1s}}{10.9s+1} \\ \frac{4.9e^{-3.4s}}{13.2s+1} \end{bmatrix} \cdot D(s) \tag{1}$$

where input signals are the reflux flow rate u_1 and the steam flow rate u_2, the output signals are the top product composition y_1 in mole fraction and the bottom product composition y_2 also in mole fraction. The influence of the feed flow rate (in mole fraction) D was taken from Deshpande and Ash (1988). The unmeasured feed flow rate, D, acts as a process disturbance. This linear model is valid around the set point $y_1 = 0.96$ and $y_2 = 0.02$ (Aceves-López & Aguilar-Martin, 2006). The time sampling is 1 min.

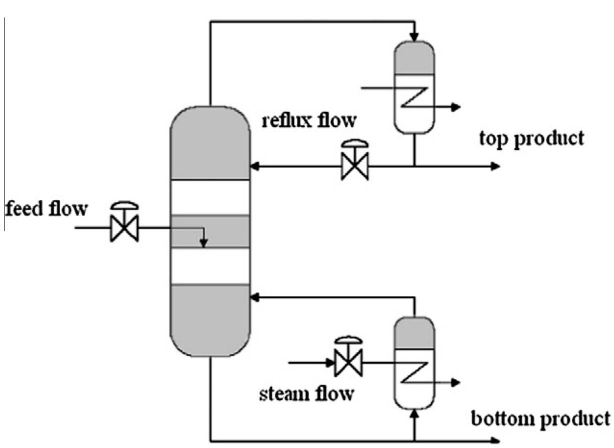

Fig. 1. Simplified schematic diagram of the distillation column (Shridhar & Cooper, 1997).

3. PI and PID control

Multiloop single-input single-output (SISO) controllers are often used to control chemical plants which have multi-input multi-output (MIMO) dynamics. The simple controller structure and the easiness to handle loop failure are the most attractive advantages of such systems. But, inevitably, interactions exist between loops, design of such controllers to meet specifications would then encounter more difficulties than that for a single loop and becomes an open research topic for years.

In this work, consider a process with n inputs and n outputs represented by Chang (2007), where

$$G(s) = \begin{bmatrix} g_{11}(s) & \cdots & g_{1n}(s) \\ \vdots & \ddots & \vdots \\ g_{n1}(s) & \cdots & g_{nn}(s) \end{bmatrix}. \tag{2}$$

A multivariable controller $K(s)$ with $n \times n$ structure is adopted, where

$$K(s) = \begin{bmatrix} k_{11}(s) & \cdots & k_{1n}(s) \\ \vdots & \ddots & \vdots \\ k_{n1}(s) & \cdots & k_{nn}(s) \end{bmatrix}. \tag{3}$$

The form for $k_{ij}(s)$, for $i, j \in \underline{n} = \{1, 2, \ldots, n\}$ is given by

$$k_{ij}(s) = Kp_{ij}\left(1 + \frac{1}{Ti_{ij} \cdot s} + Td_{ij} \cdot s\right), \tag{4}$$

where Kp_{ij} is the proportional gain, Ti_{ij} is the integral time constant, and Td_{ij} is the derivative time constant. The control law of Eq. (4) can be rewritten as

$$k_{ij}(s) = Kp_{ij} + Ki_{ij} \cdot \frac{1}{s} + Kd_{ij} \cdot s, \tag{5}$$

where $Ki_{ij} = Kp_{ij}/Ti_{ij}$ is the integral gain and $Kd_{ij} = Kp_{ij} \cdot Td_{ij}$ is the derivative gain. For convenience, let PI and PID gains for optimization, where

(i) $\theta_{ij} = [Kp_{ij}, Ki_{ij}]^T$ represents the gains vector of ith row and jth column of sub-PI controller in $K(s)$;
(ii) $\theta_{ij} = [Kp_{ij}, Ki_{ij}, Kd_{ij}]^T$ represents the gains vector of ith row and jth column of sub-PID controller in $K(s)$.

In Wood–Berry distillation column with $n = 2$, as shown in Fig. 2, the following objective function is adopted:

$$f = \sum_{k=1}^{N} k \cdot |e_1(k)| + k \cdot |e_2(k)|, \tag{6}$$

where k is the number of sample in the time domain, N is the number of samplings; $e_i(k)$ is the error signal given by difference between the output signal and the setpoint signal. The optimization problem involves finding the PI and PID such that the f performance index is minimized.

The PID controller is able to reduce response error via proportional control, and thus the process can track the input and respond properly; it can lower the output overshoot and reduce the response time through derivative control; and it can eliminate steady-state offset through integral control.