A DATA-DRIVEN APPROACH TO CASCADED INTERNAL CONTROLLERS: SIMULTANEOUS ATTAINMENT OF CONTROLLERS AND MODELS

PHƯƠNG PHÁP ĐIỀU CHỈNH SỬ DỤNG TRỰC TIẾP DỮ LIỆU THỰC NGHIỆM ĐỐI VỚI BỘ ĐIỀU KHIỂN IMC TRONG HỆ THỐNG ĐIỀU KHIỂN TẦNG: SỰ ĐẠT ĐƯỢC ĐỒNG THỜI CÁC BỘ ĐIỀU KHIỂN VÀ MÔ HÌNH ĐỐI TƯỢNG

Nguyen Thi Hien

Vietnam National University of Agriculture

Ngày nhận bài: 28/12/2020, Ngày chấp nhận đăng: 21/05/2020, Phản biện: TS. Nguyễn Ngọc Khoát

Abstract:

This paper proposes a data-driven parameter tuning of the internal model controllers (IMC) in cascade architecture with minimum phase processes. In order to perform the parameter tuning of the IMC, we utilize the fictitious reference iterative tuning (FRIT), which enables us to obtain the desired parameter of the controllers with only one-shot experiment data. The algorithm does not require mathematical process models but only a single set data collected from the closed loop system. Moreover, the proposed approach enables us to obtain both the optimal parameters of two controllers for the desired tracking property and mathematical models of the controlled process simultaneously. To show the validity of the proposal, we give illustrative examples.

Keywords:

Data-driven approach, FRIT, cascade control, IMC.

Tóm tắt:

Bài báo đề xuất sử dụng FRIT - một thuật toán dùng trực tiếp dữ liệu thực nghiệm để điều chỉnh thông số của bộ điều khiển IMC trong hệ thống điều khiển tầng với các đối tượng pha cực tiểu. Thuật toán đề xuất không đòi hỏi mô hình toán học của đối tượng điều khiển mà chỉ yêu cầu duy nhất một bộ dữ liệu vào/ra thu thập từ hệ thống. Kết quả nhận được là các bộ điều khiển với thông số tối ưu cho tín hiệu ra mong muốn của hệ thống, đồng thời nhận được mô hình toán học của đối tượng điều khiển.

Từ khóa:

Dữ liệu thực nghiệm, FRIT, điều khiển tầng, IMC.

1. INTRODUCTION

Cascade control has been implemented in industry and different applications due to their disturbance rejection, faster response and other advantages over single loop control systems [1]. Usually, the controllers are tuned sequentially, the inner loop controller is tuned first to give a faster response than the outer loop, and then, the primary controller is tuned according to the resulting system. Thus, tuning of cascade controllers is a time consuming task.

On the other hand, internal model control (IMC, [2]) is one of the effective approaches to the achievement of a desired tracking property. The utilization of IMC for cascade control yields the robustness and flexibility in tuning parameters. Thus, it provides a better system response than sequential tuning due to the adjustment of the inner loop has minimum effects on the outer loop.

In [3], Jeng *et al.* proposed an automatic tuning method for cascade control systems based on a single closed loop step test. This method identifies the required process information with the help of B-spline series expansions of the step responses. Then, two PID controllers are tuned using an IMC method. Lee *et al.* [4] proposed IMC - based PID tuning rules that enable simultaneous tuning of primary and secondary controllers. Their method is based on process models for cascade control systems. The main point of simultaneously tuning cascade controllers is to approximate the inner loop dynamics with the inner loop design target. Such an approximation allows obtaining a process model for the tuning of primary controller. However, this approximation may be inaccurate because the implemented secondary PID controller cannot guarantee meeting the inner loop design target. In [5], Cesca *et al.* proposed a model-based procedure using IMC approach for synthesizing the controllers. The suggested tuning procedure determines the controller filter time constants to assure robust stability.

It is clear that most methods in mentioned studies require the process models, thus the controller design asks an identification, which encounters difficulties in practice. In recent years, design of a data-based control system (without system identification) has been proposed, such as iterative feedback tuning (IFT, [6]), virtual reference feedback tuning (VRFT, [7]), and fictitious reference iterative tuning (FRIT, [8-9]) for the single loop control system. In contrast to the iterative tuning method (IFT), which requires many control executions, the VRFT and FRIT require only one-shot experiment. While VRFT considers error between the virtual input and actual one, FRIT focuses on error between the fictitious output and the actual one.

Compared to a model-based approach, in the data-based methods, the controller is directly designed based on the experimental data, thus the modeling step is omitted and problems of under modeling encountered in practice are avoided. Moreover, due to the special of IMC structure, it is expected that a data-driven approach to the IMC yields not only a controller but also a mathematical model of the plant. In [9], Kaneko *et al.* have succeeded in applying a data-driven

FRIT for the single loop IMC, which yields simultaneous attainment of optimal controller and a plant model. In [10-11], Nguyen *et al.* developed FRIT for cascade control systems, two PI controllers are simultaneously tuned to get the desired performance. As an application of the data-driven FRIT for cascade systems, the speed of DC motor is controlled in [11]. However, the results in [10-11] are only controllers, no any process model is achieved.

From these backgrounds, we propose a data-driven approach of FRIT for IMC parameter tuning in cascade systems. The processes we treat here are linear, time-invariant, stable and minimum phase. The algorithm does not require mathematical process models but only a set of experimental data collected from the closed-loop system. Particularly, it is expected that the application of FRIT for cascaded IMC leads to both optimal controllers for achievement of a desired performance and mathematical models that reflect dynamics of the actual process.

[Notations] Let $\Re$ and $\Re^n$ denote the set of real numbers and that of real vectors of size n, respectively. For a time series w, we use $w(t)$ to describe the value of w at time t. For a transfer function G, the output y of G with respect to u is denoted with $y = Gu$ for the enhancement of the readability. For a time series $w = \{w(\Delta), w(2\Delta), \cdots, w(N\Delta)\}$, we use the following notation

$$\|w\|_N^2 := \frac{1}{N}\sum_{k=1}^{N}\big(w(k\Delta)\big)^2.$$

2. PRELIMINARIES

2.1. Internal model control for cascade systems

An IMC for a cascade system is shown in Fig.1 [3], [5]. In this figure, C_1 and C_2 are the IMC controllers, P_1 and P_2 are the process for the loops. $\tilde{P}_2$ is a process model of the inner loop and $\tilde{P}_B$ is the equivalent process model of the outer loop. r, u and y_2, y_1 are the reference signal, the input, and the outputs, respectively.

The closed loop transfer function for the inner loop is determined as:

$$G_2 = \frac{C_2 P_2}{1 + C_2\left(P_2 - \tilde{P}_2\right)} \tag{1}$$

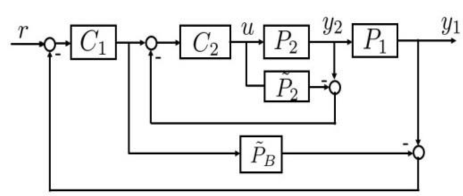

Figure 1. Internal model control for cascade structure

The transfer function $\tilde{P}_B$ is a model of equivalent process P_B composed of the inner loop and the primary plant P_1 connected in series, namely:

$$P_B = \frac{C_2 P_2}{1 + C_2\left(P_2 - \tilde{P}_2\right)} P_1 \tag{2}$$

The transfer function G_{ry} from r to y_1 can be expressed as:

$$G_{\mathrm{ry}} = \frac{C_1 C_2 P_2 P_1}{1 + C_2\left(P_2 - \tilde{P}_2\right) + C_1 C_2 P_2 P_1 - C_1 \tilde{P}_{\mathrm{B}} - C_1 C_2 \tilde{P}_{\mathrm{B}}\left(P_2 - \tilde{P}_2\right)} \quad (3)$$

Using the transfer function relations for the inner and outer loop, the respective IMC controllers are derived to satisfy the set point and disturbance rejection requirements.

2.2. Assumptions

Consider the case P_1 and P_2 are linear, time-invariant, stable and minimum phase, they are unknown except degrees of the numerator and the denominator. Assume that the process models $\tilde{P}_1$ and $\tilde{P}_2$ are parameterized with a tunable vector $\rho_{\mathrm{P}} := \left[\rho_{\mathrm{P1}}{}^{\mathrm{T}}\ \rho_{\mathrm{P2}}{}^{\mathrm{T}}\right]^{\mathrm{T}}$ as:

$$\tilde{P}_1(\rho_{\mathrm{P1}}) = \frac{a_\mu s^\mu + \cdots + a_1 s + a_0}{b_\gamma s^\gamma + \cdots + b_1 s + 1}, \quad \mu \le \gamma \quad (4)$$

and:

$$\tilde{P}_2(\rho_{\mathrm{P2}}) = \frac{a_k' s^k + \cdots + a_1' s + a_0}{b_l' s^l + \cdots + b_1' s + 1}, \ k \le l \quad (5)$$

where $\rho_{\mathrm{P1}} = \left[a_\mu \cdots a_0\ b_\gamma \cdots b_1\right]^{\mathrm{T}} \in \Re^{\mu+\gamma+1}$ and $\rho_{\mathrm{P2}} = \left[a_k' \cdots a_0'\ b_l' \cdots b_1'\right]^{\mathrm{T}} \in \Re^{k+l+1}$.

For the inner loop, from the result by Azar *et al.* [1] and Lee *et al.* [4], the IMC controller is obtained and augmented by a filter $F(\lambda_2) = \dfrac{1}{(\lambda_2 s + 1)^{n_2}}$ as shown following:

$$C_2(\rho_{\mathrm{P}}, \lambda_2) = \tilde{P}_2^{-1} F = \tilde{P}_2(\rho_{\mathrm{P}})^{-1} \frac{1}{(\lambda_2 s + 1)^{n_2}} \quad (6)$$

where n_2 must be selected to ensure that the IMC controller is proper. λ_2 adjusts the speed of the closed response in the inner loop and it should be tuned to meet the desired performance.

The IMC controller design for the outer loop is based on the process of the outer loop P_{B}, which composes of the inner loop and the primary process P_1 connected in series, then a model $\tilde{P}_{\mathrm{B}}$ also depends on ρ_{P} and λ_2. The IMC controller C_1 is designed such that the closed loop transfer function of the outer loop G_{ry} follows the reference model T_{d}. From the result in Kaneko *et al.* [9], we construct the controller C_1 as:

$$C_1(\rho_{\mathrm{P}}, \lambda_2) = \tilde{P}_{\mathrm{B}}(\rho_{\mathrm{P}}, \lambda_2)^{-1} T_{\mathrm{d}} \quad (7)$$

The reference model T_{d} should have the form:

$$T_{\mathrm{d}} = \frac{1}{(\lambda_1 s + 1)^{n_1}} \quad (8)$$

where n_1 must be selected to guarantee the controller C_1 proper. In a cascaded IMC structure, if the reference model T_{d} is given, the controllers C_1 and C_2 depend on both ρ_{P} and λ_2. For convenience, we use the following notation:

$$\rho = \begin{bmatrix} \rho_{\mathrm{P}} \\ \lambda_2 \end{bmatrix} \tag{9}$$

The closed loop system in the cascaded IMC structure with a tunable parameter vector ρ is illustrated in Fig. 2. The input u and the outputs y_2, y_1 also depend on the parameter vector ρ, so we denote them as $u(\rho)$ and $y_2(\rho), y_1(\rho)$, respectively.

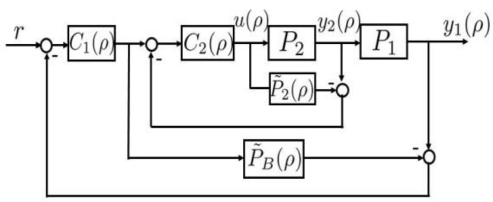

Figure 2. A cascaded IMC system with a tunable vector

2.3. Problem setting

The objective of this paper is to find a parameter vector ρ to attain the design output, which is represented by a reference model T_{d}, with the direct use of experimental data. The model-reference criterion is described as:

$$J(\rho) = \| y_1(\rho) - T_{\mathrm{d}} r \|_N^2 \tag{10}$$

Since controllers include the process models internally, it is expected that we can also simultaneously obtain appropriate models of the actual process. For this purpose, FRIT, which is briefly explained in the next section, is utilized.

3. FICTITIOUS REFERENCE ITERATIVE TUNING - FRIT [8]

In this section, the brief review of FRIT is expressed. The main idea of the FRIT scheme is to construct the model-reference criterion in the fictitious domain [8].

Consider a conventional closed loop system as Fig. 3, where r, u and y are the reference signal, the input, and the output, respectively. The controller C is parameterized by a vector ρ since the controlled plant model is unknown.

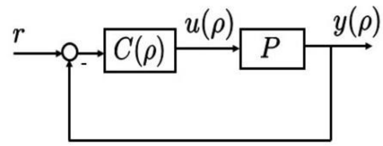

Figure 3. A conventional closed loop system with a tunable vector ρ

First, set an initial parameter vector ρ^0 of the controller and perform a one-shot experiment on the closed loop system to obtain the data $u(\rho^0)$ and $y(\rho^0)$. The controller $C(\rho^0)$ is assumed to stabilize the closed loop system such that $u(\rho^0)$ and $y(\rho^0)$ are bounded. By using the data $u(\rho^0)$ and $y(\rho^0)$, the fictitious refence signal $\tilde{r}(\rho)$ is computed as:

$$\tilde{r}(\rho) = C(\rho)^{-1} u(\rho^0) + y(\rho^0) \tag{11}$$

For a given reference model T_{d}, the cost function is described by:

$$J_{\mathrm{F}}(\rho) := \| y(\rho^0) - T_{\mathrm{d}} \tilde{r}(\rho) \|_N^2 \tag{12}$$

Then we minimize $J_{\mathrm{F}}(\rho)$ to achieve the optimal parameter vector ρ^*, which yields a desired controller. Note that the

(ISSN: 1859 - 4557)

cost function (12) with the fictitious reference signal $\tilde{r}(\rho)$ in Eq. 11 requires only the initial data $u(\rho^0)$ and $y(\rho^0)$. This means that the minimization of Eq. 12 can be performed *off-line* by using only one-shot experimental data. As for the relationship between the minimization of $J(\rho)$ and that of $J_{\mathrm{F}}(\rho)$, it was shown in Theorem 3.1 by Souma *et al.* [8] that $J(\rho^*)=0$ is equivalent to $J_{\mathrm{F}}(\rho^*)=0$ (see Theorem 3.1 in [8] for the detailed proof and discussions).

4. FRIT FOR CASCADED INTERNAL MODEL CONTROL

4.1. Simultaneous attainment of controllers and process models

Consider a cascade control system with IMC as Fig. 2. Under the assumption that the processes are unknown and they are parameterized by ρ as Eq. 4 and Eq. 5, we give the following result.

Theorem 1: For a given reference model T_{d}, assume that the controllers are described as Eq. 6 and Eq. 7, then $G_{\mathrm{ry}}(\rho)=T_{\mathrm{d}}$ holds if and only if both $P_1=\tilde{P}_1(\rho)$ and $P_2=\tilde{P}_2(\rho)$ simultaneously holds.

Proof. It follows from Eq. 3 that the '**if**' part clearly holds, with a notice that together with Eq. 2, we see $\tilde{P}_{\mathrm{B}}=\tilde{P}_1 F$ when $P_2=\tilde{P}_2$. Thus, we focus on the '**only if**' part. By implementing the controllers described in Eq. 6 and Eq. 7, the transfer function G_{ry} from r to y_1 can be expressed as:

$$G_{\mathrm{ry}}=\frac{T_{\mathrm{d}}\tilde{P}_{\mathrm{B}}^{-1}\tilde{P}_2^{-1}FP_2P_1}{1+\tilde{P}_2^{-1}F\left(P_2-\tilde{P}_2\right)+T_{\mathrm{d}}\tilde{P}_{\mathrm{B}}^{-1}\tilde{P}_2^{-1}FP_2P_1-T_{\mathrm{d}}-T_{\mathrm{d}}\tilde{P}_2^{-1}F\left(P_2-\tilde{P}_2\right)}$$

$$=\frac{T_{\mathrm{d}}\tilde{P}_{\mathrm{B}}^{-1}\tilde{P}_2^{-1}FP_2P_1}{\left(1-T_{\mathrm{d}}\right)\left(1-F\left(1-\tilde{P}_2^{-1}P_2\right)\right)+T_{\mathrm{d}}\tilde{P}_{\mathrm{B}}^{-1}\tilde{P}_2^{-1}FP_2P_1} \quad (13)$$

Since the left hand side is equal to T_{d}, Eq. 13 yields:

$$\left(1-T_{\mathrm{d}}\right)\tilde{P}_{\mathrm{B}}^{-1}\tilde{P}_2^{-1}FP_2P_1=\left(1-T_{\mathrm{d}}\right)\left(1-F\left(1-\tilde{P}_2^{-1}P_2\right)\right) \quad (14)$$

If we can achieve $P_2=\tilde{P}_2$ then $P_1=\tilde{P}_1$ simultaneously holds. (Q.E.D).

4.2. Utilization of FRIT for the simultaneous attainment

Let consider a cascaded IMC system described in Fig. 2 with minimum phase processes. Assume that we can collect the input/output data $\left\{u(\rho^0),\, y_2(\rho^0),\, y_1(\rho^0)\right\}$ from the closed loop system with an initial setting ρ^0. By using a set of the initial data, we introduce the fictitious reference signal $\tilde{r}(\rho)$ described by:

$$\begin{aligned}\tilde{r}(\rho)&=C_1(\rho)^{-1}C_2(\rho)^{-1}u(\rho^0)-C_1(\rho)^{-1}\tilde{P}_2u(\rho^0)\\&\quad-C_2(\rho)^{-1}\tilde{P}_{\mathrm{B}}u(\rho^0)+\tilde{P}_2\tilde{P}_{\mathrm{B}}u(\rho^0)+\\&\quad+C_1(\rho)^{-1}y_2(\rho^0)-\tilde{P}_{\mathrm{B}}y_2(\rho^0)+y_1(\rho^0)\end{aligned}$$

(15)

And we minimize the cost function:

$$J_{\mathrm{F}}(\rho):=\left\|y_1(\rho^0)-T_{\mathrm{d}}\tilde{r}(\rho)\right\|_N^2 \quad (16)$$

Consider the meaning of the minimization of Eq. 16. We can see that the output of the system with respect to the signal expressed in Eq. 15 always equals to the initial one $y_1(\rho^0)$ for any parameter vector ρ

$$G_{\mathrm{ry}}(\rho)\tilde{r}(\rho) \equiv y_1(\rho^0) \tag{17}$$

Indeed, we can validate (17) by using the trivial relations: $y_2(\rho) = \frac{1}{P_1} y_1(\rho)$ and $u(\rho) = \frac{1}{P_1 P_2} y_1(\rho)$.

Substituting Eq. 17 to Eq. 16 enables us to see that the cost function (16) can be also rewritten as:

$$J_{\mathrm{F}}(\rho) = \left\| \left(1 - \frac{T_{\mathrm{d}}}{G_{\mathrm{ry}}(\rho)}\right) y_1(\rho^0) \right\|_N^2 \tag{18}$$

This implies that the minimization of $J_{\mathrm{F}}(\rho)$ in Eq. 16 equals to that of the relative error of the desired transfer function T_{d} and the closed loop transfer function G_{ry} with ρ under the influence of $y_1(\rho^0)$.

Note that the cost function (16) with the fictitious reference signal $\tilde{r}(\rho)$ in Eq. 15 requires only a set of data $\left\{u(\rho^0), y_2(\rho^0), y_1(\rho^0)\right\}$, which means the minimization of Eq. 16 can be performed *off-line* by using one-shot experimental data.

4.3. Algorithm

The algorithm of the proposed approach can be summarized as following:

1. Parameterize the process with the unknown parameter vector ρ as Eq. 4 and Eq. 5.

2. The controllers are also parameterized with respect to ρ as Eq. 6 and Eq. 7.

3. Set an initial parameter vector ρ^0 and perform the closed loop experiment to obtain a set of data $\left\{u(\rho^0), y_2(\rho^0), y_1(\rho^0)\right\}$.

4. Compute the fictitious reference signal $\tilde{r}(\rho)$ by using Eq. 15.

5. Construct the cost function $J_{\mathrm{F}}(\rho)$ as Eq. 16 and minimize it by an off-line non-linear optimization.

6. Obtain $\rho^* = \arg\min J_{\mathrm{F}}(\rho)$ which yields both desired controllers $C_1(\rho^*), C_2(\rho^*)$ and mathematical models $\tilde{P}_1(\rho^*), \tilde{P}_2(\rho^*)$ of the actual process.

5. SIMULATION RESULTS

In this section, we give examples to show the validity of the proposed approach. The first-order and second-order, minimum phase plants are considered in Example 1 and Example 2, respectively.

5.1. Example 1

Consider a cascade system with the unknown first-order, minimum phase plants as: $P_1 = \frac{3}{5s+1}$ and: $P_2 = \frac{1}{2s+1}$. Then they are parameterized as:

$\tilde{P}_i = \dfrac{K_i}{\tau_i s + 1}$ (with $i = 1, 2$). For the inner loop we use the filter: $F(\lambda_2) = \dfrac{1}{\lambda_2 s + 1}$. Assume that we can achieve the desired transfer function of the inner loop, thus the outer internal model $\tilde{P}_{\mathrm{B}}$ has the parameterized form: $\tilde{P}_{\mathrm{B}} = \dfrac{1}{\lambda_2 s + 1} \dfrac{K_1}{\tau_1 s + 1}$. The unknown parameter vector here $\rho := [K_1\ \tau_1\ K_2\ \tau_2\ \lambda_2]^{\mathrm{T}}$, and we use the reference model: $T_{\mathrm{d}} = \dfrac{1}{(2s+1)^2}$ for the system.

With the initial parameter vector $\rho^0 = [2\ 2\ 2\ 2\ 2]^{\mathrm{T}}$, we perform a one-shot experiment on the cascade control system to obtain the initial data $u(\rho^0), y_2(\rho^0)$ and $y_1(\rho^0)$, which are described in Fig. 4 and Fig. 5 (the solid line). Note that the controllers with the initial setting ρ^0 are assumed to be able to stabilize the closed loop system such as to yield bounded input/output [8]. In Fig. 5, we also plot the reference signal r (the dot-and-dash line) and the desired output $T_{\mathrm{d}} r$ (the dotted line). By applying the proposed algorithm, the optimal parameters are obtained as $\rho^* = [3.000\ 4.947\ 0.984\ 1.988\ 1.880]^{\mathrm{T}}$. We implement these parameters to the system in Fig. 2 and perform the final experiment. The results are illustrated in Fig. 6. In this figure, the reference signal r, the optimal output $y_1(\rho^*)$ and the desired output $T_{\mathrm{d}} r$ are drawn by the dot-and-dash line, the solid line and the dotted line, respectively. From Fig. 6, we see that the actual output $y_1(\rho^*)$ and the desired output $T_{\mathrm{d}} r$ are almost the same, which implies that the desired controllers are achieved by using ρ^*.

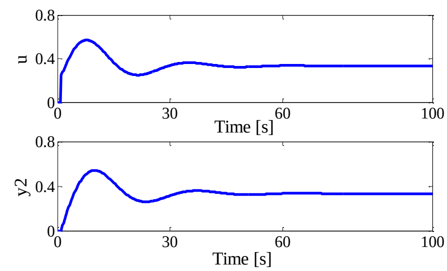

Figure 4. The input signal $u(\rho^0)$ and the output signal $y_2(\rho^0)$ in Example 1

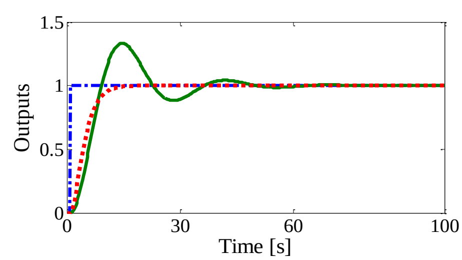

Figure 5. The reference signal r (the dot-and-dash line), the actual output $y_1(\rho^0)$ (the solid line) and the desired output $T_d r$ (the dotted line) in Example 1

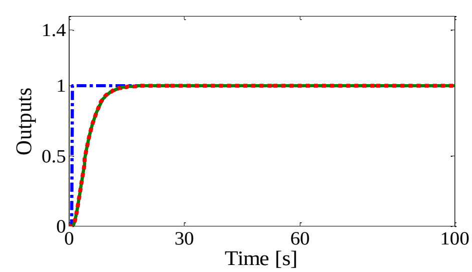

Figure 6. The reference signal r (the dot-and-dash line), the optimal output $y_1(\rho^*)$ (the solid line) and the desired output $T_d r$ (the dotted line) in Example 1

On the other hand, by using ρ^*, the plant models are obtained as: $\tilde{P}_1 = \frac{3.000}{4.947s+1}$ and: $\tilde{P}_2 = \frac{0.984}{1.988s+1}$. Compared with the poles and gains of the actual plant, we see that they are also well-identified.

From these results, we can see that the optimal parameter vector ρ^* yields both controllers for a desired output and mathematical models of the actual plants.

5.2. Example 2

In this case, the proposed approach is applied for the unknown second - order plants as: $P_1 = \frac{s+1}{3s^2+5s+1}$ and $P_2 = \frac{0.5s+1}{2s^2+3s+1}$. Thus, the parameterized models of the plants are: $\tilde{P}_1 = \frac{\rho_1 s+\rho_2}{\rho_3 s^2+\rho_4 s+1}$ and: $\tilde{P}_2 = \frac{\rho_5 s+\rho_6}{\rho_7 s^2+\rho_8 s+1}$. We use the same form of the filter and reference model as in example 1, then the unknown vector $\rho := [\rho_1\ \rho_2\ \rho_3\ \rho_4\ \rho_5\ \rho_6\ \rho_7\ \rho_8\ \lambda_2]^{\mathrm{T}}$. With the initial setting: $\rho^0 = [2\ 2\ 2\ 2\ 2\ 2\ 2\ 2\ 2]^{\mathrm{T}}$, we collect a set of data $\{u(\rho^0), y_2(\rho^0), y_1(\rho^0)\}$ that are described in Fig. 7 and Fig. 8. The proposed algorithm is applied and we obtain the optimal parameter vector as $\rho^* = [0.270\ \ 0.997\ \ 1.849\ \ 4.144\ \ 1.197\ \ 0.979\ \ 2.236\ \ 2.543\ \ 1.185]^{\mathrm{T}}$. After implementing ρ^* to the system in Fig. 2, we obtain the optimal output described in Fig. 9. From this figure, we can see that the achieved output $y_1(\rho^*)$ (the solid line) can meet the reference one $T_d r$ (the dotted line), that means the vector ρ^* yields optimal controllers.

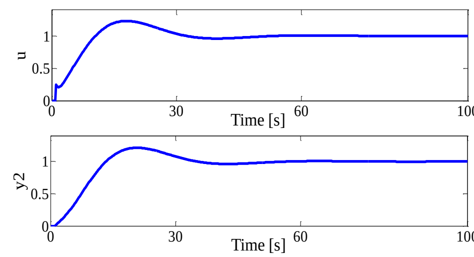

Figure 7. The input signal u(p^0) and the output signal y$_2$(p^0) in Example 2

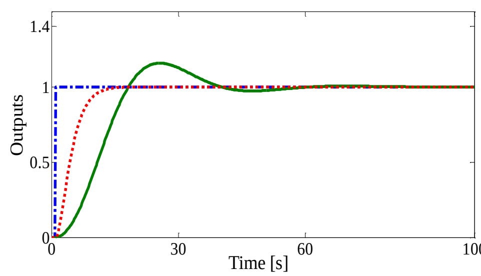

Figure 8. The reference signal r (the dot-and-dash line), the optimal output y$_1$(p*) (the solid line) and the desired output T$_d$r (the dotted line) in Example 2

Moreover, by using ρ^* we obtain the plant models as: $\tilde{P}_1 = \frac{0.27s+0.997}{1.849s^2+4.144s+1}$ and $\tilde{P}_2 = \frac{1.197s+0.979}{2.236s^2+2.543s+1}$. It seems that, the poles and zeros of the actual plants are not identified. Fig. 10 and Fig. 11 show the frequency characteristics of the actual plants and the obtained models. In these two figures, characteristics of

P_i, $\tilde{P}_i(\rho^*)$ and $\tilde{P}_i(\rho^0)$ are illustrated by the dotted line, the solid line and the dot-and-dash line, respectively. It is seen that the frequency characteristics of P_i and those of $\tilde{P}_i(\rho^*)$ are almost the same in frequency range of reference model T_d. That means the models $\tilde{P}_i(\rho^*)$ appropriately reflect the dynamics of the actual plants.

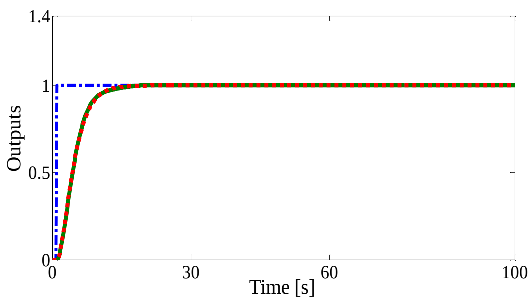

Figure 9. The reference signal r (the dot-and-dash line), the optimal output $y_1(p^*)$ (the solid line) and the desired output $T_d r$ (the dotted line) in Example 2

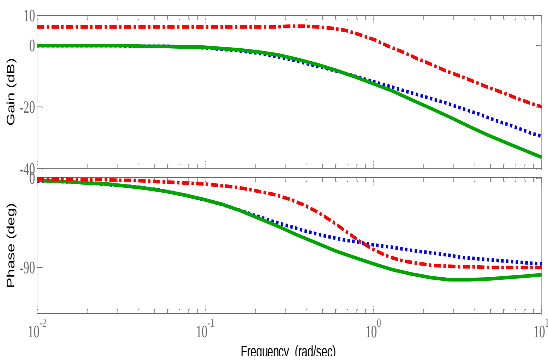

Figure 10. Frequency characteristics: P_1 (the dotted lines), $\tilde{P}_1(\rho^*)$ (the solid lines), and $\tilde{P}_1(\rho^0)$ (the dot-and-dash lines) in Example 2

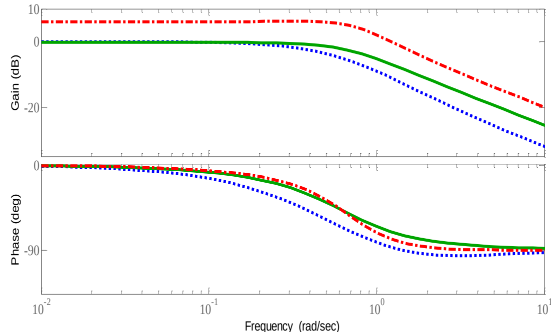

Figure 11. Frequency characteristics: P_2 (the dotted lines), $\tilde{P}_2(\rho^*)$ (the solid lines), and $\tilde{P}_2(\rho^0)$ (the dot-and-dash lines) in Example 2

6. CONCLUSIONS

In this paper, we have proposed a data-driven approach to the cascaded IMC with fictitious reference iterative tuning (FRIT). The processes we consider here are linear, time-invariant, stable and minimum phase. The algorithm directly designs controllers based on the one-shot input/output data collected from the closed-loop system, and it does not require an identification. The approach enables us to obtain not only desired controllers but also mathematical models that reflect the dynamics of the actual process.

Future direction of this study is to extend the proposed method to various processes (e.g. with unstable zeros and/or time-delay) to show its useful and effective. The comparison with other data-driven approaches will also be considered in the future researches.

REFERENCES

(ISSN: 1859 - 4557)

[1] A.T. Azar and F.E. Serrano, Robust IMC-PID tuning for cascade control systems with gain and phase margin specifications, Neural Computing and Applications, Springer, Vol. 25, 2014, pp. 983–995.

[2] M. Morari and E. Rafiriou, Robust Process Control, PTR Prentice Hall, Englewood Cliffs, New Jersey, 1989.

[3] J. Jeng and M. Lee, Simultaneous automatic tuning of cascade control systems from closed-loop step response data, Journal of Process Control, Vol. 22, 2012, pp. 1020–1033.

[4] Y. Lee and S. Park, PID controller tuning to obtain desired closed loop responses for cascade control systems", Ind. Eng. Chem. Res., Vol. 37, 1998, pp. 1859–1865.

[5] M.R. Cesca and J.L. Marchetti, IMC design of cascade control, Proceedings of the European Symposium on Computer Aided Process Engineering – 15, Vol. 20, 2005, pp. 1243–1248.

[6] H. Hjalmarsson, M. Gevers, S. Gunnarsson and O. Lequin, Iterative Feedback Tuning: Theory and Applications, IEEE Control Systems Magazine, Vol. 18, No. 4, 1998, pp. 26 – 41.

[7] M.C. Campi, A. Lecchini, and S. M. Savaresi, Virtual reference feedback tuning: a direct method for design of feedback controllers, Automatica, Vol. 38, No. 8, 2002, pp. 1337–1346.

[8] S. Souma, O. Kaneko and T. Fujii, A new method of controller parameter tuning based on input-output data- fictitious reference iterative tuning (FRIT), Proceedings of the 8th IFAC Workshop on Adaption and Learning Control and Signal Processing, 2004, pp. 788–794.

[9] O. Kaneko, H.T. Nguyen, Y. Wadagaki, and S. Yamamoto, Fictitious Reference Iterative Tuning for Non-Minimum Phase Systems in the IMC Architecture: Simultaneous Attainment of Controllers and Models, SICE Journal of Control, Measurement, and System Integration, Vol. 5, No. 2, 2012, pp. 101–108.

[10] H.T. Nguyen and O. Kaneko, Fictitious reference iterative tuning for cascade control systems, Proceedings of the SICE Annual Conference, 2015, pp. 774–777.

[11] H.T. Nguyen and O. Kaneko, Fictitious reference iterative tuning for cascade PI controllers of DC motor speed control systems, IEEJ Transactions on Electronics, Information and Systems, Vol. 136, No. 5, 2016, pp. 710–714.

Biography:

Nguyen Thi Hien, received B.E. and M.E. degrees in Electrical Engineering from Vietnam National University of Agriculture, Vietnam in 2000 and 2002, respectively, and Ph.D. in Control Engineering from Kanazawa University, Japan in 2013. She is a lecturer at Faculty of Engineering, Vietnam National University of Agriculture, Hanoi, Vietnam.

Her research interests include control systems and its applications.