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Disturbance-rejection-based tuning of proportional–integral–derivative controllers by exploiting closed-loop plant data

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ABSTRACT

A systematic data-based design method for tuning proportional–integral–derivative (PID) controllers for disturbance attenuation is proposed. In this method, a set of closed-loop plant data are directly exploited without using a process model. PID controller parameters for a control system that behaves as closely as possible to the reference model for disturbance rejection are derived. Two algorithms are developed to calculate the PID parameters. One algorithm determines the optimal time delay in the reference model by solving an optimization problem, whereas the other algorithm avoids the nonlinear optimization by using a simple approximation for the time delay term, enabling derivation of analytical PID tuning formulas. Because plant data integrals are used in the regression equations for calculating PID parameters, the two proposed algorithms are robust against measurement noises. Moreover, the controller tuning involves an adjustable design parameter that enables the user to achieve a trade-off between performance and robustness. Because of its closed-loop tuning capability, the proposed method can be applied online to improve (retune) existing underperforming controllers for stable, integrating, and unstable plants. Simulation examples covering a wide variety of process dynamics, including two examples related to reactor systems, are presented to demonstrate the effectiveness of the proposed tuning method.

1. Introduction

Proportional–integral–derivative (PID) controllers are the most extensively used process control technique in the chemical process industry because of their simplicity, robustness, and wide range of applicability. Therefore, numerous design (tuning) methods for PID controllers have been devised over the past several decades [1]. Although a PID controller has only three adjustable parameters, the optimization of these parameters is often challenging for control engineers working on site. Moreover, in many practical cases, PID controllers are poorly tuned because of the lack of a systematic tuning procedure.

A typical category of methods for tuning PID controllers is based on the model-based design approach, such as the direct synthesis [2–4] and internal model control (IMC) [5–9] methods. Model-based tuning methods employ an open-loop process model and therefore involve a two-step procedure. The process model is first identified using experimental data and system identification techniques, and subsequently, the PID controller is tuned using the model parameters. An open-loop test, such as a step test or pulse test, is typically used to obtain appropriate plant data for model identification. This may be time-consuming and upset routine plant operations or even cause process runaway for non-self-regulating (integrating and open-loop unstable) plants. Closed-loop identification techniques [10–12] are the main alternatives that can be used to perform online controller tuning. Nevertheless, a major problem is that identifying the process model from plant data involves approximations. Therefore, the effectiveness of model-based tuning methods degrades for higher-order process dynamics because of inevitable modeling errors.

An attractive approach for avoiding plant-model mismatch is to directly design controllers from plant input–output data, which does not require identifying process models. Methods employing this approach are referred to as mode-free or data-based controller tuning methods, such as the virtual reference feedback tuning (VRFT) [13–15] and fictitious reference iterative tuning (FRIT) [16] methods. Given a set of plant input–output data, these methods can be used to determine the controller parameters to allow the corresponding closed-loop response for set-point changes to be as close as possible to a predefined (desired) reference trajectory. However, through these direct tuning methods, determining an appropriate reference model is difficult because the process model is unknown. The use of an inappropriate reference model (e.g., unreasonable time delay for the reference trajectory) degrades the

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control performance and can lead to an unstable control system. To determine the reference model appropriately, an extended FRIT method [17] in which the reference model parameters are optimized together with the PID controller parameters was proposed. However, the resulting nonlinear optimization problem becomes complicated because many parameters are optimized simultaneously. The VRFT design, originally developed for discrete-time systems, has been extended to continuous-time systems for designing PID controllers [18,19] and cascade control systems [20,21]. Only the time delay in the reference model is determined by solving a nonlinear optimization problem, and the controller parameters can be calculated using simple linear regression. However, the optimization problem is formulated in the frequency domain and thus requires the calculation of the frequency responses of the plant input–output data and the estimation of the upper bound of the concerned frequency range.

Previous data-based controller tuning methods have typically been developed on the basis of servo control, because the concerned reference model is used to define the set-point response. The resulting controllers therefore show high set-point tracking performance, but their disturbance rejection may be unsatisfactory. This conflict in controller design, which also exists in model-based design methods, is especially pronounced for lag-dominant processes for which the ratio of the time delay to the time constant is low. For example, the conventional IMC–PID controller provides favorable set-point responses but sluggish disturbance responses for lag-dominant processes [5,8]. Therefore, model-based PID tuning methods for improved disturbance rejection have been suggested [2,7–9]. The classical Ziegler–Nichols (ZN) method [22] is also considered as a PID tuning method for favorable disturbance suppression. In addition to PID control, several disturbance-rejection-based control techniques such as minimum variance control [23], active disturbance rejection control [24,25], and disturbance-observer-based control [26] have been developed. Nevertheless, the application of data-based tuning methods for PID controllers that emphasizes regulatory control has received little attention. The development of data-based tuning methods based on disturbance rejection is more desirable for three main reasons. First, disturbance rejection is more crucial than set-point tracking in many process control applications. Second, the set-point tracking performance can be improved separately by using a two-degree-of-freedom control structure that is simply performed through set-point weighting in a PID controller [27]. Third, the reference model for disturbance rejection can be represented as a unified expression that is independent of the dynamic behavior (stable, integrating, or unstable dynamics) of the controlled plant [28].

In this study, we developed a systematic data-based method under the VRFT design framework for tuning PID controllers on the basis of disturbance rejection. The controller tuning requires only one-shot closed-loop experimental data and does not involve the identification of a process model. Furthermore, the structure and complexity of the process have no restrictions. The method is therefore applicable to different types of stable, integrating, and unstable plants. The present VRFT design framework is similar to that in the previous work [28]; however, it is emphasized that the subsequent derivation to obtain optimal controller parameters in the proposed method is quite different from the previous method. The relevant optimization problem for controller tuning is formulated in the time domain on the basis of plant data integrals and two novel algorithms to calculate the PID parameters are proposed, which is the major contribution of the present work. Compared with the aforementioned frequency-domain-based methods [18,19,28], the proposed tuning method exploits plant measurements in a more direct manner while providing greater immunity against measurement noises. The first algorithm determines the optimal time delay parameter in the reference model by solving a nonlinear optimization problem. The second algorithm, which is an alternative to the first algorithm, uses the first-order Taylor series approximation for the time delay to avoid nonlinear optimization; therefore, the resulting computation (linear regression) is simple, and analytical PID tuning formulas, which are not available in the previous data-based tuning methods, can be derived. Every control system should provide a specific degree of robustness to preserve the closed-loop dynamics for possible variations in the process. The proposed tuning method has a single design parameter that enables a designer to manage the trade-off between control performance and system robustness. Although the controllers are designed for disturbance rejection, a set-point weighting parameter through simple calculation can be used to improve the control performance for set-point changes without influencing the disturbance response.

The remainder of this paper is organized as follows. Section 2 describes the extension of the VRFT design framework to the proposed disturbance-rejection-based controller tuning method. Section 3 presents the two algorithms for calculating PID parameters and elucidates the calculation of set-point weighting parameters. Section 4 summarizes the controller tuning procedures and discusses several practical issues in implementing the algorithms. In Section 5, simulation examples are presented to demonstrate the effectiveness of the proposed method. Finally, concluding remarks are presented in Section 6.

2. Data-based PID controller tuning for disturbance rejection

Consider a feedback control system consisting of a plant $G(s)$ and a PID controller $G_C(s)$ (Fig. 1). The ideal PID controller is given by

$$G_C(s) = K_C\left(1 + \frac{1}{\tau_I s} + \tau_D s\right) \quad (1)$$

where K_C, τ_I, and τ_D denote the proportional gain, integral time, and derivative time, respectively. Let $T_d(s)$ be the desired closed-loop transfer function for load disturbance $D(s)$, and it defines the target of PID controller tuning. Therefore, the desired closed-loop transfer function for set-point $R(s)$ becomes $G_C(s)T_d(s)$. The proposed PID controller tuning involves obtaining an approximate solution to a model-reference problem in continuous time, as depicted in Fig. 2(a). In this figure, the output $Y(s)$ is related to the set-point (reference signal) by

$$Y(s) = G_C(s)T_d(s)R(s) \quad (2)$$

The objective of the proposed tuning method is to obtain parameters for the PID controller to allow the corresponding feedback control system in Fig. 1 to behave as closely as possible to the reference model. In this data-based design framework, the process model is unidentified, and only one set of plant input–output data, $u(t)$ and $y(t)$, is available (having been obtained from a closed-loop test).

Consider the schematic diagram shown in Fig. 2(b) under the VRFT design framework. The available output data $y(t)$ are used, and the reference signal is obtained from Eq. (2) as

$$\hat{R}(s) = G_C^{-1}(s)\, T_d^{-1}(s)\, Y(s) \quad (3)$$

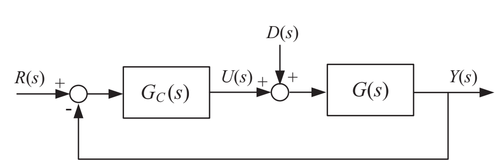

Fig. 1. Block diagram of the feedback control system.