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Data-driven IMC for Non-Minimum Phase Systems - Laguerre Expansion Approach -

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***Abstract*— This paper proposes a data-driven parameter tuning of the internal model controller (IMC) for non-minimum phase plants. 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 controller with only one-shot experiment data. Particularly, we propose an embedding of the internal mathematical model which is described by Laguerre expansion for describing non-minimum phase plants. Moreover, we show that the proposed approach enables us to obtain not only a desired controller but also a well-approximated mathematical model of the actual non-minimum phase plant simultaneously.**

***Index Terms*— data-driven approach, fictitious reference iterative tuning, non-minimum phase, internal model control, Laguerre expansion**

I. INTRODUCTION

Internal model control (IMC)[1] is one of the effective approaches for the achievement of a desired tracking property [1]. With an internal model implemented in parallel to the linear plant, the controller can compensate the mismatch between the actual plant and its model. In the cases where the internal model exactly reflects the dynamics of the plant, the IMC completely yields the desired tracking property. Conversely, in the cases of no knowledge of a plant, the direct use of the data (which we call *data-driven approach*) that have a fruitful information of the plant yields a more desirable IMC with respect to the desired specification. Particularly, there are many cases in which the structure of a controller has already been fixed with unknown parameters from the view points on the enhancement of the implementation. From such points of view, there are some studies on the data-driven approaches to the controller parameter tuning of the IMC in [2]-[7].

The application of iterative feedback tuning (IFT) [8] to the IMC was studied in [2]. The IFT is a tuning method that iteratively updates the variable parameters of the controller to minimize the error between the actual output and the desired one. This minimization can be computed as a non-linear optimization technique, e.g., the Gauss-Newton method, in which the approximations of the gradient, the Hessian, and so on, consist of the experimental data. This means that IFT requires *many* experiments to update the parameters of the controller. Thus, it spends considerable expense and time, which are crucial issues with respect to practical points of view. The application of virtual reference feedback tuning (VRFT) [9] to IMC was studied in [3]. Differently from IFT, VRFT requires only *one-shot* experiment for the achievement of a desired output, and thus the time and expense for obtaining the optimal parameters are drastically reduced. However, in [3], the controller is assumed to be linearly parameterized which implies that the flexibility and the freedom of the controller are restricted.

In [4]-[7], FRIT, which was proposed by some of the authors in [10], is utilized for the controller parameter tuning of the IMC or the Smith compensator. Similarly to VRFT, FRIT is also a controller parameter tuning that achieves the desired output with only one-shot experimental data. However, FRIT considers the minimization of the error between the fictitious output and the actual one while the VRFT focuses on the error between the virtual input and the actual one, so FRIT is intuitively understandable with respect to obtaining a desired output. Moreover, the methods proposed in [4]-[7] treat the controller whose denominator and numerator are parameterized, which implies that more effective tuning of the IMC can be performed. In fact, by focusing the feature that the IMC includes a mathematical model, the authors provided a method of the simultaneous attainment of not only a desired controller but also a model of the plant in [4]-[7] while the results in [2] and [3] can not be applicable for such a simultaneous attainment. From the practical points of view, we can utilize the obtained model for finding out information on model uncertainties, monitoring the actual status of a plant, detecting an aging variation of a plant, re-designing more advanced controllers, and so on. From the theoretical point of view, there is a crucial interplay which can not be separated between a mathematical model and a designed controller as stated in [11]. As for this point, it is natural to treat the data as an interface connect a model and a controller from more broader perspective. Thus, it is meaningful to simultaneously obtain not only a desired controller but also a mathematical model of a plant.

By the way, there are many systems with a non-minimum phase behavior which can not be neglected in various applications [12]. For non-minimum phase systems, there exist studies on data-driven parameter tuning such as [13] with IFT, [14] with VRFT. Both of them cannot be applied for

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[1]In this paper, the terminology of "IMC "is used for the "internal model control" or the "internal model controller".

the simultaneous attainment [2]. In [6] and [7], we have also proposed a new approach for non-minimum phase systems by factorizing the system model into the minimum phase and non-minimum phase parts under the assumption that we know the number of unstable zeros. However, in the cases of no knowledge or only partial knowledge of a system, a non-minimum phase system can not be parameterized in the same way as the result in [6] and [7].

From these backgrounds, we propose a data-driven parameter tuning of the IMC for non-minimum phase plants by utilizing FRIT under the situation where we do not know any information of non-minimum phase property. Here, we propose the embedding of the internal mathematical model which is described by Laguerre expansion ([16]-[17]) for the treatment of non-minimum phase plants. We also show that the proposed results are not only an optimal controller for the achievement of a desired tracking property but also a mathematical model of the plant.

The paper is organized as follows: Section 2 are preliminaries and problem setting. Section 3 address a summary of FRIT scheme, a one-shot data-based method for tuning controller parameters. The main results of the paper are expressed in Section 4, a Laguerre expansion approach for non-minimum phase systems in IMC framework with FRIT. A numerical simulation in the Section 5 shows the validity of the algorithm. Finally, some conclusions are given in Section 6.

II. PRELIMINARIES AND PROBLEM SETTING

A. Notations and Assumptions

Let L_2 denote a space of squared integrable functions. Let u and y denote the input and output data (of a closed loop system) obtained in the finite time, respectively. N denote a number of the sampled data. A transfer function from input u to the output y of a system is described by $G(s) = \frac{N(s)}{D(s)}$, where $N(s)$ and $D(s)$ are coprime. The output y of G with respect to u is the solution of the differential equation $D(\frac{d}{dt})y = N(\frac{d}{dt})u$. However, for the enhancement of the readability, we use the notation $y = Gu$. Throughout of this paper, we often omit the notation $'s'$ from a rational function whose indeterminate is s. For a time signal w, we denote a value of w at the time t as $w(t)$. In order to denote a delayed signal of the time signal w with a time lag τ, we use a simple notation $e^{-\tau s}w$, i.e., $(e^{-\tau s}w)(t) = w(t-\tau)$ for all time t, for the enhancement of the readability.

B. Problem Setting

A system we address in this paper is linear, time-invariant, single-input/single-output, strictly proper, stable and non-minimum phase. Let P and $\tilde{P}$ denote the actual plant and its mathematical model implemented in the IMC, respectively. We consider a closed loop system with IMC in Fig. 1. Since we have no knowledge of the plant P, so its model $\tilde{P}$ is parametrized by a tunable vector ρ_P. For example, each element of ρ_P corresponds to an unknown coefficient of

[2]The method in [14] can identify only zeros.

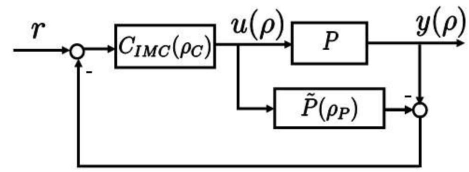

Fig. 1. A closed loop system with IMC

each term in the polynomials of the denominator/numerator. Similarly, we suppose that the feedback controller C_{IMC} are parameterized by a tunable vector ρ_C. With the notation $\rho = [\rho_C \ \rho_P]^{\mathrm{T}}$, the input u and output y also depend on ρ, so we denote them as $u(\rho)$ and $y(\rho)$, respectively.

Let T_d denote a reference model from r to y of the closed loop system. Then $T_d r$ denotes the desired output. In addition, since the controller include the tunable mathematical model of a plant, it is expected that the internal model in IMC also leads an appropriate model of the actual plant. Thus, the objective is to minimize the model-reference criterion as

$$J(\rho) = \frac{1}{N}\sum_{t=1}^{N}(y(\rho,t) - T_d r(t))^2. \tag{1}$$

and simultaneously such that $\tilde{P}(\rho_P)$ approximates P as closely as possible. In other words, the problem is to simultaneously attain both of a desired controller and a model with the direct use of the data.

Moreover, it is preferable that the simultaneous attainment can be performed with as few data as possible. From this reason, we utilize fictitious reference iterative tuning (FRIT), which is briefly explained in the next section, for this purpose.

III. FICTITIOUS REFERENCE ITERATIVE TUNING - FRIT

This section is a brief review of FRIT [10] as an effective tool to solve our problem. This is a data based method with only one-shot experiment. The main ideas of FRIT scheme is to construct the model-reference criterion in the fictitious domain. Consider Fig. 2 for a conventional closed loop system, here the controller C is parameterized by

$$C(\rho) = \frac{\sum_{i=0}^{\mu_C}\rho_i s^i}{\sum_{i=1}^{\nu_C}\rho_{\mu_C+i}s^i + 1} \tag{2}$$

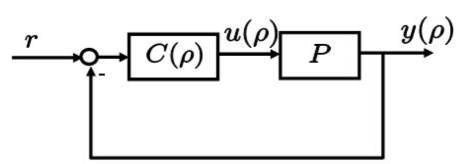

Fig. 2. A conventional closed loop system

where $\rho = [\rho_0 \ \rho_1 \ \dots \ \rho_{\mu_C} \ \dots \ \rho_{\nu_C}]^{\mathrm{T}} \in \mathbb{R}^{\mu_C+\nu_C+1}$. The input and output are denoted as $u(\rho)$ and $y(\rho)$, respectively.

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: $u^0 := u(\rho^0)$ and $y^0 := y(\rho^0)$. The controller $C(\rho_0)$ is assumed to be able to stabilize the closed loop so as to yield the bounded input and output. Then, use the data u^0 and y^0, compute the fictitious reference signal $\tilde{r}(\rho)$ [15] [3] with a parameter vector ρ as

$$\tilde{r}(\rho) = C^{-1}(\rho)u^0 + y^0. \tag{3}$$

Note that the fictitious output responding to the fictitious reference signal $\tilde{r}$ is always equal to the initial one y^0. Indeed, together with the trivial relation $Pu^0 = y^0$, we see

$$\tilde{y}(\rho) = \frac{PC(\rho)}{1+PC(\rho)}\tilde{r}(\rho) := y^0. \tag{4}$$

For a given reference model T_d, we introduce the following cost function described by

$$J_F(\rho) = \sum_{t=0}^{N} \left(y^0(t) - T_d\tilde{r}(\rho,t)\right)^2. \tag{5}$$

Then we minimize $J_F(\rho)$ and implement $\tilde{\rho}^* := \arg\min_\rho J_F(\rho)$ to the controller. Note that (5) with $\tilde{r}(\rho)$ in (3) requires only u^0 and y^0. This means that the minimization of (5) can be performed *off-line* by using only one-shot experimental data. As for the relationship between the minimization of (5) and that of (1), we obtain the following result.

Proposition 1: For a parameter $\tilde{\rho}^*$, $J(\tilde{\rho}^*) = 0$ holds if and only if $J_F(\tilde{\rho}^*) = 0$ holds. □

See Theorem 3.1 in [10] for the detailed proof and discussions. This proposition implicitly means that the minimization of $J_F(\rho)$ is deeply related to that of $J(\rho)$.

IV. A DATA-DRIVEN IMC FOR NON-MINIMUM PHASE SYSTEMS - LAGUERRE EXPANSION APPROACH

A. The basic idea

With an unknown non-minimum phase plant P, a model $\tilde{P}$ of the plant can be parameterized as

$$\tilde{P}(\rho) = \tilde{P}_m(\rho_m)\tilde{P}_n(\rho_n) \tag{6}$$

where

$$\tilde{P}_m(\rho_m) = \frac{\sum_{i=0}^{\mu}\rho_i s^i}{\sum_{i=1}^{\nu}\rho_{\mu+i}s^i + 1}, \qquad \mu \le \nu \tag{7}$$

$$\tilde{P}_n(\rho_n) = \sum_{k=1}^{M}\eta_k L_k(s,a). \tag{8}$$

[3]The fictitious reference was proposed by [15] in the unfalsified control framework. However, we use it for the different purpose.

In (7), $\tilde{P}_m(\rho_m)$ is the parameterized minimum phase part. On the other hand, (8) describes the parameterized non-minimum phase part by using the Laguerre expansion

$$L_k(s,a) = \frac{\sqrt{2a}}{s+a}\left(\frac{s-a}{s+a}\right)^{k-1} \tag{9}$$

with coefficients η_k for $k = 1, \cdots, M$. The reason why we use the Laguerre expansion for describing the non-minimum phase part is that the Laguerre function plays a role as the orthogonal bases for approximation of any stable linear time-invariant systems [16], [17]. Although it is ideal that M is to be selected as infinity, the Laguerre expansion is truncated as the sum of the finite expansion because it should be implemented in the IMC.

The parameter $a > 0$ in (9) affects not only to convergence rate but also to quadratic error of the approximation [18]-[20]. Moreover, it also impacts on the steady state error of the tracking property that will be discussed in the next section. Thus, we here consider a as a tunable parameter.

From the above, the unknown parameter vector for the internal mathematical model is

$$\rho := \begin{bmatrix} \rho_m \\ \rho_n \end{bmatrix} \tag{10}$$

with

$$\rho_m = [\rho_0 \ \rho_1 \dots \ \rho_\mu \ \dots \rho_\nu]^{\mathrm{T}} \in \mathbb{R}^{\mu+\nu+1}. \tag{11}$$

and

$$\rho_n = [\eta_1 \dots \ \eta_M \ a]^{\mathrm{T}} \in \mathbb{R}^{M+1}. \tag{12}$$

By the way, since limitation of the tracking property is deeply related to the non-minimum phase behavior of a system, the reference model T_d would have the same unstable zeros and/or time delay as the system [13], [14], [21]. However, it is assumed that we have no information of the plant model. Thus, we set $T_d = T_{dm}\tilde{P}_n(\rho_n)$ as the desired model and it is expressed as

$$T_d = T_{dm}\sum_{k=1}^{M}\eta_k L_k(s,a). \tag{13}$$

where T_{dm} is a reference model which is given by users and to be with the minimum phase property.

B. Main results

As stated earlier, since the IMC involve the mathematical model, it is expected that the achievement of the desired tracking yields the obtainment of the mathematical model of the actual plant. In order to achieve such a simultaneous attainment of a controllers and models in the IMC architecture. we give the following result.

Theorem 1: Assume that the controller $C_{IMC}(\rho)$ described

$$C_{IMC} = T_{dm}\tilde{P}_m(\rho_m)^{-1}. \tag{14}$$

Then, the following equivalence holds

$$P = \tilde{P}(\rho) \Leftrightarrow G_{ry}(\rho) = T_{dm}\tilde{P}_n(\rho_n). \tag{15}$$

Proof. It follows from the basic concept of IMC [1] that the '⇒' part clearly holds. Thus, we focus on the '⇐' part. In Fig. 1, the transfer function G_{ry} from r to y can be described as

$$G_{ry} = \frac{C_{IMC}P}{1 + C_{IMC}(P - \tilde{P})}. \tag{16}$$

By substituting (14), (16) yields

$$G_{ry} = \frac{T_{dm}\tilde{P}_m^{-1}P}{1 - T_{dm}\tilde{P}_n + T_{dm}\tilde{P}_m^{-1}P}. \tag{17}$$

Since the left hand side of (17) is equal to $T_{dm}\tilde{P}_n(\rho_n)$, we obtain

$$\tilde{P}_m^{-1}P = \tilde{P}_n - T_{dm}\tilde{P}_n\tilde{P}_n + T_{dm}\tilde{P}_m^{-1}P\tilde{P}_n. \tag{18}$$

Under assumption $(1 - T_{dm}\tilde{P}_n(\rho_n)) \neq 0$, $P = \tilde{P}(\rho)$ holds. □

Theorem 1 implies that we can also obtain a mathematical model of the actual plant by achieving the desired output. Fig. 3 illustrates the IMC with the controller described as (14). Since we use the feedback controller C_{IMC} described by (14), we do not use the parameter ρ_C for C_{IMC} and we use only ρ henceforth.

By rewriting Fig. 3 as Fig. 2, the controller $C(\rho)$ can be computed as

$$C(\rho) = \frac{C_{IMC}}{1 - C_{IMC}\tilde{P}(\rho)} = \frac{T_{dm}}{1 - T_d}\tilde{P}_m(\rho_m)^{-1}. \tag{19}$$

For eliminating the steady state error of the closed loop system, the controller $C(\rho)$ must have the integral action. Regarding this issue, we give the following theorem.

Theorem 2: Assume that a given reference model $T_{dm}(s)$ satisfies

$$T_{dm}(0) = 1. \tag{20}$$

Then, the steady state error of the closed loop system depicted in Fig. 3 is eliminated if and only if the following equation holds

$$\sum_{k=1}^{M}(-1)^{k-1}\eta_k = \sqrt{a/2}. \tag{21}$$

Proof. We firstly prove the 'if' part. From the equality: $\sum_{k=1}^{M}(-1)^{k-1}\eta_k = \sqrt{a/2}$ and the characteristic of Laguerre functions, it can be readily shown that

$$\lim_{s\to 0}\tilde{P}_n = 1. \tag{22}$$

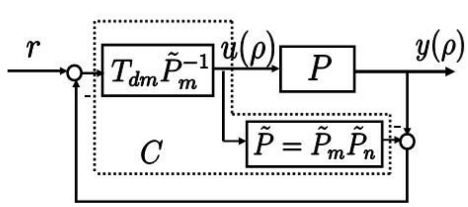

Fig. 3. IMC with the feedback controller described as (14)

On the other hand, from (19) we have

$$\lim_{s\to 0}C(\rho) = \lim_{s\to 0}\frac{T_{dm}\tilde{P}_m^{-1}}{1 - T_{dm}\tilde{P}_n} \tag{23}$$

Implementing (20) and (22), (23) yields

$$\lim_{s\to 0}C(\rho) = \infty. \tag{24}$$

Equation (24) means that the controller $C(\rho)$ has the integral action which can eliminate the steady state error of the system. Thus, the 'if' part is proved.

The 'only if' part is easily proved by using the above steps in reverse order. □

From (21), we have

$$\eta_M = \sqrt{a/2} - \sum_{k=1}^{M-1}(-1)^{k-1}\eta_k \tag{25}$$

for the controller to be the integral action. Thus, ρ_n is an intrinsical M-element parameter vector and we use the following denote henceforth

$$\rho_n = [\eta_1 \ \ldots \ \eta_{M-1} \ a]^{\mathrm{T}}. \tag{26}$$

C. FRIT for IMC

Apply FRIT for the purpose of obtaining an optimal parameter vector of the controller in Fig. 3, the fictitious reference $\tilde{r}$ in (3) can be rewritten as

$$\tilde{r}(\rho) = \frac{1 - T_{dm}\tilde{P}_n(\rho_n)}{T_{dm}}\tilde{P}_m(\rho_m)u^0 + y^0 \tag{27}$$

with $\tilde{P}_m$ described by (7) and $\tilde{P}_n$ described by (8) , respectively. Implement $\tilde{r}(\rho)$ into (5) which is rewritten as

$$J_F(\rho) = \frac{1}{N}\sum_{t=1}^{N}(y^0(t) - T_{dm}\sum_{k=1}^{M}\eta_k L_k(s,a)\tilde{r}(\rho,t))^2 \tag{28}$$

together with (25). As a result of the minimization of $J_F(\rho)$, we obtain an optimal parameter vector of the controller:

$$\rho^* = \arg\ \min_{\rho} J_F(\rho). \tag{29}$$

If the minimized value of J_F can be regarded as a small number, we can regard that the optimal parameters ρ^* yield not only a desired controller $C(\rho^*)$, but also a mathematical model of plant $P = \tilde{P}(\rho^*)$ as a result of Theorem 1.

D. Algorithm

The algorithm of the proposal method is summarized as following:

1) Parameterize the minimum phase and the non-minimum phase parts of plant model with arbitrary order of Laguerre expansion as (7) and (8)
2) The parameter vector ρ is determined by ρ_m and ρ_n as (11) and (26), respectively.
3) Set an initial parameter vector ρ^0 and perform a one-shot experiment to obtain the data u^0 and y^0.
4) Calculate the fictitious reference signal $\tilde{r}(\rho)$ by using (27), construct the cost function $J_F(\rho)$ as (28) and minimize it by an *off-line* non-linear technique.

5) Obtain the optimal parameter vector $\rho^* = \arg\min_\rho J_F(\rho)$ which yields both a desired controller and a mathematical model of the plant.

V. EXAMPLE

In order to show the validity of the algorithm, we apply the proposed approach for an unknown plant with a time-delay and unstable zeros as

$$P = \frac{3(s^2 - 5s + 6)}{(3s+1)(s^2+2s+5)} e^{-0.5s}.$$

Parameterize the plant by a first-order MP part $\tilde{P}_m$

$$\tilde{P}_m(\rho_m) = \frac{\rho_1}{\rho_2 s + 1}.$$

and a Laguerre approximation for NMP part

$$\tilde{P}_n(\rho_n) = \sum_{k=1}^{M} \eta_k(a) L_k(s,a)$$

The desired model has some tunable parameters

$$T_d(\rho_n) = \frac{1}{2s+1} \sum_{k=1}^{M} \eta_k L_k(s,a).$$

Then, the unknown parameter vectors

$$\rho_m = [\rho_1 \ \rho_2]^{\mathrm{T}}$$

$$\rho_n = [\eta_1 \cdots \ \eta_{M-1} \ a]^{\mathrm{T}}$$

We set $M = 5$ and the initial parameter vectors as $\rho_m^0 = [2 \ 2]^{\mathrm{T}}$ and $\rho_n^0 = [0.6 \ 0.3 \ 0.3 \ 0.2 \ 3.0]^{\mathrm{T}}$. We perform one-shot experiment with the closed loop system, the initial input u^0 and output y^0 are respectively illustrated in Fig. 4 and Fig. 5. In Fig. 5, the initial output y^0, the reference signal r and the reference output $T_{dm}\tilde{P}_n(\rho_n^0)r$ are drawn as the solid line, the dot-and-dash line, and the dotted line, respectively. We then apply the proposed algorithm, the optimal parameters are obtained: $\rho_m^* = [3.5012 \ 2.8684]$ and $\rho_n^* = [-0.1085 \ 0.3556 \ 1.3071 \ -1.1121 \ 2.9718]$. Implement these parameters to Fig. 3 and perform the final experiment, the result is shown in Fig. 6. In this figure, the optimal output $y(\rho^*)$, the reference signal r and the desired output $T_{dm}\tilde{P}_n(\rho_n^*)r$ are drawn by the solid line, the dot-and-dash line and the dotted line, respectively. From Fig. 6, we see that the actual output $y(\rho^*)$ and the desired output $T_{dm}\tilde{P}_n(\rho_n^*)r$ are almost the same, which implies that the desired controller is achieved by using ρ^*.

In addition, with the obtained parameters, we can compare the actual plant P and its model $\tilde{P}(\rho^*)$ with respect to frequency response as Fig. 7 and Fig. 8. In these two figures, characteristics of $P, \tilde{P}(\rho^*), \tilde{P}(\rho^0)$ and $T_{dm}\tilde{P}_n(\rho_n^*))$ are illustrated by the dotted line, the solid line, the dashed line and the dot-and-dash line, respectively. The frequency characteristics of P and those of $\tilde{P}(\rho^*)$ are almost the same in frequency rank of reference model T_d. That means the model $\tilde{P}(\rho^*)$ appropriately reflects the dynamics of the actual plant.

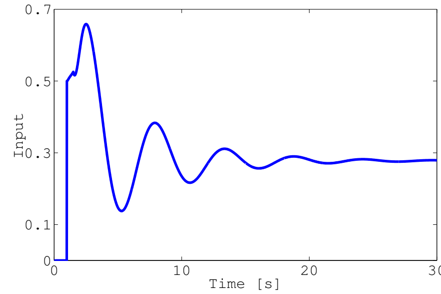

Fig. 4. The the initial input u^0

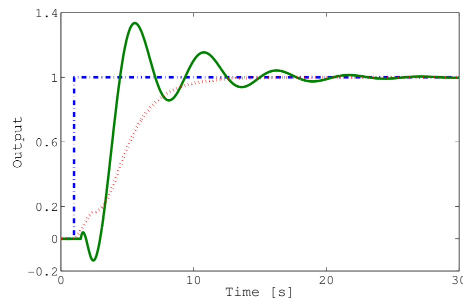

Fig. 5. The reference signal r (the dot-and-dash line), the initial output y^0 (the solid line) and the desired output $T_{dm}\tilde{P}_n(\rho_n^0))$ (the dotted line)

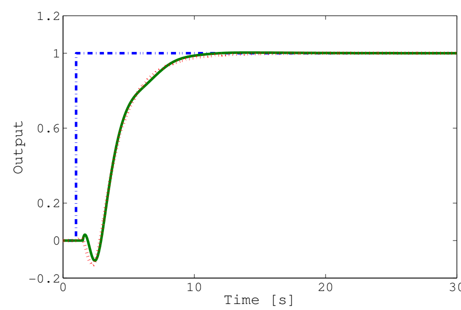

Fig. 6. The reference signal r (the dot-and-dash line), the optimal output $y(\rho^*)$ (the solid line) and the desired output $T_{dm}\tilde{P}_n(\rho_n^*))$ (the dotted line)

From these results, it is concluded that, by applying the proposed approach, we can obtain simultaneously a controller for the desired tracking property and a mathematical model of the actual plant.

VI. CONCLUSIONS

In this paper, we have extended one of applications of a data-based controller tuning method by utilizing fictitious reference iterative tuning (FRIT) in the IMC framework. With the combination of the Laguerre expansion, the approach has shown its validity for the case of non-minimum phase systems with no any information of the number of unstable zeros and/or time delay. The proposed approach enables us to obtain not only a desired controller but also a mathematical model of the actual plant.

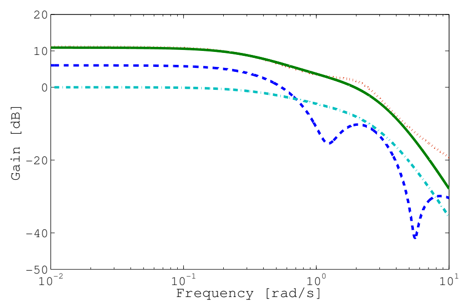

Fig. 7. Gain characteristics: P (the dotted line), $\tilde{P}(\rho^*)$ (the solid line), $\tilde{P}(\rho^0))$ (the dashed line), and $T_{dm}\tilde{P}_n(\rho_n^*))$ (the dot-and-dash line)

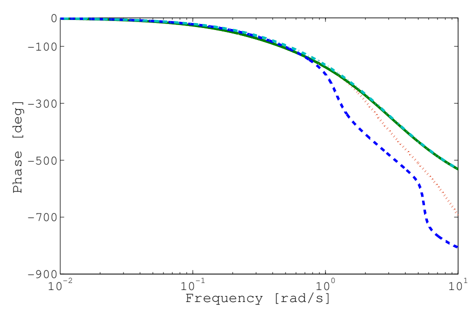

Fig. 8. Phase characteristics: P (the dotted line), $\tilde{P}(\rho^*)$ (the solid line), $\tilde{P}(\rho^0))$ (the dashed line), and $T_{dm}\tilde{P}_n(\rho_n^*))$ (the dot-and-dash line)

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