Dissertation

Parametrization of Data-driven Controller with Kautz Expansions

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DOCTORAL DISSERTATION

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Abstract

In recent years, the data-driven controller design receives attention from many control engineers and researchers as it requires only the measured input and output (I/O) data of the system. The controller can be designed by direct utilization of the measured I/O data since these data reflect the dynamics of an actual system. In this way, a plant model identification step from the physical laws or from the measured data can be skipped, and as the results, it can reduce time and cost for the identification step and can avoid the dependence of the controller design on the plant model (which may be under-modeled).

Different kinds of data-driven controller tuning methods have been developed by many researchers and each method has its own advantages. In this research work, we will focus on fictitious reference iterative tuning (FRIT), one of the data-driven methods, to design the controller. FRIT requires only one-shot (i.e a single experiment is needed) experimental input and output data to obtain the optimal parameters for the controller.

The merit of FRIT is that the plant model can be obtained simultaneously as a by-product of the controller tuning. The obtained plant model can be used to re-design of the more advanced controller for the system. So, the plant model structure selection strategy is also essential. In real world, non-minimum phase zeros or time delay may be inherent parts of the actual system so they need to be considered in the plant model structure. Special orthonormal basis functions, Laguerre and Kautz series, can solve this problem and they are being used in identification of the stable and linear systems in many research work.

This research work combines the benefits of FRIT and special orthonormal basis functions to obtain the controller for the desired set point tracking and the plant model simultaneously. Furthermore, plants with complex poles cannot be avoided in practical applications and Kautz series can approximate them more effectively than Laguerre series. Truncated Kautz series will be used to parametrize the controller and to approximate the plant model. Kautz series in general need priori information of the system poles. In our proposed method, these Kautz poles are also tunable parameters.

In this research work, firstly, we consider FRIT in internal model control (IMC) structure of the conventional feedback loop system. Then we extend our research to two degree-of-freedom (2DoF) control structure. The parameters of the feedforward controller is approximated by the Kautz expansions. By using Kautz expansions in FRIT, some assumptions about the plant model (e.g, the priori knowledge of the relative degree and the number of unstable zeros of the plant) that are used in former FRIT methods can be reduced.

In this research work, we consider stable, linear time-variant (LTI) continuous-time single-input-single-output (SISO) systems. The controller is tuned for a step reference signal using data from noise-free simulations. The validity of our proposed method is shown with several numerical examples of non-minimum phase systems, time-delay systems and poorly damped systems. We also show the effectiveness of our proposed method with an illustrated example using the actual parameters of the vibrating system for positioning control and model estimating of that system.

Contents

Acknowledgements **i**

Abstract **iii**

Contents **v**

List of Figures **vii**

1 Introduction **1**

1.1 Motivation and objectives 1

1.2 Background 3

1.3 Outline of the dissertation 7

2 Paremetrization of Feedback Controller with Kautz Expansions using FRIT in IMC Structure **9**

2.1 Introduction 9

2.2 Problem formulation 10

2.3 Concept of fictitious reference iterative tuning 11

2.3.1 FRIT in IMC control scheme 13

2.3.2 FRIT in IMC for non-minimum phase system 13

2.3.3 Simultaneous attainment of the controller and the plant model in FRIT-IMC 14

2.4 Plant model in Kautz expansion 15

2.4.1 Setting constraint to compensate for the steady state error 17

2.5 Algorithm 17

2.6 Numerical example 18

2.7 Summary 22

3 Parametrization of Feedforward Controller with Kautz Expansions using FRIT in 2DoF Structure 23

3.1 Introduction . . . 23

3.2 Problem formulation . . . 24

3.3 FRIT in 2DoF control structure . . . 25

3.3.1 FRIT in 2DOF control for non-minimum phase plant . . . 26

3.3.2 Simultaneous attainment of controller and plant model in 2DoF-FRIT 27

3.4 Parametrization of the feedforward controller in Kautz expansions . . . 28

3.4.1 Setting constraint to compensate for the steady state error . . . 29

3.5 Numerical example . . . 30

3.6 Summary . . . 34

4 Set Point Tracking and Model Estimation for Time Delay System 35

4.1 Introduction . . . 35

4.2 Problem setting . . . 36

4.3 FRIT for 2DOF control architecture . . . 37

4.4 Parameterized models by Kautz expansions . . . 38

4.5 Comparison with the previous FRIT methods . . . 38

4.6 Numerical Example . . . 40

4.7 Summary . . . 44

5 Positioning Control and Model Estimation of the Vibrating System 45

5.1 Introduction . . . 45

5.2 Problem formulation . . . 46

5.3 Unknown plant Model . . . 46

5.4 Positioning Control . . . 48

5.5 Estimation of vibrating system . . . 50

5.6 Summary . . . 52

6 Conclusions and Future Work 53

Bibliography 55

Publications 63

List of Figures

1.1 A concept of model matching technique 4

2.1 Basic internal model control (IMC) structure 10
2.2 Concept of fictitious reference iterative tuning 12
2.3 IMC structure with feedback controller 13
2.4 Initial output $y(\rho^0)$ and the desired output $T_d(\rho^0)r$ with the step reference input 19
2.5 Optimal output $y(\rho^*)$ and the desired output $T_d(\rho^*)r$ 19
2.6 Gain characteristics of the plant and plant model with Kautz model order 3 20
2.7 Phase characteristics of the plant and plant model with Kautz model order 3 20
2.8 Initial output $y(\rho^0)$ with the measurement noise and the desired output $T_d(\rho^0)r$ of the system with Kautz model order 3 21
2.9 Optimal output $y(\rho^*)$ with the measurement noise and the desired output $T_d(\rho^*)r$ of the system with Kautz model order 3 21
2.10 Gain characteristics of the plant and plant model with noise 22
2.11 Phase characteristics of the plant and plant model with noise 22

3.1 Two-degree-of-freedom control structure 24
3.2 Two-degree-of-freedom control structure for non-minimum phase plant . . 27
3.3 Initial output $y(\rho^0)$, (solid line), the desired output, $T_d(\rho^0)r$, (dash-dot line) and the step reference input of the closed loop system (dotted line) . 30
3.4 Optimal output $y(\rho^*)$ (solid line), the desired output $T_d(\rho^*)r$ (dash-dot line) and step reference input of the closed loop system (dotted line) 31
3.5 Frequency responses of plant and plant model 31
3.6 Initial output $y(\rho^0)$, (solid line) with measurement noise, the desired output, $T_d(\rho^0)r$, (dash-dot line) and the reference input of the closed loop system (dotted line) 32

3.7 Optimal output $y(\rho^*)$ (solid line) with measurement noise, the desired output $T_d(\rho^*)r$ (dash-dot line) and the reference input of the closed loop system (dotted line) 32
3.8 Frequency responses of plant and plant model with measurement noise is considered 33
3.9 The optimal outputs of Laguerre order 6, Laguerre order 20, Kautz order 3 compared with the desired output of Kautz order 3 and the step response of nominal reference model 33
3.10 Frequency responses of plant and plant models with Laguerre order 6, Laguerre order 20 and Kautz order 3 34

4.1 FRIT in 2DOF control architecture for time delay system 36
4.2 The initial output $y(\rho^0)$ and the desired output $T_d(\rho^0)r$ (dash-dot line) . . 40
4.3 Initial output $y(\rho^*)$ and the desired output $T_d(\rho^*)r$ 41
4.4 Gain characteristics of the plant and plant model 41
4.5 Phase characteristics of the plant and plant model 41
4.6 Optimal outputs with Laguerre order 6 (solid-line), Kautz order 3 (dash-dot line) and Pade order 4 (dotted line) compared with the nominal reference model 43
4.7 Frequency characteristics of plant (solid line) and plant model with Laguerre order 6 (dashed line), Kautz order 3 (dashed-dot line) and Pade order 4 (dotted line), with optimal parameters 43

5.1 Schematic of mass-spring-damper system coupled to electromagnetic transducer (It is simplified diagram of the vibrating control system in [52]) . . . 46
5.2 Step responses of the actual closed loop transfer function, T_{ry} (solid line), and the desired closed loop transfer function, T_d (dash-dot line), with initial parameters 49
5.3 Initial input (dash-dot line) after initial experiment and optimal input (solid line) after optimization 49
5.4 Initial output (dash-dot line) after initial experiment and optimal output (solid line) after optimization 49

5.5 Step responses of the actual closed loop transfer function, T_{ry} (solid line), and the desired closed loop transfer function, T_d (dash-dot line) with optimal parameters 50
5.6 Step responses of plant (solid line) and plant model (dash-dot line) with initial parameters 50
5.7 Frequency responses of plant (solid line) and plant model (dash-dot line) with initial parameters 51
5.8 Step responses of plant (solid line) and plant model (dash-dot line) with optimal parameters 51
5.9 Frequency responses of plant (solid line) and plant model (dash-dot line) with optimal parameters 52
5.10 The gain characteristics of plant (solid line) and plant model (dash-dot line) to show the peak values of them 52

Chapter 1

Introduction

1.1 Motivation and objectives

A variety of controller designs which directly utilize the measured input and output data of the system (data-based) rather than using the mathematical model of the plant (model-based) have been developed by many researchers more than two decades ago. In contrast to the model-based controller design, the data-driven (data-based) controller design techniques skip the system identification steps for the plant model, as a consequence, these techniques can avoid the dependence of the controller on the plant model which can be under-modeled and model-mismatch in the model-based controller design.

In most of the data-driven controller tuning methods, (for example, in iterative feedback tuning (IFT) [3, 4, 7], virtual reference feedback tuning (VRFT) [8, 9] and fictitious reference iterative tuning (FRIT) [14, 15, 16, 20] in unfalsified control [1] and etc.), the controllers are designed in model reference framework and a fixed controller structure is used. The most important thing is how to design the reference model and the controller structure in order to reflect the actual closed loop system. The choice of the desired reference model is the critical issue when the plant to be controlled contains time-delay or non-minimum phase parts which are inherent in most practical applications. Since the plant is unknown, it is desirable to give some freedom to the reference model to overcome this issue.

The reference model with tunable parameters has been considered in [6, 7, 10, 12, 16, 20] to cope the mismatch between the desired reference model and the actual closed-loop transfer function which contains the time-delay or non-minimum phase plant. To design such a reference model with tunable parameters, orthonormal basis functions, Laguerre functions and Kautz functions with truncated model can be used as the alternatives to rational transfer functions. In [6, 7], the truncated Laguerre series was used for tunable closed loop reference model to obtain the desired set point tracking. In these research, the priori knowledge of the poles in Lagauerre series has been used.

The reference model of tunable parameters with Laguerre expansions was also considered in fictitious reference iterative tuning in internal model control (IMC) and two degree-of-freedom (2DoF) control architectures [21, 22]. The simultaneous attainment of controller and plant model with one-shot experimental input-output data and without using the prior knowledge of Laguerre poles has been discussed. The attainment of the plant model from one-shot experimental data is meaningful from practical point of view as the obtained plant model can be used for monitoring the actual status of the plant, the re-design of the more advanced controller and so on. In [22, 21], the desired set point tracking and model estimation have been done very well for non-minimum phase and time delay systems with Laguerre expansions.

In practical applications, the unknown system may introduce oscillatory behavior and Laguerre functions cannot approximate such systems very well. Laguerre approximations are suitable for well-damped systems [35] but it cannot approximate the system with complex poles very well with the appropriate small model order. So Laguerre functions are extended to two-parameter Kautz functions [27] for approximating the system with the complex conjugate poles [32]. Actually, Kautz functions are the general forms of Laguerre functions and they have more flexibility than Laguerre functions.

This research aims to extend the application area of the former work of [21, 22] to the systems with oscillatory behavior and the controllers as well as the desired reference model will be parametrized with Kautz expansions.

The objectives of this research work are as follows;

1) to design the reference model with free parameters instead of the fixed reference model in order to reflect the actual closed loop system, using Kautz expansions

2) to parametrize the data-driven the controllers in Kautz expansions with fictitious reference iterative tuning

3) to obtain the approximate model of the unknown plant as well as the optimal controller for the desired tracking.

1.2 Background

This section discusses the needs of data-driven controller tuning over model-based control and briefly introduces some data-driven controller tuning methods which have similar characteristics (for example, the methods that are mainly used for controlling the linear time-invariant, single-input and single-output systems with off-line input and output data sets in fixed controller structure). The effectiveness of the orthonormal basis functions are also figured out and the special orthonormal basis functions, Laguerre and Kautz functions, are also briefly discussed.

Model-based and data-driven controller tuning

In the applications of model based control theory, the first step is modeling the plant, or identifying the plant model, and then designing the controller based on this plant model assuming that it represents the actual system. The modeling or identification of the plant is necessary to the model based control. The practical industries, such as the chemical industry, metallurgy, machinery, electronics, electricity, transportation and so on, have production technologies and equipments in a large scale and production processes have become more complex. Modeling processes using the physical laws or identification has become more difficult. For this reason, traditional model based control theory has become impractical for control issues in such kind of enterprises.

In recent years, several data-driven techniques have been proposed as an alternative to the model-based approaches described above. In a data-driven approach, the data are used directly to minimize a control criterion. The identification and controller design steps are thus lumped together, resulting in a direct “data-to-controller” algorithm. Compared to a model-based approach, the modeling step is omitted and the problem of undermodeling of the plant is avoided. Furthermore, since there is no intermediate model, the structure of the designed controller does not depend on the structure of this model, and the order and structure of the controller can be fixed. Both model based and data driven control has their own advantages. Model based control is suitable when the accurate mathematical models or roughly accurate mathematical models with moderate uncertainties are available. Data-driven control is appropriate when the mathematical models are complicated with too high order and too much nonlinearity or the mathematical models are difficult to establish or unavailable.

Previous data-driven controller tuning methods related to the research work

Unfalsified control

Unfalsifed control [1] is designed by input and output data of the controlled plant and it is a type of switching control method. The controller which cannot stabilize the control system is falsified before it is inserted into the feedback loop. An invertible controller candidate set, cost-detectable performance specifications and the switching mechanism are the main elements of the unfalsified control.

With the measured data $u(\theta), y(\theta)$, the fictitious reference signal $\tilde{r}_j(\theta)$ of controller C_j can be expressed as

$$\tilde{r}(\theta) = C_j^{-1}(u(\theta)) + y(\theta) \tag{1.1}$$

In unfalsified control, in order to select an appropriate replacement for the falsified controller, a switching mechanism is needed. For a finite controller set, the scheme has to evaluate all the controller candidates and select the optimal controller switching into the closed loop system. Due to the combination of the performance requirement and controller structure, the approximate update of the unfalsified set can be computed analytically, resulting in a computationally cheap algorithm [13].

Model reference control

Data-driven controller tuning methods mostly use the model reference control.

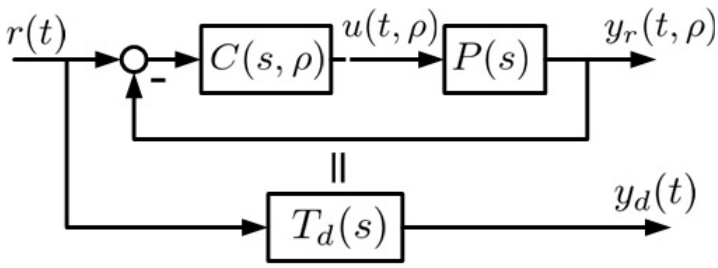

Figure 1.1: A concept of model matching technique

In the model reference control design, the designer creates a transfer function whose behavior is the one expected from the closed-loop system. This target transfer function is called the desired reference model, $T_d(s)$. The response desired for the closed-loop system under a given reference signal $r(t)$ is then $y_d(t) = T_d(s)r(t)$. The response actually obtained in closed-loop from the reference signal is $y_r(t, \rho)$ defined above, which should be as close as possible to $y_d(t)$. Then the controller design consists in finding the controller parameters that make these two signals as close as possible to each other.

The performance index related to model reference criterion is described by

$$\begin{aligned} J^{MR}(\rho) &= \|y_r(t, \rho) - y_d(t)\|^2 \\ &= \|y_r(t, \rho) - T_d(s)r(t)\|^2 \end{aligned} \tag{1.2}$$

With this setting, the objective is to find the optimal parameter, $\rho^* := \arg\min_\rho J^{MR}(\rho)$, using the input, $u(t, \rho)$, and output, $y(t, \rho)$.

Iterative feedback tuning (IFT)

Iterative feedback tuning (IFT) was first proposed in [30]. The control objective is formulated as a desired trajectory for the given reference signal. The control objective is then minimized using a gradient approach to find a (local) optimum, with the initial controller as a starting point. It is iterative in nature. At each iteration, closed-loop experiments are performed and the response of the plant is used directly to estimate the gradient. No plant model is needed and the estimate of the gradient is unbiased. IFT was initially developed for LTI SISO systems. The method was then extended to LTI MIMO systems [27]. Analysis of the method for nonlinear systems is provided in [26]. Performance of the method has been shown in several application examples, see [28] for an overview. A gradient approach that is similar to IFT is proposed in [37].

Virtual reference feedback tuning (VRFT)

Virtual reference feedback tuning (VRFT) is a method for optimizing the reference tracking criterion [8]. It is non-iteravite (one-shot) in nature, that is controller parameters are estimated based on one batch of experimental input and output data. By using a specific filtering scheme, an error signal corresponding to an approximate model reference error can be evaluated for each controller using only one experiment and no iterations are needed to minimize an approximate model reference criterion. The error between the input of the plant and the output of the controller is minimized to get the optimal parameter for the controller. If the controller is parameterized linearly, the optimization problem becomes convex and converge to global optimum. The method is developed for noise-free measurements. For noisy measurements, the use of instrumental variable is proposed. The method has been extended to the two degree-of-freedom controllers [9] and to the nonlinear plants [11].

Fictitious reference iterative tuning (FRIT)

Fictitious reference iterative tuning (FRIT) [14, 15] is a data-driven controller tuning method which needs a single set of experimental input and output data of the plant. It uses the concept of fictitious reference in unfalsified control [1]. When it was introduced in [14], the feedback controller tuning for the conventional closed loop system was considered. Extension to 2DoF system is considered in [17]. The merit of FRIT is the simultaneous attainment of controller and plant model with one-shot experimental data [19]. FRIT in internal model control structure (IMC) and 2DoF control structure is considered for the simultaneous attainment of controller and plant model in [16, 20, 24].

Orthonormal basis functions

In many areas of signal, system, and control theory, orthonormal basis functions play an important role in the issues of analysis and design, to increase the speed of convergence in a series expansion and to obtain a good approximation by retaining only a finite number of expansion coefficients [36]. In this section, the special orthonormal basis functions, Laguerre functions and two-parameter Kautz functions are introduced briefly. For more details, the readers are referred to [39].

Laguerre expansions

Laguerre functions are the special orthonormal basis functions and they are used in system identification and reduced-order modeling. They are suitable for accurate modeling of the systems with dominant first-order dynamics.

The Laguerre functions in continuous form [28]is

$$L_i(a) = \frac{\sqrt{2a}}{(s+a)}\left[\frac{s-1}{s+1}\right]^{i-1} \tag{1.3}$$

where $a > 0$, and i is are non-negative integers. Laguerre functions in discrete form is

$$L_i(a) = \frac{\sqrt{1-a^2}}{z-a}\left[\frac{1-az}{z-a}\right]^{i-1} \tag{1.4}$$

where $|a| < 1$, and i is are non-negative integers.

Kautz expansions

Kautz functions are generalized form of Laguerre functions. Kautz functions are suitable for the systems with dominant second-order resonant dynamics.

Two-parameter Kautz functions in continuous form [28] can be expressed in

$$\Psi_{2k-1}(b,c) = \frac{\sqrt{2b}s}{s^2+bs+c}\left[\frac{s^2-bs+c}{s^2+bs+c}\right]^{k-1} \tag{1.5}$$

$$\Psi_{2k}(b,c) = \frac{\sqrt{2bc}}{s^2+bs+c}\left[\frac{s^2-bs+c}{s^2+bs+c}\right]^{k-1} \tag{1.6}$$

where $b > 0, \quad c > 0$, and k are non-negative integers. In discrete form [32] is

$$\Psi_{2k-1}(b,c) = \frac{\sqrt{1-c^2}(z-b)}{z^2+b(c-1)z-c}\left[\frac{-cz^2+b(c-1)z+1}{z^2+b(c-1)z-c}\right]^{k-1} \tag{1.7}$$

$$\Psi_{2k}(b,c) = \frac{\sqrt{(1-c^2)(1-b^2)}}{z^2+b(c-1)z-c}\left[\frac{-cz^2+b(c-1)z+1}{z^2+b(c-1)z-c}\right]^{k-1} \tag{1.8}$$

where $|b| < 1, \quad |c| < 1$, and k are non-negative integers.

1.3 Outline of the dissertation

We now proceed to give a summary of the contents of this dissertation. The material presented in this thesis is based on the papers of Hnin Si and Osamu Kaneko [48, 49, 50, 51]. Here we summarize the contents of the thesis.

Chapter 2. This chapter discusses the parameterization of feedback controller with

Kautz expansions. For simultaneous attainment of controller and plant model, FRIT in internal model control (IMC) structure is considered. The desired reference model and the feedback controller are parameterized by the Kautz expansions. We also set the constraints to compensate for steady state error. The validity of the proposed method is shown with numerical example of poorly damped system. Measured input and output data with measurement noise are also considered in simulation.

Chapter 3. This chapter proposes a new method for the feedforward controller parameter tuning for poorly damped system. Simultaneous attainment of the controller and the plant model with one-shot experimental data is obtained with the use of FRIT in two degree-of-freedom (2DoF) control structure. Feedforward controller and the desired reference model are parameterized in Kautz expansions. Steady state error constraint is also considered in this method. The effect of measurement noise in the output data is also simulated in the numerical example. The effectiveness of the our proposed method is also shown in comparison with Laguerre expansions.

Chapter 4. In this chapter, we try to control and approximate time delay system with FRIT in 2DoF control structure. Different from the previous research, we unify the lumped part and time delay part as a parametrized lumped transfer function with Kautz expansions. A numerical example is used to show the validity of our method. Time delay approximation methods, such as Pade approximation and Laguerre approximations, are also considered and the results are compared with the model approximated by the Kautz expansions.

Chapter 5. Positioning control and model estimation of the vibrating system is considered in this chapter to show the practical application of our proposed method. Actual parameters of the mass-spring-damper system are used to built the plant model to get the simulated initial input and output data. The simulation results are satisfactory.

Chapter 6. We discuss the results and future work of our proposed method.

Chapter 2

Paremetrization of Feedback Controller with Kautz Expansions using FRIT in IMC Structure

2.1 Introduction

Designing a controller based on a mathematical model (model-based approach) is the most rational strategy for achieving the desired specifications. In many industrial applications, the identification of simple and reliable mathematical model is difficult and time-consuming process, and as a result, the designed controller could not realize the estimated performance. In such a situation, an alternative and effective approach is to use the experimental closed loop data directly for fine-tuning of the implemented controller. Such kind of controller tuning is called data-driven controller tuning and it only used measured input and output data of closed loop system. In addition, it is meaningful to obtain a more refined mathematical model simultaneously with the optimal controller because this model can be used for fault detection and for monitoring the operated system. Parametrization of controller in the internal model control (IMC) scheme can attain the plant model and the optimal controller simultaneously [2]. With the internal model control (IMC) scheme, the data-driven approach to realize the controller and the plant model at the same time with fictitious iterative tuning (FRIT) using only one-shot experimental data has been done in [16, 22].

According to reference [22], for a class of well-damped systems, the second author and his colleagues developed a data-driven approach in which the internal model is parameterized by the truncated Laguerre expansion. Utilizing fictitious reference iterative tuning (FRIT) proposed in [14] and [15], not only a model and a controller can be realized simultaneously but also the mechanism of the simultaneous achievement of the model and the controller can be explained based on the analysis of the cost function that is to be minimized in the off-line calculation. As stated in [29] and [32], Laguerre approximation and finite impulse response (FIR) approximation are not suitable for poorly damped linear time-invariant systems. Although the Laguerre approximation is superior to FIR modeling, it cannot describe the systems with several scattered dominating poles appropriately. Moreover, in this case, the resonant poles lead to slow convergence because they have complex conjugate pairs. The problem of the orthogonalization of a set of continuous time exponential functions has been solved by Kautz as stated in [27]. The Laguerre basis functions are extended to two-parameter Kautz functions which can have complex poles as stated in [29],[32] and [28].

This chapter presents the controller parameter tuning and model approximation of the system which may have complex poles. For simultaneous attainment of the controller and the plant model, fictitious reference iterative tuning (FRIT) in internal model control (IMC) structure is considered. Truncated Kautz series is used to parametrize the desired reference model to avoid the mismatch between the actual closed loop and the desired reference model.

2.2 Problem formulation

The internal model control (IMC) [2] structure with tunable parameters is illustrated in Fig. 2.1.

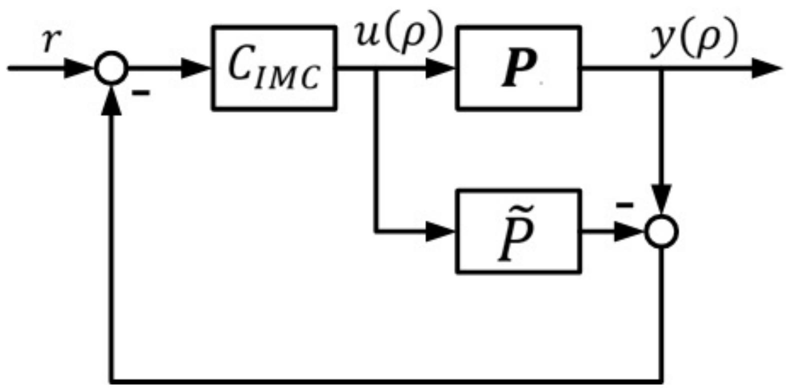

Figure 2.1: Basic internal model control (IMC) structure

The plant, P, is assumed to be single-input single-output (SISO), linear time-invariant (LTI) and has stable dynamics. P is also assumed to be unknown and it may have unstable zeros or complex poles. The implemented internal model is denoted by $\tilde{P}$, which is parameterized by a tunable parameter vector ρ_P as

$$\tilde{P}(\rho_P, s) = \frac{\rho_{P,\mu}s^{\mu} + ... + \rho_{P,1}s + \rho_{P,0}}{\rho_{P,\mu+v}s^{v} + ... + \rho_{P,\mu+1}s + 1} \tag{2.1}$$

where $\rho_P := [\rho_{P,0} \;\; \rho_{P,1} \;\; ...\rho_{P,\mu+v}]$. The feedback controller C_{IMC} is parametrized as

$$C_{IMC}(\rho_C, s) = \frac{\rho_{C,d}s^{d} + ... + \rho_{C,1}s + \rho_{C,0}}{\rho_{C,d+l}s^{l} + ... + \rho_{C,d+1}s + 1} \tag{2.2}$$

where $\rho_C := [\rho_{C,0} \;\; \rho_{C,1} \;\; ... \;\; \rho_{C,d+l}]$. The reference model from r to y of the closed loop is denoted by T_d . The desired output is denoted by $y_d = T_d r$. As shown in [16], if the feedback controller is set as

$$C_{IMC} = T_d \tilde{P}(\rho_P)^{-1} \tag{2.3}$$

then it is possible to obtain the desired output. Therefore, (2.3) is used as the feedback controller instead of (2.2) and the plant model of (2.1) will be parametrized by truncated Kautz expansions. The notation ρ will be used instead of ρ_P. Input u and output y depend on ρ, so they can be denoted by $u(\rho)$ and $y(\rho)$, respectively. The transfer function from r to $y(\rho)$ of the closed loop system with tunable parameter is denoted by $T_{ry}(\rho, s)$. In this research, the measured data are assumed to be noise-free data for simplicity.

2.3 Concept of fictitious reference iterative tuning

The concept of FRIT [15] in the closed loop system is illustrated by Fig. 2.2.

First of all, the initial parameter vector, ρ^0, have to be chosen by the designer. Then, the first experiment is performed in the closed loop system with $C(\rho^0)$ and the initial data $u^0 := u(\rho^0)$ and $y^0 := y(\rho^0)$ is obtained. In this case, $C(\rho^0)$ is assumed to tentatively stabilize the closed loop system such that u^0 and y^0 are bounded. By using u^0 and y^0, the fictitious reference signal, $\tilde{r}(\rho)$, is described by

$$\tilde{r}(\rho) = C(\rho)^{-1}u^0 + y^0 \tag{2.4}$$

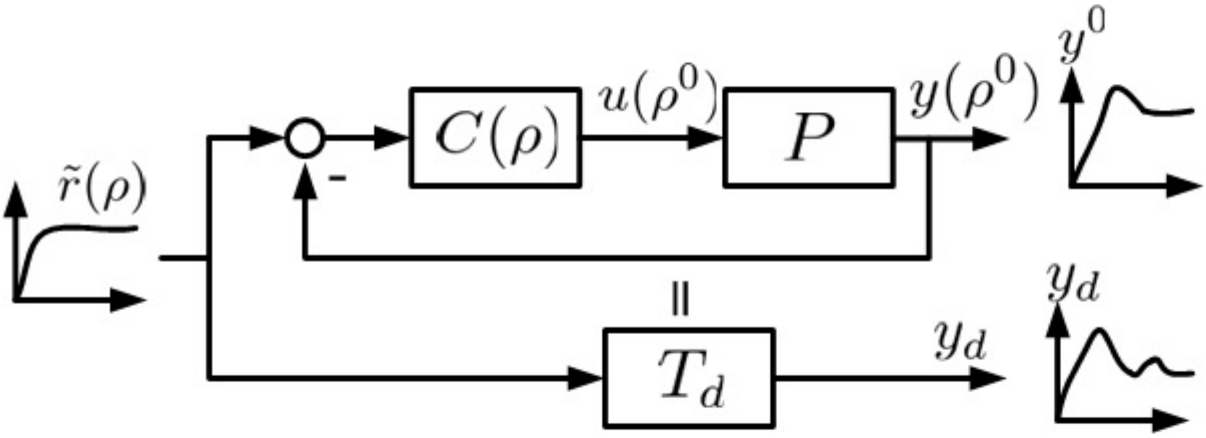

Figure 2.2: Concept of fictitious reference iterative tuning

Using the trivial relation of the initial experiment, $y^0 = Pu^0$, the output of the closed loop transfer function, $T_{ry}(\rho)$, from the reference input, $r(t)$, to the output, $y(t)$, using the fictitious reference signal, $\tilde{r}(\rho)$, can be obtained as

$$\begin{aligned} T_{ry}(\rho)\tilde{r}(\rho) &= \frac{PC(\rho)}{1+PC(\rho)}\tilde{r}(\rho) \\ &= \frac{PC(\rho)}{1+PC(\rho)}\left(\frac{1}{C(\rho)}u^0 + y^0\right) \\ &= \frac{PC(\rho)}{1+PC(\rho)}\left(\frac{1}{C(\rho)P} + 1\right)y^0 \\ &= y^0 \end{aligned} \tag{2.5}$$

which holds for any parameter ρ. According to (2.5), the actual output of the closed loop $T_{ry}(\rho)$ with respect to the fictitious reference signal, $\tilde{r}(\rho)$, is completely equal to the initial output, y^0. The conventional cost function for the model reference control is

$$J(\rho) = \|T_{ry}(\rho)r - T_d r\|^2 \tag{2.6}$$

Using (2.5) and the fictitious reference signal of (2.4), the cost function to be minimized in FRIT is

$$J_F(\rho) = \|y^0 - T_d\tilde{r}(\rho)\|^2 \tag{2.7}$$

It can be clearly seen that (2.7) with the fictitious reference, $\tilde{r}(\rho)$, requires only u^0 and y^0. This means that the minimization of $J_F(\rho)$ can be performed *off-line* by using only one-shot experimental data. This is a practical advantage of FRIT.

2.3.1 FRIT in IMC control scheme

The FRIT in IMC control structure is shown in Fig. 2.3.

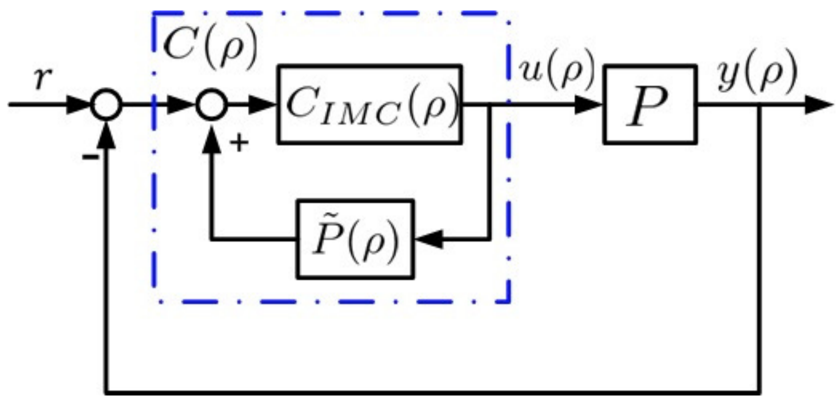

Figure 2.3: IMC structure with feedback controller

The feedback controller, $C(\rho)$, of Fig.2.3 with the plant model, $\tilde{P}(\rho)$, and the internal model controller, $C_{IMC}(\rho)$, is

$$C(\rho) = \frac{C_{IMC}(\rho)}{1 - C_{IMC}(\rho)\tilde{P}(\rho)} \tag{2.8}$$

By substituting (2.3) into (2.8), then

$$C(\rho) = \frac{T_d\tilde{P}(\rho)^{-1}}{1 - T_d\tilde{P}(\rho)^{-1}\tilde{P}(\rho)} = \frac{T_d}{1 - T_d}\tilde{P}(\rho)^{-1} \tag{2.9}$$

As there is an inverse plant model in (2.3) and (2.9), these equations are only applicable for the minimum phase plants. Non-minimum phase systems are considered as follows.

2.3.2 FRIT in IMC for non-minimum phase system

For non-minimum phase system, the plant model can be parametrized as

$$\tilde{P}(\rho) = \tilde{P}_n(\rho_n)\tilde{P}_m(\rho_m) \tag{2.10}$$

where $\tilde{P}_n(\rho_n)$ and $\tilde{P}_m(\rho_m)$ are the non-minimum phase part and the minimum phase part of the plant, respectively. To avoid the mismatch between the desired reference model and the actual closed loop system, it is desirable to add the free parameters in the reference model [7, 16] as

$$T_d(\rho) = T_{d0}\tilde{P}_n(\rho_n) \tag{2.11}$$

where T_{d0} is the nominal reference model. Then, the feedback controller of (2.9) becomes

$$C(\rho) = \frac{T_{d0}}{1 - T_{d0}\tilde{P}_n(\rho_n)}\tilde{P}_m(\rho_m)^{-1} \tag{2.12}$$

and the closed loop transfer function from the input to the output is

$$T_{ry}(\rho) = \frac{C(\rho)P}{1 + C(\rho)P} = \frac{T_{d0}\tilde{P}_m(\rho_m)^{-1}P}{1 + T_{d0}\tilde{P}_m(\rho_m)^{-1}(P - \tilde{P}(\rho))} \tag{2.13}$$

2.3.3 Simultaneous attainment of the controller and the plant model in FRIT-IMC

In this section, the cost function of (2.7) is analyzed. It can be derived as follows.

$$\begin{aligned} J_F(\rho) &= \|y^0 - T_d(\rho)\tilde{r}(\rho)\|^2 \\ &= \left\| y^0 - \frac{T_d(\rho)}{T_{ry}(\rho)} y^0 \right\|^2 \end{aligned} \tag{2.14}$$

Using (2.13) in (2.14), the cost function becomes

$$\begin{aligned} J_F(\rho) &= \left\| \left(1 - T_{d0}\tilde{P}_n(\rho_n) \frac{(1 + T_{d0}\tilde{P}_m(\rho_m)^{-1}(P - \tilde{P}(\rho)))}{T_{d0}\tilde{P}_m(\rho_m)^{-1}P} \right) y^0 \right\|^2 \\ &= \left\| \left(1 - \frac{\tilde{P}(\rho)}{P}\left(1 + T_{d0}\tilde{P}_m(\rho_m)^{-1}(P - \tilde{P}(\rho))\right) \right) y^0 \right\|^2 \\ &= \left\| \left(1 - \frac{\tilde{P}(\rho)}{P} - \frac{T_{d0}\tilde{P}_m(\rho_m)^{-1}\tilde{P}(\rho)(P - \tilde{P}(\rho))}{P} \right) y^0 \right\|^2 \\ &= \left\| \left(1 - \frac{\tilde{P}(\rho)}{P} - T_{d0}\tilde{P}_n(\rho_n)\left(1 - \frac{\tilde{P}(\rho)}{P}\right) \right) y^0 \right\|^2 \\ &= \left\| \left(1 - \frac{\tilde{P}(\rho)}{P} \right)(1 - T_{d0}\tilde{P}_n(\rho_n))y^0 \right\|^2 \\ &= \left\| \left(1 - \frac{\tilde{P}(\rho)}{P} \right)(1 - T_d(\rho))y^0 \right\|^2 \end{aligned} \tag{2.15}$$

(2.14) shows the identification of the closed loop system and (2.15) shows the attainment of the plant model simultaneously.

2.4 Plant model in Kautz expansion

Kautz expansion [27] is used for the identification of the stable linear time-invariant systems in the literature [28, 29, 32, 31, 32, ?, 39], especially for the systems with an oscillatory behavior [30, 37, 40] and also used in model reduction [38].

Kautz expansion is the sum of two functions, even function and odd function, which are given by

$$\Psi_{2k-1}(b,c) = \frac{\sqrt{2b}s}{s^2+bs+c}\left[\frac{s^2-bs+c}{s^2+bs+c}\right]^{k-1} \tag{2.16}$$

$$\Psi_{2k}(b,c) = \frac{\sqrt{2bc}}{s^2+bs+c}\left[\frac{s^2-bs+c}{s^2+bs+c}\right]^{k-1} \tag{2.17}$$

where $b>0, \quad c>0$, and k is a nonnegative integer. (2.16) and (2.17) represent Kautz model expansions of the odd terms and even terms, respectively. Kautz functions depend on two parameters, b and c, where b and c are real numbers. The selection of these two parameters influences in the computation of the suitable coefficients to obtain a stable plant. Kautz poles are the functions of the optimization parameters; frequency and damping factor. In [29] and [32], it is clarified that the Kautz models are constructed with the prior knowledge of the dominating time constants and damping factor of the system.

Here, the plant model parameterized by Kautz expansion with truncated model order is described as

$$\tilde{P}(\eta,b,c) = \sum_{k=1}^{M}[\eta_{2k-1}\Psi_{2k-1}(b,c)+\eta_{2k}\Psi_{2k}(b,c)] \tag{2.18}$$

where η_i, $(i=1,2,\cdots,2M)$ are the tunable coefficients and M is the model order of the Kautz function. By substituting (2.16) and (2.17) in (2.18), the parameterized model can be rewritten as follows .

$$\tilde{P}(\eta,b,c) = \frac{\sqrt{2b}}{s^2+bs+c}\sum_{k=1}^{M}\left\{(\eta_{2k-1}s+\eta_{2k}\sqrt{c})\ \left(\frac{s^2-bs+c}{s^2+bs+c}\right)^{k-1}\right\} \tag{2.19}$$

The plant model in (2.19) contains the unstable zeros and it is not invertible. So the plant model is decomposed as

$$\tilde{P} = \frac{\tilde{N}}{\tilde{D}} = \frac{\tilde{N}}{\tilde{N}'}\frac{\tilde{N}'}{\tilde{D}} \tag{2.20}$$

by inserting a stable polynomial, $\tilde{N}'$, with the order $2M-1$ or $2M$.

Here, $\tilde{N}'$ is expressed as follows

$$\tilde{N}'(\rho_d) = \rho_{d_{2M}} s^{2M} + \rho_{d_{2M-1}} s^{2M-1} + ... + \rho_{d_1} s + 1 \tag{2.21}$$

After this decomposition, the minimum phase and the possibly[1] non-minimum phase are given by

$$\tilde{P}_m(b,c) = \frac{\tilde{N}'}{\tilde{D}} = \frac{\sqrt{2b}\tilde{N}'}{(s^2+bs+c)^M} \tag{2.22}$$

$$\tilde{P}_n(\eta,b,c) = \frac{\tilde{N}}{\tilde{N}'} = \frac{\sum_{k=1}^{M}\{(\eta_{2k-1}s+\eta_{2k}\sqrt{c})(s^2+bs+c)^{M-k}(s^2-bs+c)^{k-1}\}}{\tilde{N}'} \tag{2.23}$$

respectively.

In [32], [37] and [38], Kautz expansion is used to approximate the resonant systems with the known values of the two parameters (b and c) or with the calculation of these two parameters from the prior knowledge of the frequency and the damping ratio.

Here, in the research with FRIT, the information of the plant is assumed to be unknown and the two parameters, b and c, as well as η_i and ρ_d are tuned. Let a tunable parameter vector ρ be $\rho = [\rho_n^T \ \ \rho_m^T]^T$ where $\rho_n = [\eta_{odd}^T \ \ \eta_{even}^T]^T$ and $\rho_m = [\rho_{m1} \ \ \rho_{m2} \ \ \rho_d]^T$, respectively. Here η_{odd} and η_{even} are an even and odd coefficient parameter vectors, respectively, of length M. Parameters ρ_{m1} and ρ_{m2} represent b and c, respectively. $\rho_d = [\rho_{d_{2M}} \ \ ... \ \ \rho_{d_1}]^T$ is the tunable parameter vector for $\tilde{N}'$. By inserting the tunable parameters in (2.22) and (2.23), the minimum phase plant can be expressed as

$$\tilde{P}_m(\rho_m) = \frac{\sqrt{2\rho_{m1}}\tilde{N}'(\rho_d)}{(s^2+\rho_{m1}s+\rho_{m2})^M} \tag{2.24}$$

[1]The terminology 'possibly' implies that this part might be minimum phase in some case.

and the possibly non-minimum phase plant is expressed as

$$\tilde{P}_n(\rho) = \frac{\sum_{k=1}^{M}\{(\eta_{2k-1}s + \eta_{2k}\sqrt{\rho_{m2}})(s^2+\rho_{m1}s+\rho_{m2})^{M-k}(s^2-\rho_{m1}s+\rho_{m2})^{k-1}\}}{\tilde{N}'(\rho_d)} \tag{2.25}$$

2.4.1 Setting constraint to compensate for the steady state error

In order to achieve the desired performance, the designed system has to produce a zero steady state error.

$$\lim_{s\to 0} C(\rho, s) = \lim_{s\to 0} \frac{T_{d0}\tilde{P}_m^{-1}(\rho_m)}{1 - T_{d0}\tilde{P}_n(\rho)} \tag{2.26}$$

If the reference model T_{d0} is given such that $T_{d0}(0) = 1$, then (2.26) can be rewritten as

$$\lim_{s\to 0} C(\rho, s) = \lim_{s\to 0} \frac{\tilde{P}_m^{-1}(\rho_m)}{1 - \tilde{P}_n(\rho)} \tag{2.27}$$

The steady state error is eliminated if and only if $\lim_{s\to 0} C(\rho, s) = \infty$. According to (2.27), $\tilde{P}_n(\rho, 0)$ must be 1. This implies that we have to add the constraint

$$\sum_{k=1}^{M} \eta_{2k} = \frac{1}{\sqrt{\rho_{m2}}(\rho_{m2})^{M-1}} \tag{2.28}$$

From the constraint given in (2.28), the last even coefficient of the Kautz expansion can be expressed as

$$\eta_{2M} = \frac{1}{\sqrt{\rho_{m2}}(\rho_{m2})^{M-1}} - \sum_{k=1}^{M-1} \eta_{2k} \tag{2.29}$$

for the compensation of the steady state error. Then η_{even} becomes an even coefficient parameter vector of length $M - 1$.

2.5 Algorithm

The algorithm for finding the optimal parameters of the proposed method is summarized as follows.

1. The plant model is estimated using Kautz expansion with the specified order M as in (2.19).

2. The plant model is then decomposed as shown in (2.20), (2.22) and (2.23).

3. Parameter vector ρ is determined using ρ_n and ρ_m where $\rho_n = [\eta_{odd}^T \quad \eta_{even}^T]^T$ and $\rho_m = [\rho_{m1} \quad \rho_{m2} \quad \rho_d]^T$, respectively.

4. Initial parameter vector ρ^0 is set and then one-shot experiment is conducted to obtain the initial input ,$u(\rho^0)$, and the initial output, $y(\rho^0)$, data of the plant.

5. Fictitious reference signal, $\tilde{r}(\rho)$, is calculated using (2.4). Cost function $J_F(\rho)$ is constructed as shown in (2.7), and it is minimized using the off-line data with nonlinear optimization. In this research, CMA-Evolution Strategy [34] is used for nonlinear optimization.

6. After optimization, the optimal parameter vector $\rho^* = \arg\min_\rho J_F(\rho)$ is obtained.

7. The optimal parameters are implemented in the closed loop system, and the simulated result is analyzed.

2.6 Numerical example

In order to show the validity of the proposed method, an illustrated example is given as follows. The unknown plant which may contain unstable zero and complex conjugate poles is considered as follows

$$P = \frac{s^2 - 1.6s + 4}{s^4 + 1.8s^3 + 5.32s^2 + 2.4s + 4} \tag{2.30}$$

The desired system is assigned as (2.11) by including the possibly non-minimum phase part and the reference model is chosen as

$$T_{d0} = \frac{1}{2s+1} \tag{2.31}$$

We set the model order $M = 3$ and the initial parameter vectors as $\eta_{odd}^0 = [1 \quad 1 \quad 1]^T$, $\eta_{even}^0 = [0.33 \quad 0.33]^T$ and $\rho_m^0 = [1 \quad 1 \quad 1 \quad 6 \quad 15 \quad 20 \quad 15 \quad 6]^T$. After setting the initial parameters, a one-shot experiment is performed on the closed loop system to obtain the initial input and output data. Sampling period $\triangle = 0.1$ s is used in this example.

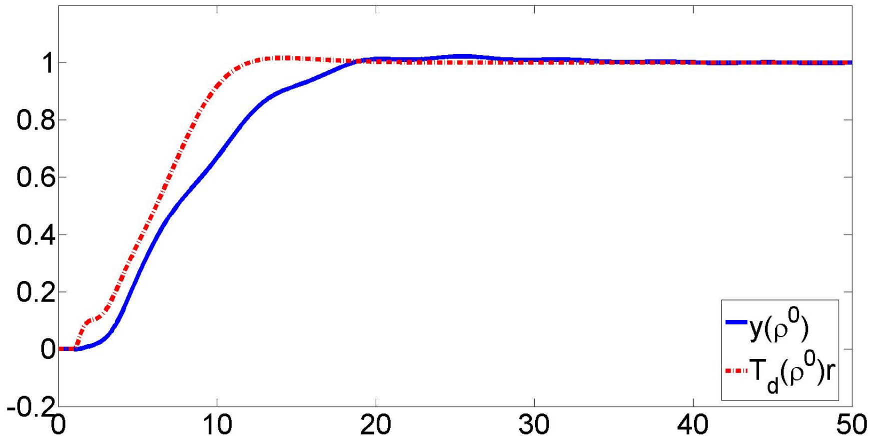

Figure 2.4: Initial output $y(\rho^0)$ and the desired output $T_d(\rho^0)r$ with the step reference input

Initial output $y(\rho^0)$ and the desired output $T_d(\rho^0)r$ after the one-shot experiment can be seen in Fig. 2.4.

Using these initial input and output values and minimizing the cost function of (2.7), the optimal parameter vector is obtained as $\rho^* := [\rho_n^{*T} \ \ \rho_m^{*T}]^T$ where $\rho_n^* = [-0.8006 \ 0.9695 \ -0.1658 \ 0.8431 \ -0.1718]^T$ and $\rho_m^* = [0.5273 \ 1.0093 \ 1.3163 \ 7.3183 \ 13.6187 \ 20.0475 \ 14.0621 \ 4.6720]^T$, respectively. Then, the final experiment is performed by using ρ^*.

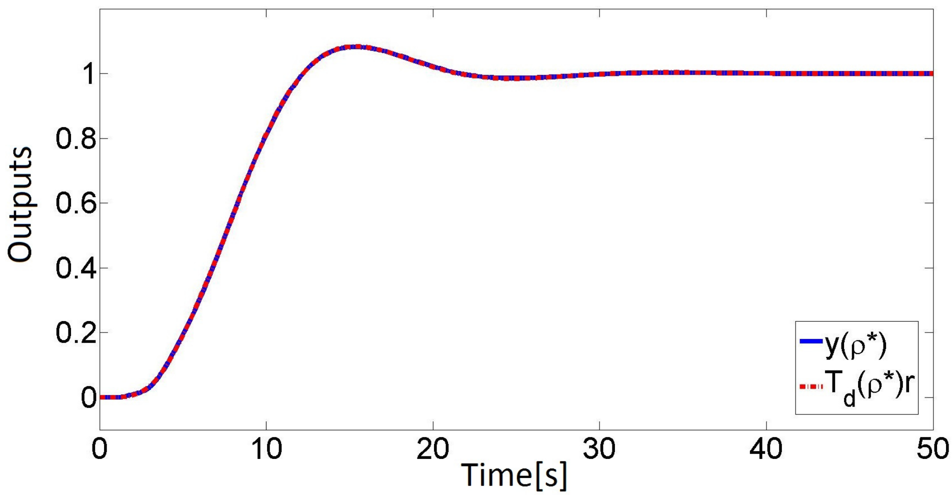

Figure 2.5: Optimal output $y(\rho^*)$ and the desired output $T_d(\rho^*)r$

In Fig. 2.5, it can clearly be seen that the optimal output $y(\rho^*)$ and the desired output $T_d(\rho^*)$ are almost the same. It means that the desired set point tracking has been done with the optimal controller.

To check the approximation of the plant model, frequency responses of the plant and plant model are simulated in Fig. 2.6 and 2.7 and the simulated results show that the plant model reflects the actual plant, especially in the low frequency.

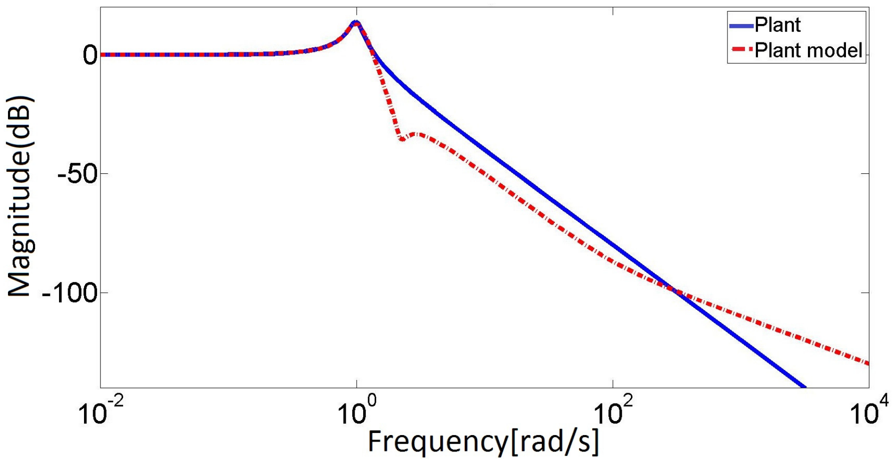

Figure 2.6: Gain characteristics of the plant and plant model with Kautz model order 3

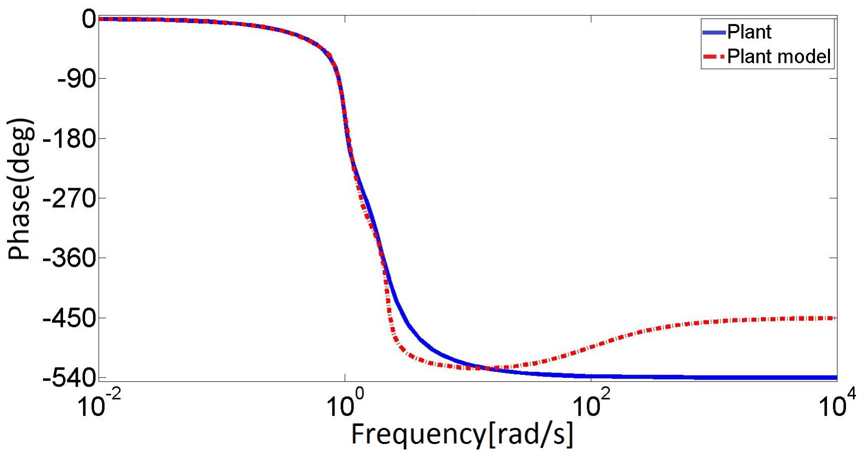

Figure 2.7: Phase characteristics of the plant and plant model with Kautz model order 3

So both the plant model and the optimal controller for the desired set point tracking are obtained simultaneously with our proposed method.

Even though the measured data are assumed as noise-free in the problem formulation, the initial output with measurement noise is also considered to check the effect of the measurement noise. Gussian white noise with variance amplitude of 1.1x10^{-3} is added to the output of the initial experiment. Fig. 2.8 shows the initial output of the system with the measurement noise in comparison with the desired output. Using these initial values with measurement noise, the optimal parameters are tuned by minimizing the cost function. Optimal outputs of the system in Fig. 2.9 show that desired output can still be achievable even in the presence of the measurement noise.

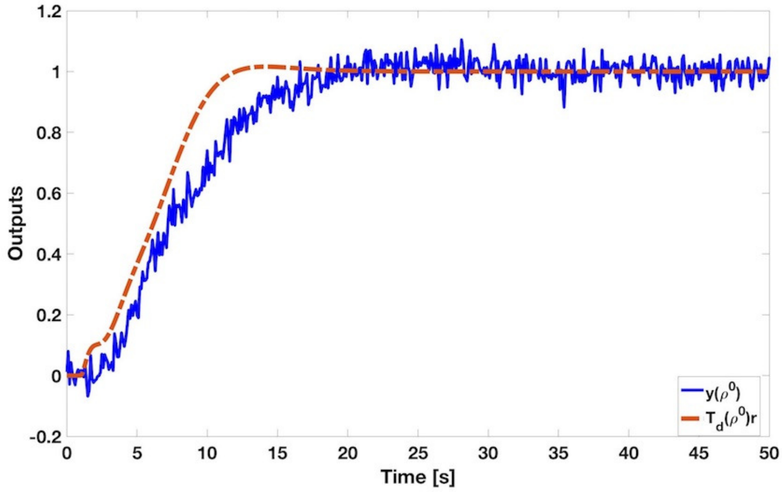

Figure 2.8: Initial output $y(\rho^0)$ with the measurement noise and the desired output $T_d(\rho^0)r$ of the system with Kautz model order 3

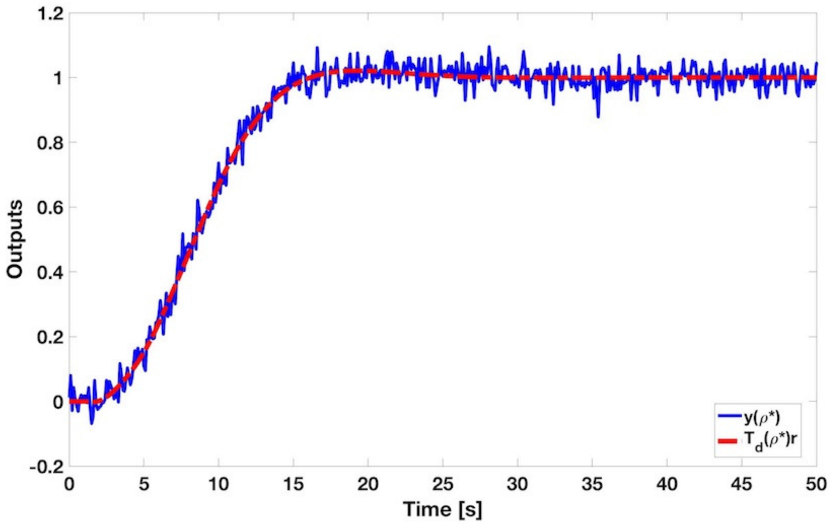

Figure 2.9: Optimal output $y(\rho^*)$ with the measurement noise and the desired output $T_d(\rho^*)r$ of the system with Kautz model order 3

The frequency responses of the plant and plant model with the optimal parameters with the measurement noise are shown in Fig, 2.10 and 2.11. Even though the gain and phase of the plant model is changed, it can still approximate the resonant peak of the actual plant. So our proposed method is still effective when the measured data with noise are used.

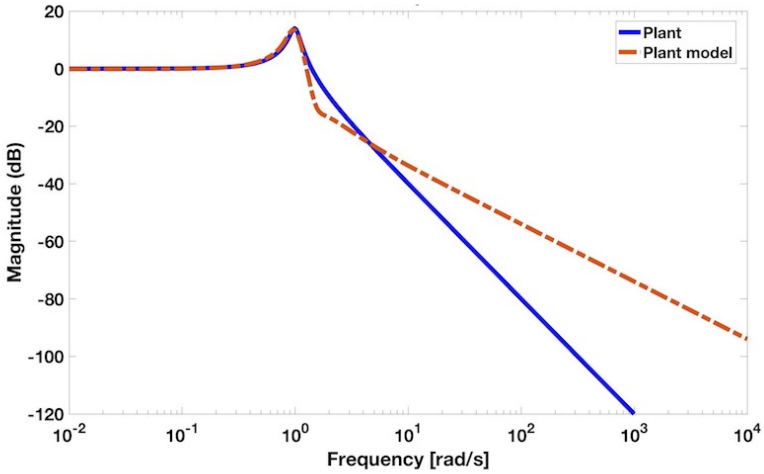

Figure 2.10: Gain characteristics of the plant and plant model with noise

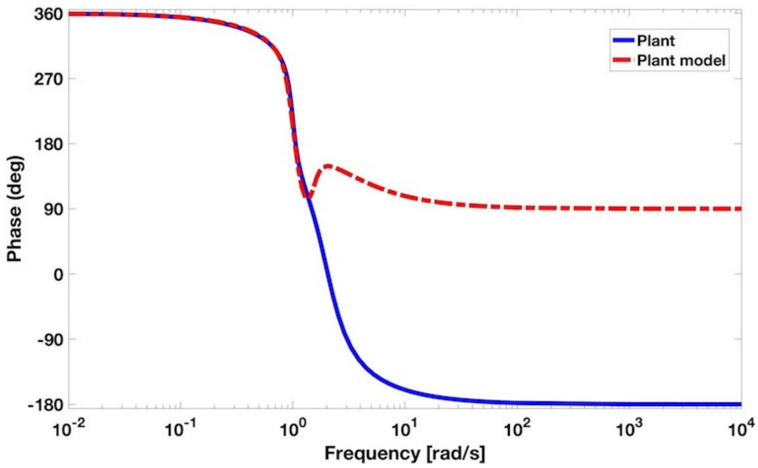

Figure 2.11: Phase characteristics of the plant and plant model with noise

2.7 Summary

In this chapter, the parametrization of the feedback controller with Kautz expansion in internal model control structure has been discussed. With the application of FRIT to the IMC, it is possible to realize a plant model and a controller simultaneously using only one-shot experimental data. The validity of the proposed method is examined with a system that contains unstable zeros and complex conjugate pairs of poles. We simulated the system with and without measurement noise. In the future research work, the performance of the obtained controller and the accuracy of the identified model will be clarified from the quantitative point of view. Noise, stability, and the effect of the initial controller will be analyzed from both the theoretical and practical points of view.

Chapter 3

Parametrization of Feedforward Controller with Kautz Expansions using FRIT in 2DoF Structure

3.1 Introduction

In the modern industries, the change of set point variable is frequently required and sometimes the plant with the controller in the closed loop is unknown. In such cases of practical importance, the conventional feedback control is not compatible and two-degree-of-freedom (2DoF) control structure has received attention in the literature [5, 9, 33, 17, 20, 18]. It is well-known that the desired tracking property can be achieved if a feedforward controller is written as a product of the inverse of the plant model and the desired closed loop. So the model-based feedforward results in good performance if the mathematical model the plant is accurate enough to reflect the behavior of the true process.

In the case where the dynamics of a plant is unknown, applying fictitious reference iterative tuning (FRIT) in the 2DoF architecture yields the desired tracking property as well as the plant model. In FRIT, only a one-shot experimental input and output data is needed to find the optimal parameters of the controller. FRIT in 2DoF control structure has been introduced in [17] and the optimal parameter tuning for both the controller and the plant model have been done simultaneously in [18, 20]. The proposed methods in [17, 18] can only applicable for the minimum phase systems and the non-minimum phase systems are considered in [20]. In these studies, the relative degree of the plant and the number of non-minimum phase zeros are assumed to be known.

To reduce such assumptions, the special orthonormal basis function, Laguerre expansions, has been used in [21] for the parametrization of the feedforward controller and the reference model. In Laguerre structure, the real valued poles are used and so Laguerre expansions are suitable for approximation of the well-damped systems. Since the systems in the real applications are much more complicated, it is desirable to consider the complex valued poles to characterize such kind of systems.

In the previous chapter, the feedback controller parameterized by Kautz expansion for the poorly damped system is studied using FRIT in IMC structure. In this chapter, we extend our research to two degree-of-freedom control structure and the feedforward controller is parameterized by the Kautz expansion. FRIT is used to get simultaneous attainment of the controller and the plant model with only one-shot experimental data.

3.2 Problem formulation

Two degree-of-freedom architecture with a tunable parameter vector ρ is illustrated in Fig. 3.1.

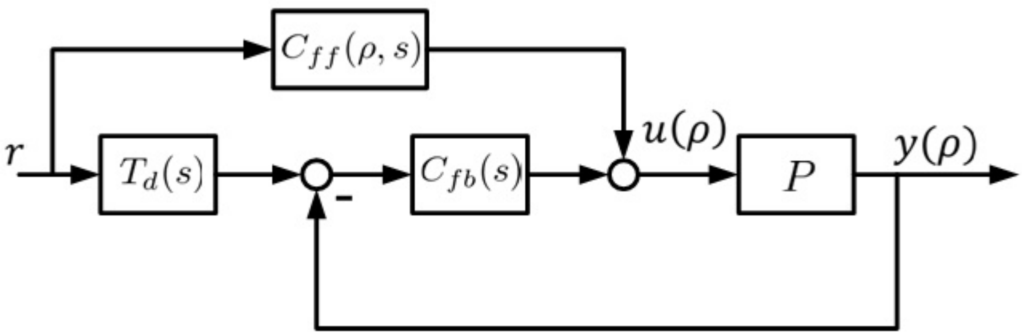

Figure 3.1: Two-degree-of-freedom control structure

A plant to be controlled is considered as a linear, time-invariant, single input-single output, stable plant. The plant is assumed to be unknown and it is already operated in the closed loop system with the fixed feedback controller, C_{fb}. The feedback controller C_{fb}, is assumed to stabilize the closed loop system so as to obtain the bounded experimental data. The feedforward controller $C_{ff}(\rho)$ is considered with a tunable parameter vector ρ.

Let $T_{ry}(\rho)$ be a closed loop transfer function from r to y and it can be described by

$$T_{ry}(\rho) = \frac{P(C_{ff}(\rho) + T_d C_{fb})}{1 + PC_{fb}} \tag{3.1}$$

$u(\rho)$ and $y(\rho)$ are the experimental input and output data, obtained in the closed loop with controller parameter ρ. A mathematical model of the plant is denoted as $\tilde{P}$. If it is possible to set $P = \tilde{P}$, it is well-known that

$$C_{ff}(\rho) = T_d \tilde{P}(\rho)^{-1} \tag{3.2}$$

yields that $T_{ry}(\rho) = T_d$. The cost function is defined by

$$J(\rho) = \|y(\rho) - T_d r\|^2 \tag{3.3}$$

The problem in this chapter focuses on the point for deriving the parameter vector ρ^0 such that $y(\rho) = T_{ry}(\rho)r$ achieves the desired output and the identification of the unknown plant simultaneously based on the experimental data. For simplicity, the experiment data is assumed as noise-free data.

3.3 FRIT in 2DoF control structure

FRIT in 2DoF control structure is introduced in [17] for closed loop system identification. In [17], both the feedback and the feedforward controller are tuned, however, in this research, it is assumed that the system is already operated in the closed loop with the fixed feedback controller which gives the stabilized output. As in the FRIT of the conventional feedback control system, an initial parameter vector, ρ is chosen by the designer. Then, an initial experiment is performed in the 2DoF system of Fig. 3.1 with the initial parameter vector, ρ^0, with the tunable feedforward controller $C_{ff}(\rho^0)$.

The fictitious reference equation with initial input u^0 and output y^0 in the two degree-of-freedom control structure is described by

$$\tilde{r}(\rho) = \frac{u^0 + C_{fb} y^0}{C_{ff}(\rho) + T_d C_{fb}} \tag{3.4}$$

Using the trivial relation for the initial experiment, $y^0 = Pu^0$, the actual output of the closed loop system of Fig. 3.1 with respect to the fictitious reference, $\tilde{r}(\rho)$, of (3.4) can be derived as

$$\begin{aligned} y(\rho) &= T_{ry}(\rho)\tilde{r}(\rho) \\ &= \left(\frac{P(C_{ff}(\rho) + T_d C_{fb})}{1 + PC_{fb}}\right)\left(\frac{u^0 + C_{fb}y^0}{C_{ff}(\rho) + T_d C_{fb}}\right) \\ &= \frac{Pu^0 + PC_{fb}y^0}{1 + PC_{fb}} \\ &= y^0. \end{aligned} \tag{3.5}$$

The cost function to be minimized with FRIT in 2DoF control structure is

$$J_F(\rho) = \|y^0 - T_d\tilde{r}(\rho)\|^2 \tag{3.6}$$

Since the reference model T_d of Fig. 3.1 is fixed and it may not reflect the actual closed loop system when the unknown plant contains non-minimum phase or time delay part. Furthermore, the feedforward controller of (3.2) can only applicable to the minimum phase systems. So, the FRIT in 2DoF control for non-minimum phase part is considered in the following section.

3.3.1 FRIT in 2DOF control for non-minimum phase plant

In the case of non-minimum phase systems, the plant model is parameterized in terms of the minimum phase part and non-minimum phase part as follows [20]

$$\tilde{P}(\rho) = \tilde{P}_m(\rho_m)\tilde{P}_n(\rho_n) \tag{3.7}$$

$\tilde{P}_m(\rho_m)$ and $\tilde{P}_n(\rho_n)$ of (3.7) are the minimum phase and non minimum phase parts of the plant model respectively. To reflect the actual closed loop system with the non-minimum phase part, the desired reference model should include the information on non-minimum phase properties and it is defined as

$$T_d(\rho_n) = T_{d0}\tilde{P}_n(\rho_n) \tag{3.8}$$

Substituting (3.7) and (3.8) into (3.2), the feedforward controller for the non minimum phase system as follows

$$C_{ff}(\rho_m) = T_{d0}\tilde{P}_m(\rho_m)^{-1} \tag{3.9}$$

By using (3.8) and (3.9), we can re-illustrated Fig. 3.1 as Fig. 3.2.

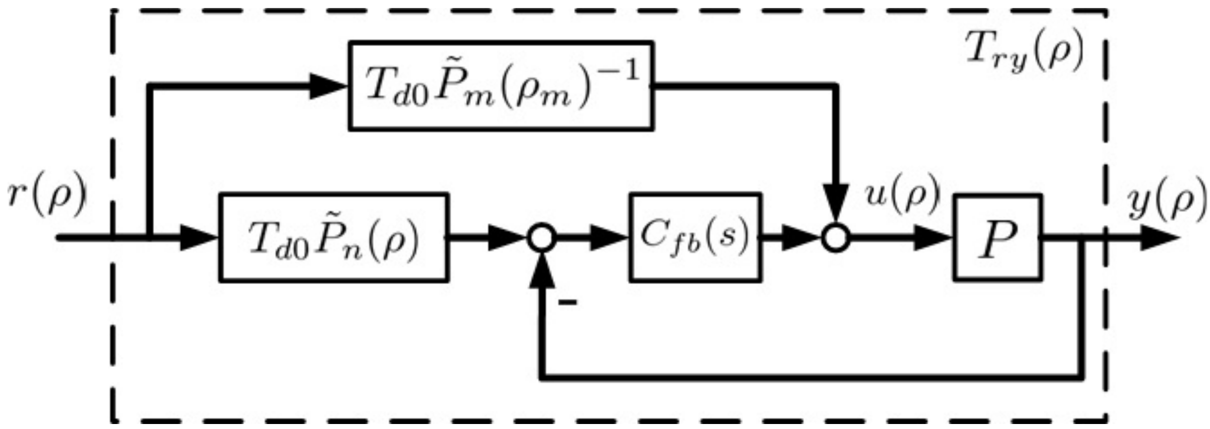

Figure 3.2: Two-degree-of-freedom control structure for non-minimum phase plant

The closed loop transfer function from reference signal $r(\rho)$ to $y(\rho)$ of Fig. 3.2 is denoted by

$$T_{ry}(\rho) := \frac{P(T_{d0}\tilde{P}_m(\rho_m)^{-1} + T_{d0}\tilde{P}_n(\rho)C_{fb})}{1 + PC_{fb}} \tag{3.10}$$

Cost function to be minimized in 2DoF-FRIT control structure for non-minimum phase system is re-defined as

$$J_F(\rho) = \|y^0 - T_{d0}\tilde{P}_n(\rho)\tilde{r}(\rho)\|^2 \tag{3.11}$$

3.3.2 Simultaneous attainment of controller and plant model in 2DoF-FRIT

For the simultaneous attainment of controller and plant model, the definition of cost function of FRIT in 2DoF control structure is analyzed. The cost function with the tunable reference model is

$$J_F(\rho) = \|y^0 - T_d(\rho)\tilde{r}(\rho)\|^2 \tag{3.12}$$

Substituting the relation of (3.5), $T_{ry}(\rho)\tilde{r}(\rho) = y^0$, into (3.12), it becomes

$$\begin{aligned} J_F(\rho) &= \left\| y^0 - \frac{T_d(\rho)}{T_{ry}(\rho)} y^0 \right\|^2 \\ &= \left\| \left(1 - \frac{T_d(\rho)}{T_{ry}(\rho)}\right) y^0 \right\|^2 \end{aligned} \tag{3.13}$$

(3.13) shows that the optimal parameters for the closed loop identification can be obtained by minimizing the cost function. For the identification of the plant model, (3.4) is used in the (3.12), then

$$\begin{aligned} J_F(\rho) &= \left\| y^0 - T_d(\rho) \left(\frac{u^0 + C_{fb} y^0}{C_{ff}(\rho) + T_d(\rho) C_{fb}} \right) \right\|^2 \\ &= \left\| y^0 - T_d(\rho) \left(\frac{u^0 + C_{fb} y^0}{T_d(\rho) \tilde{P}(\rho)^{-1} + T_d(\rho) C_{fb}} \right) \right\|^2 \\ &= \left\| y^0 - \tilde{P}(\rho) \left(\frac{u^0 + C_{fb} y^0}{1 + \tilde{P}(\rho) C_{fb}} \right) \right\|^2 \\ &= \left\| (y^0 - \tilde{P}(\rho) u^0) \frac{1}{1 + \tilde{P}(\rho) C_{fb}} \right\|^2 \\ &= \left\| \left(1 - \frac{\tilde{P}(\rho)}{P}\right) \frac{1}{1 + \tilde{P}(\rho) C_{fb}} y^0 \right\|^2 \end{aligned} \tag{3.14}$$

(3.14) shows that the minimization of cost function can also yield the optimal parameters for the identification of the unknown plant model. (3.13) and (3.14) are analysis results of (3.12) and they show simultaneous attainment of the controller and the plant model. Only (3.12) is used in the optimization procedure.

3.4 Parametrization of the feedforward controller in Kautz expansions

Plant model approximated by the truncated Kautz series with model order, M, can be described as

$$\tilde{P}(\eta, b, c) = \frac{\sqrt{2b}}{s^2 + bs + c} \left[\sum_{i=1}^{M} \eta_{2i-1} s \left(\frac{s^2 - bs + c}{s^2 + bs + c} \right)^{i-1} + \eta_{2i} \sqrt{c} \left(\frac{s^2 - bs + c}{s^2 + bs + c} \right)^{i-1} \right] \tag{3.15}$$

Similar to the previous chapter, the plant model is parametrized into minimum phase part and non-minimum phase part as

$$\tilde{P}(\eta, b, c) = \tilde{P}_m(b, c)\tilde{P}_n(\eta, b, c) \tag{3.16}$$

$$\tilde{P}_m(b, c) = \frac{\sqrt{2b}N'}{(s^2 + bs + c)^M} \tag{3.17}$$

$$\tilde{P}_n(\eta, b, c) = \frac{1}{N'}\sum_{i=1}^{M}\left[(\eta_{2i-1}s + \eta_{2i}\sqrt{c})(s^2 + bs + c)^{M-i}(s^2 - bs + c)^{i-1}\right] \tag{3.18}$$

N' is a stable polynomial to make the minimum phase and non-minimum phase parts proper. Here, we consider N' as a fixed polynomial, $(s+1)^{2M}$, to reduce the free parameters in the plant model. The optimal parameter, ρ, is defined as $\rho := [\rho_m^T \;\; \rho_n^T]^T$, where, $\rho_m := [b \;\; c]^T$ and $\rho_n := [\eta_{odd}^T \;\; \eta_{even}^T]^T$.

3.4.1 Setting constraint to compensate for the steady state error

In order to achieve the desired performance, the designed system has to produce a zero steady state error. The steady state error to the unit step change of the set point variable becomes zero robustly if

$$\lim_{s \to 0} T_{ry}(\rho) = 1 \tag{3.19}$$

To satisfy this condition, the feedback controller must contain the integrator [33]. With this specification, (3.19) becomes

$$\lim_{s \to 0} T_{d0}\tilde{P}_n(\rho) = 1 \tag{3.20}$$

As it can be chosen as $T_{d0}(0) = 1$, $\lim_{s\to 0}\tilde{P}_n(\rho, s)$ must be 1. This implies that the constraint is added as

$$\sum_{i=1}^{M}\eta_{2i} = \frac{1}{c^{(M-\frac{1}{2})}} \tag{3.21}$$

From the constraint given in (3.19), the last even coefficient can be expressed as

$$\eta_{2M} = \frac{1}{c^{(M-\frac{1}{2})}} - \sum_{i=1}^{M-1}\eta_{2i} \tag{3.22}$$

for the compensation of the steady state error. Then η_{even} becomes an even coefficient parameter vector of length $M-1$.

3.5 Numerical example

To show the validity of the proposed method, the non-minimum phase plant with complex conjugate poles is considered (the same plant as in chapter 2). The transfer function of unknown plant is defined as

$$P = \frac{s^2 - 1.6s + 4}{s^4 + 1.8s^3 + 5.32s^2 + 2.4s + 4} \tag{3.23}$$

Reference model is defined as

$$T_{d0} = \frac{1}{2s+1} \tag{3.24}$$

and feedback controller which satisfies (3.19) is defined as

$$C_{fb} = \frac{0.2}{s^2 + s} \tag{3.25}$$

In this example, the model order is considered as $M = 3$ so N' is considered as $(s+1)^6$. Sampling period, $\triangle = 0.01\ s$, is used in the example. Initial parameter vector is set as $\rho^0 = [0.2 \quad 0.2 \quad 0.1 \quad 0.2 \quad 0.1 \quad 0.5 \quad 1]^T$ and the initial experiment is performed in 2DoF control system of Fig. 3.2.

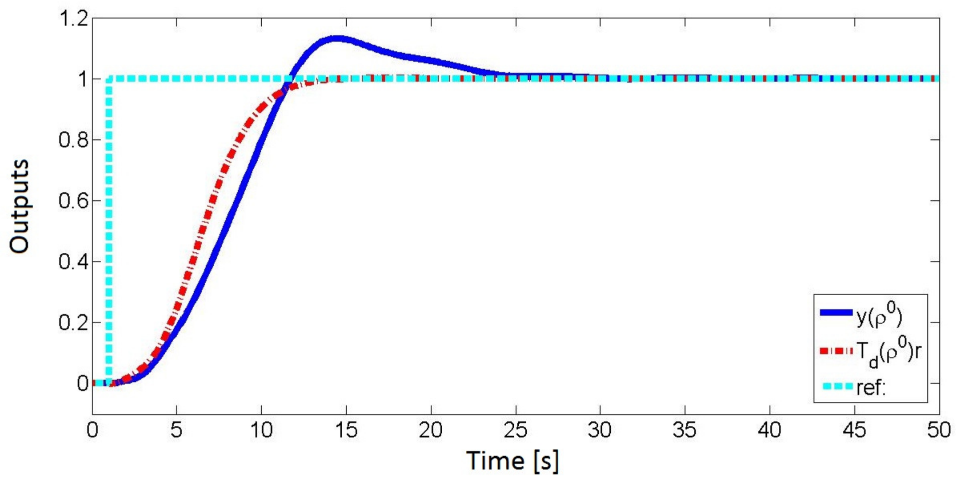

Figure 3.3: Initial output $y(\rho^0)$, (solid line), the desired output, $T_d(\rho^0)r$, (dash-dot line) and the step reference input of the closed loop system (dotted line)

Initial output, y^0, and the desired output $T_d(\rho^0)r$ of the experiment can be seen in Fig. 3.3. Then, the minimization of cost function of (3.12) has been done with off-line nonlinear optimization using the initial input and output data.

As a result, the optimal parameter vector $\rho^* = [-0.7705 \ \ 1.0604 \ \ -0.1341 \ \ 0.8091 \ \ -0.2167 \ \ 0.6267 \ \ 1.0388]^T$ is obtained. Using this optimal values in $C_{ff}(\rho)$ and $T_d(\rho)$, the second experiment of the 2DoF system is performed again. From Fig. 3.4, it can be clearly seen that the optimal output $y(\rho^*)$ and the desired output $T_d(\rho^*)r$ are almost the same. The unstable zeros approximated by the Kautz model are $0.8497 \pm 1.7826i$, while those of actual plant are $0.8 \pm 1.833i$. So, our proposed method can also approximate the number and locations of unstable zeros of the actual plant.

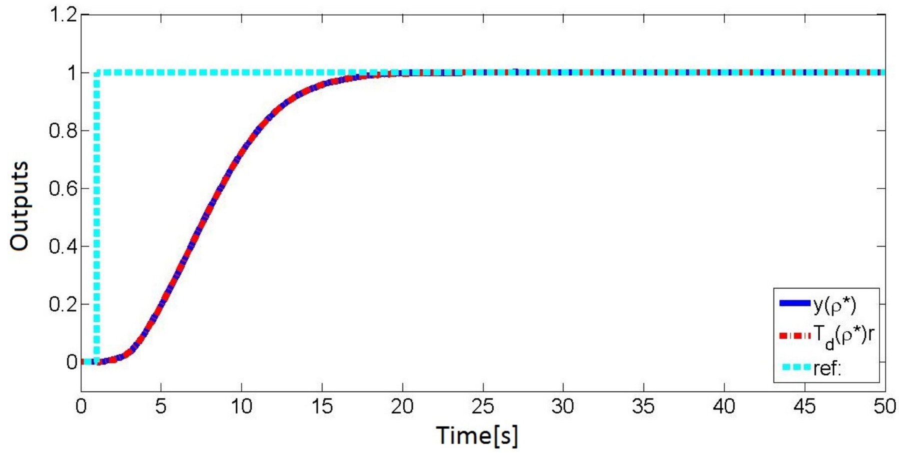

Figure 3.4: Optimal output $y(\rho^*)$ (solid line), the desired output $T_d(\rho^*)r$ (dash-dot line) and step reference input of the closed loop system (dotted line)

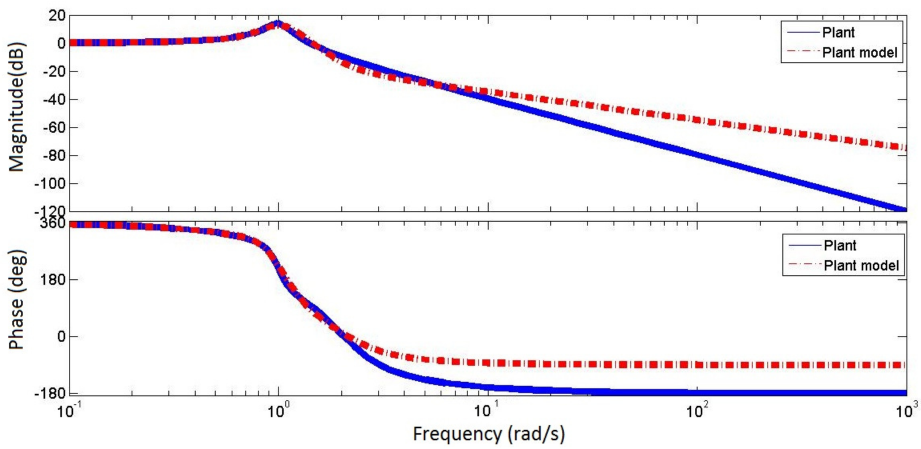

Figure 3.5: Frequency responses of plant and plant model

Frequency responses of plant and plant model can be seen in Fig. 3.5. From the simulation results, the desired set point tracking and the model estimation in the low frequencies is done very well with our proposed method.

Even though the measured data are assumed as noise-free data in the problem formulation, the initial output with measurement noise is also considered to check the effect of measurement noise. Gussian white noise with variance amplitude of 1.1x10^{-3} is added to the output of the initial experiment.

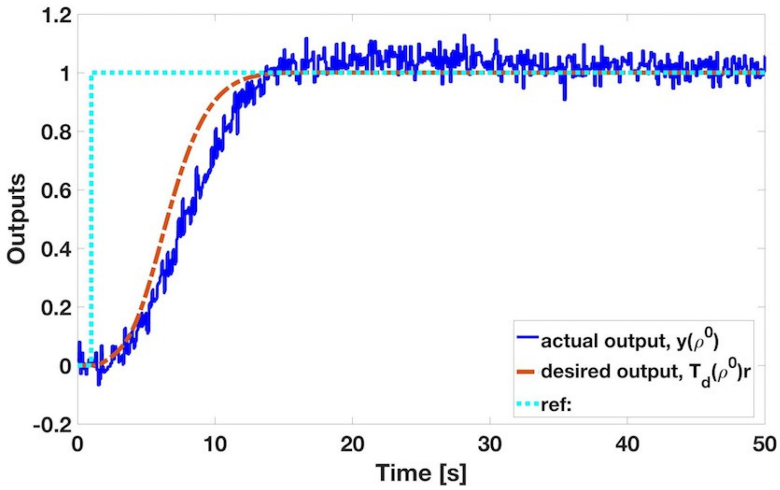

Figure 3.6: Initial output $y(\rho^0)$, (solid line) with measurement noise, the desired output, $T_d(\rho^0)r$, (dash-dot line) and the reference input of the closed loop system (dotted line)

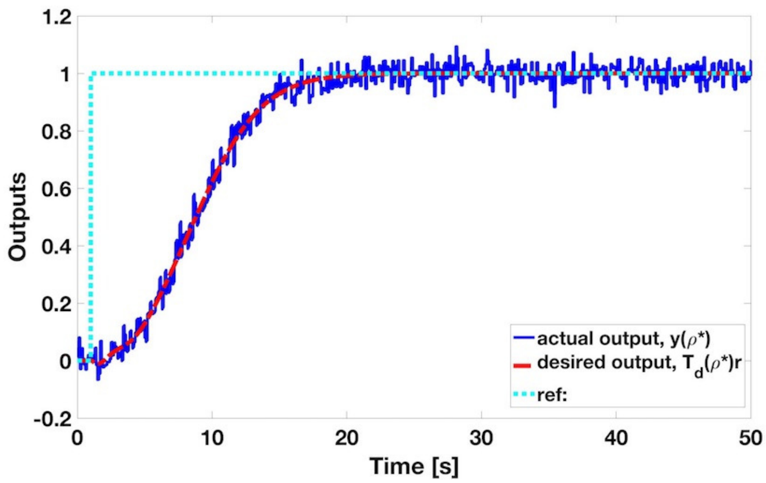

Figure 3.7: Optimal output $y(\rho^*)$ (solid line) with measurement noise, the desired output $T_d(\rho^*)r$ (dash-dot line) and the reference input of the closed loop system (dotted line)

Fig. 3.6 shows the initial output of the system with measurement noise, the desired output and the step reference. Using these initial output values with measurement noise, the cost function is minimized to get the optimal parameters. Fig. 3.7 shows that the desired output can still be achievable in the presence of measurement noise. The plant model estimated by the optimal parameters of noise-added output is shown in Fig. 3.8. It can be seen from the figure that the measurement noise can affect the identification of the unknown plant model.

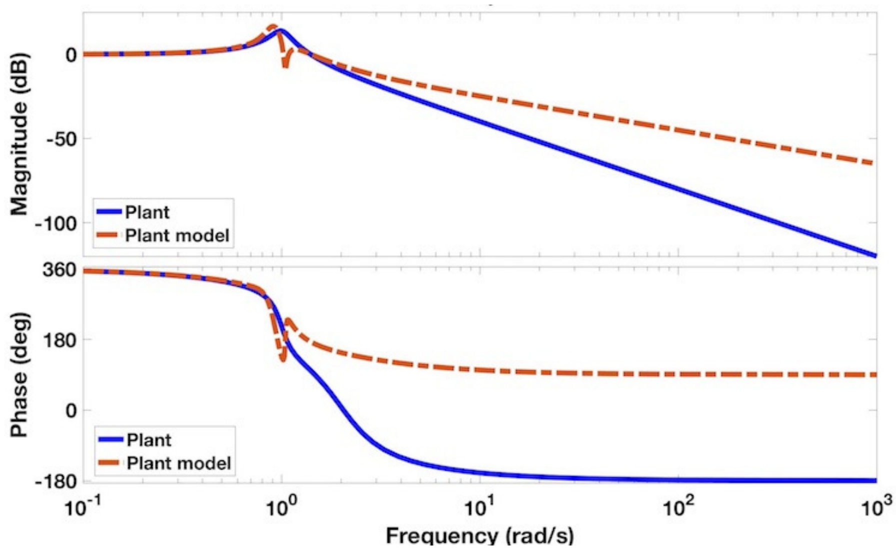

Figure 3.8: Frequency responses of plant and plant model with measurement noise is considered

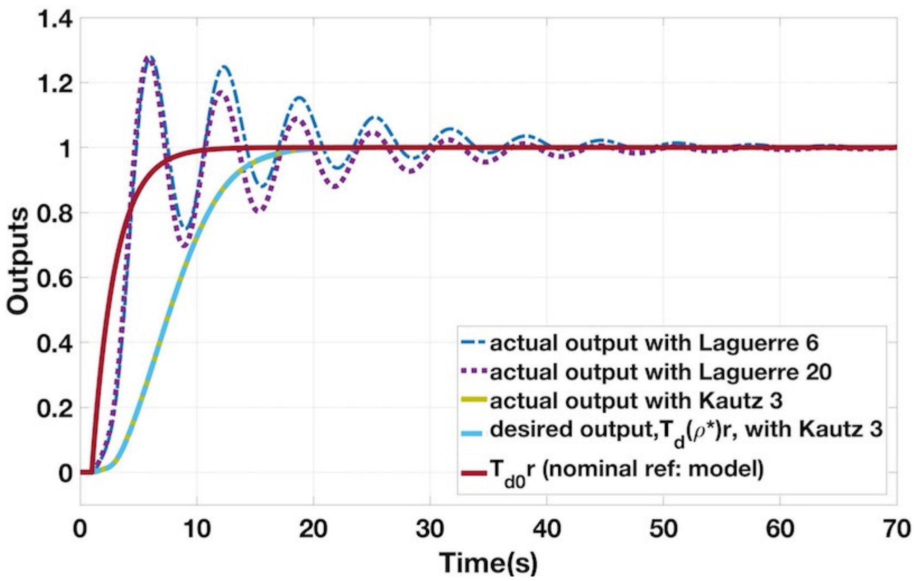

Figure 3.9: The optimal outputs of Laguerre order 6, Laguerre order 20, Kautz order 3 compared with the desired output of Kautz order 3 and the step response of nominal reference model

The effectiveness of our proposed method with Kautz expansions for poorly damped system is shown in comparison with Laguerre expansions. The controller and the desired

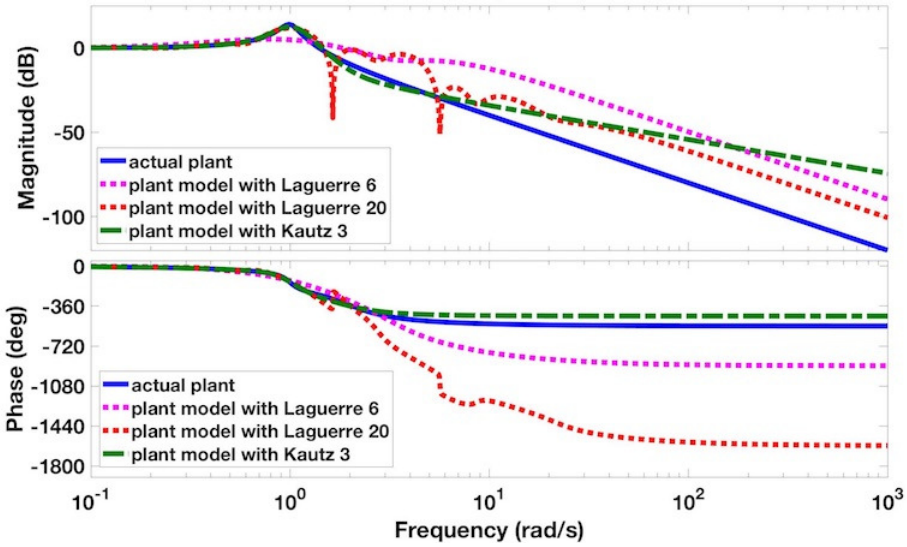

Figure 3.10: Frequency responses of plant and plant models with Laguerre order 6, Laguerre order 20 and Kautz order 3

reference model parameterized by Lauguerre expansions with model order 5 and 20 are considered and the optimal outputs are compared with that of Kautz model order 3. In Fig. 3.9, the optimal outputs of Lauguerre order 6 and 20 cannot follow the desired set point whereas, Kautz model order can follow it. It means that Laguerre approximation needs very much high order than Kautz approximation for the poorly damped systems.

3.6 Summary

In this chapter, the plant model estimation and set point tracking for the poorly damped system using Kautz expansions is discussed. FRIT in 2DoF control structure is used and the validity of our proposed method is shown with numerical example. The output with measurement noise is also considered and the simulated results are shown. The effectiveness of Kautz approximation for poorly damped system is also compared with Laguerre approximations.

Chapter 4

Set Point Tracking and Model Estimation for Time Delay System

4.1 Introduction

Time delays appear frequently in many practical systems. They often cause instability and poor performance. So, many researchers in the field of control theory try to design the robust controllers for the time-delay systems. Approximation and control of time-delay system with the feedback controller has been studied in both the data-driven and model based approach [23, 24, 26, 43, 42] .

The system with a feedforward controller plus the feedback controller can give better performance than that with the feedback controller only, so the researchers also pay attention to the two degree-of-freedom (2DOF) control system (in e.g., [33] and its references). The feedforward controller design for time-delay system is considered in [41] which is a kind of model-based controller design. In the data-driven framework, the feedforward controller tuning for time-delay system has been considered in [44, 25]. In most of the research works, the structure of lumped part is assumed to be known and the time-delay part is approximated by the well-known Pade approximation and a special orthonormal basis function, Laguerre expansions.

Different from the previous researches, this chapter proposes a new method to control and approximate the time-delay system with Kautz expansions which is also the special orthonormal basis function. FRIT in 2DoF controller structure is used for simultaneous attainment of the controller and plant model from one-shot experimental data. In the proposed method, the structure of the lumped part is unknown and the lumped part and the time delay part are constructed together as a parameterized lumped transfer function.

4.2 Problem setting

In this section, we address the 2DOF control system with tunable feedforward controller for linear time-delay systems as shown in Fig. 4.1 with a fixed feedback controller. The feedback controller is assumed to stabilize the closed loop system.

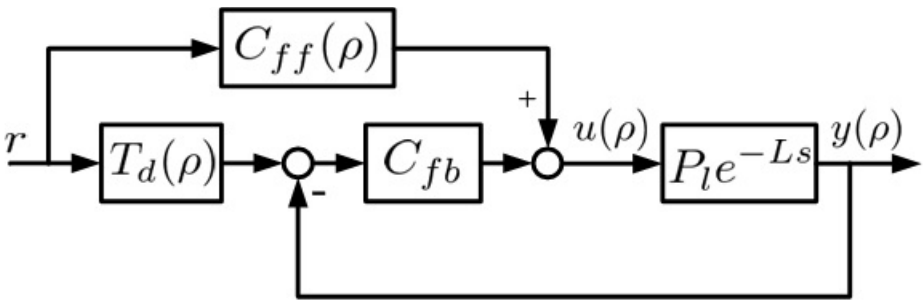

Figure 4.1: FRIT in 2DOF control architecture for time delay system

A plant to be addressed here is a single-input, single-output, linear time invariant system with time-delay as

$$P = P_l(s)e^{-Ls} \tag{4.1}$$

where $P_l(s)$ and L are the lumped part and time delay of the system, P, respectively. It is assumed that the information of the system, i.e., P, is unknown.

Let $T(\rho, s)$ be transfer function from r to y and it can be described by

$$T(\rho) = \frac{P(C_{ff}(\rho) + T_d C_{fb})}{1 + PC_{fb}} \tag{4.2}$$

A mathematical model of the plant which is implemented in the controller is denoted as $\tilde{P}(\rho)$. If it is possible to set $P = \tilde{P}(\rho)$, it is well-known that

$$C_{ff}(\rho) = T_d \tilde{P}(\rho)^{-1} \tag{4.3}$$

yields the achievement of the desired closed loop system as $T(\rho) = T_d$.

To obtain optimal parameters for the controller, the cost function to be minimized is defined by

$$J(\rho) = \|y(\rho) - T_d r\|^2 \tag{4.4}$$

The problem in this chapter focuses on the point for deriving the parameter vector, ρ, such that minimization of (4.4) achieves the desired output and an approximate model of the unknown time-delay plant simultaneously.

4.3 FRIT for 2DOF control architecture

At first, the initial parameter,ρ^0, is set by the designer and a one-shot experiment is performed to obtain the initial data $u(\rho^0)$ and $y(\rho^0)$, respectively. Then the fictitious reference signal for 2DOF structure is computed as in [15] by the equation

$$\tilde{r}(\rho) = \frac{u(\rho^0) + C_{fb} y(\rho^0)}{C_{ff}(\rho) + T_d(\rho) C_{fb}}. \tag{4.5}$$

Since the time-delay part works as the limitation of the tracking performance, it is natural to be included in the transfer function. As the plant is unknown, which implies that the time-delay part is also unknown. Similar to the previous studies such as [20, 25, 26], the desired reference model which contains the time-delay part is considered as

$$T_d(\rho) = T_{d0} \tilde{P}_n(\rho_n) \tag{4.6}$$

where T_{d0} is a nominal reference model. Then the feedforward controller in (4.3) becomes

$$C_{ff}(\rho) = T_{d0} \tilde{P}_m(\rho_m)^{-1} \tag{4.7}$$

The cost function is described by

$$J_F(\rho) = \left\| y(\rho^0) - T_d(\rho)\tilde{r}(\rho) \right\|^2. \tag{4.8}$$

Similar to our previous derivations in chapter 2 and 3, this cost function can be also written as

$$J_F(\rho) = \left\| \left(1 - \frac{T_d(\rho)}{T(\rho)}\right) y(\rho^0) \right\|^2 \tag{4.9}$$

and

$$J_F(\rho) = \left\| \left(1 - \frac{\tilde{P}(\rho)}{P}\right) \frac{1}{1 + \tilde{P}(\rho) C_{fb}} y(\rho^0) \right\|^2 \tag{4.10}$$

simultaneously. The equations of both of (4.9) and (4.10) imply that the minimization of (4.8) leads to the attainment of both of the desired tracking property and more accurate mathematical model. This minimization of cost function (4.8) can be completely done in the off-line because the required materials are only the initial data.

4.4 Parameterized models by Kautz expansions

In this section, Kautz expansions is utilized to approximate the mathematical model implemented in the feedforward controller of (4.7) and the desired tracking transfer function in (4.6). Time-delay plant model estimated by using Kautz expansions is described as

$$\begin{aligned}\tilde{P}(\eta, b, c) &= \sum_{i=1}^{M}[\eta_{2i-1}\Psi_{2i-1}(b,c) + \eta_{2i}\Psi_{2i}(b,c)] \\ &= \frac{\sqrt{2b}}{s^2+bs+c}\sum_{i=1}^{M}\left[(\eta_{2i-1}s + \eta_{2i}\sqrt{c})\left(\frac{s^2-bs+c}{s^2+bs+c}\right)^{i-1}\right] \qquad (4.11)\end{aligned}$$

As the plant contains time delay, the plant model is parametrized with minimum phase and non-minimum phase part similar to the previous chapter. Here, $\tilde{P}_m$ and $\tilde{P}_n$ are defined as

$$\tilde{P}_m(b,c) = \frac{\sqrt{2b}N'}{(s^2+bs+c)^M} \qquad (4.12)$$

$$\tilde{P}_n(\eta, b, c) = \frac{1}{N'}\sum_{i=1}^{M}[(\eta_{2i-1}s + \eta_{2i}\sqrt{c})(s^2+bs+c)^{M-i}(s^2-bs+c)^{i-1}] \qquad (4.13)$$

N' is a stable polynomial to make $\tilde{P}_m$ and $\tilde{P}_n$ proper. Let the tunable parameter vector ρ be $\rho = [\rho_n^T \ \ \rho_m^T]^T$, where $\rho_n = [\eta_{odd}^T \ \ \eta_{even}^T]^T$ and $\rho_m = [b \ \ c]^T$ respectively. η_{odd} and η_{even} are even and odd coefficient parameter vectors, respectively.

4.5 Comparison with the previous FRIT methods

Many studies have been done for controlling the time delay systems with fictitious reference iterative tuning (FRIT) [23, 24, 25, 26]. So it is necessary to compare these studies with the current approach to show the differences in the plant model design, the reference model design and the controller design.

Plant model design

In [26], the pre-filter design to improve the set point tracking for the time delay system is considered and the simultaneous attainment of the plant model is beyond the scope. In [23, 24, 25], simultaneous attainment of the model and controller is considered and the delay plant model in parametrized with a tunable lumped part and a time delay part. Time delay parts are approximated by Pade approximations or Laguerre expansions. The relative degree or the numbers of poles and zeros of the plant model are assumed to be known.

In the current approach, the delay plant model is parametrized with the truncated Kautz series as (4.11) by unifying lumped part and time delay part. The information of the plant (i.e relative degree or the number of poles and zeros) is not necessary.

Reference model design

For the reference model design, all of the previous research [26, 23, 24, 25] consider the tunable reference model that reflects the actual closed loop system. So the reference model contain nominal reference model given by the designer and Pade or Larguerre approximated time delay.

In the current research, the reference model design is similar to [26, 23, 24, 25] and the time delay part is approximated by (4.13) using the Kautz expansions.

Controller design

For the simultaneous attainment of the controller and the plant model, the controller includes the inverse of the plant model. The controller design of [26] does not include the plant model and it is simple. In [24, 25], to make the feedback or feedforward controller proper, the design of nominal reference model depends on the relative degree of the plant model, so some information of the plant is necessary.

In this proposed method of the feedforward controller design (4.7), the design of nominal reference model does not depend on the plant model and the user can design it freely for the desired response.

4.6 Numerical Example

To show the effectiveness of the proposed method, we illustrate a numerical example.

The transfer function of the unknown plant, the nominal reference model and the feedback controller are defined as

$$P = \frac{1}{(0.1s+1)(s+1)}e^{-7s} \tag{4.14}$$

$$T_{d0} = \frac{1}{2s+1} \tag{4.15}$$

$$C_{fb} = \frac{0.05}{s} \tag{4.16}$$

In this example, N' is considered as a fixed polynomial, $(s+1)^{2M}$, and model order, $M = 3$. $\rho^0 = [0.2\ \ 0.2\ \ 0.1\ \ 0.2\ \ 0.1\ \ 0.5\ \ 1]^T$ is used as the initial parameter vector and the initial experiment is performed in 2DOF control system of Fig. 4.1. Initial output $y(\rho^0)$ and desired output $T_d(\rho^0)r$ of the experiment can be seen in Fig. 4.2. Then, minimization of cost function (4.7) has been done with off-line nonlinear optimization using initial input, output data obtained from initial experiment.

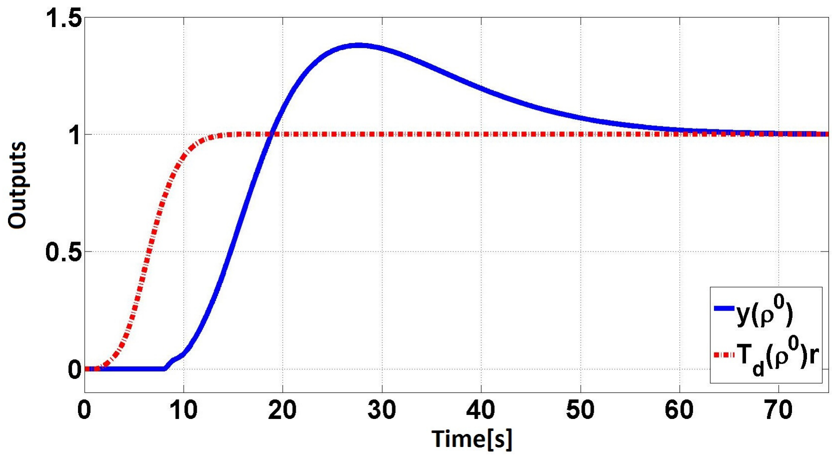

Figure 4.2: The initial output $y(\rho^0)$ and the desired output $T_d(\rho^0)r$ (dash-dot line)

As a result, we obtain optimal parameter vector $\rho^* = [-0.0689\ \ -0.1944\ \ -0.1372\ \ 0.0536\ \ -0.0232\ \ 2.0005\ \ 1.26]^T$. Using these optimal values in $C_{ff}(\rho)$ and $T_d(\rho)$, the experiment of the 2DOF system is done again. From Fig.4.3, it can be clearly seen that the optimal output $y(\rho^*)$ and the desired output $T_d(\rho^*)r$ are almost the same.

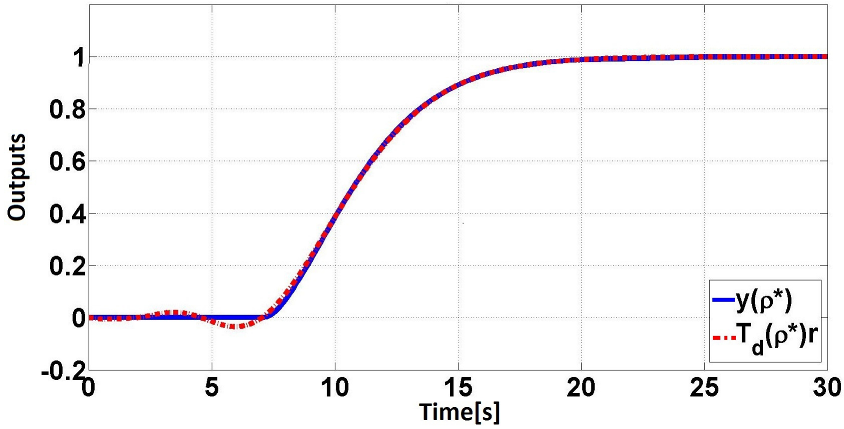

Figure 4.3: Initial output $y(\rho^*)$ and the desired output $T_d(\rho^*)r$

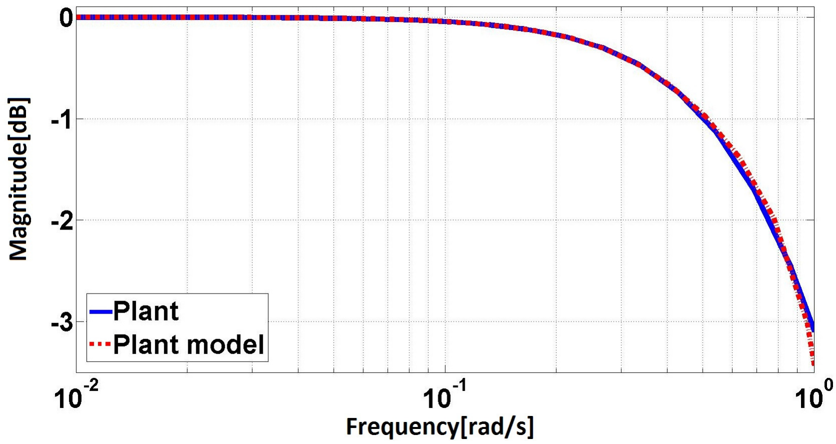

Figure 4.4: Gain characteristics of the plant and plant model

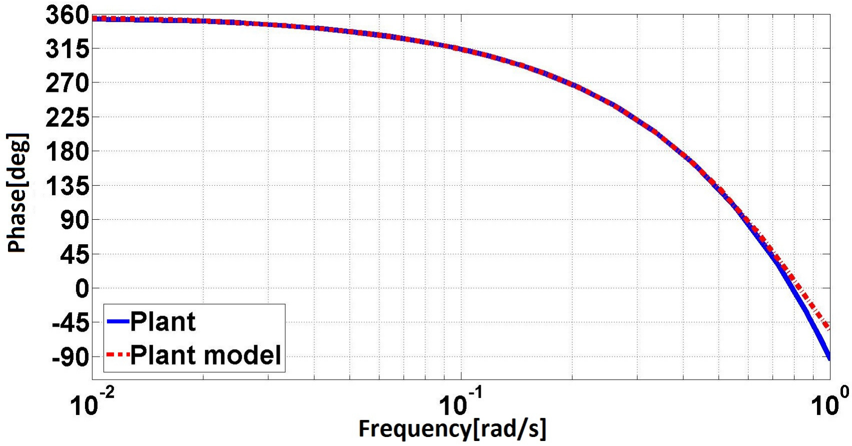

Figure 4.5: Phase characteristics of the plant and plant model

It means that the optimal output of the proposed method can follow the desired set point for the time-delay system. Fig. 4.4 and 4.5 show the gain and phase characteristics of actual plant and plant model approximated by Kautz expansion.

The proposed method with Kautz expansions is also compared by other time-delay approximation methods such as Pade approximations and Laguerre expansions. Same numerical example is used and also, the same nominal reference model and the feedback controller are used in the comparison.

In Pade approximation method for the time-delay system with FRIT, the minimum phase part is defined as

$$\tilde{P}_{m(Pade)} = \frac{\rho_0}{\rho_1 s + 1} \tag{4.17}$$

and the non-minimum phase part (time-delay part) with Pade approximation of order 4 is described as

$$\tilde{P}_{n(Pade)}(L) = \frac{1 - \frac{L}{2}s + \frac{3L^2}{28}s^2 - \frac{L^3}{84}s^3 + \frac{L^4}{1680}s^4}{1 + \frac{L}{2}s + \frac{3L^2}{28}s^2 + \frac{L^3}{84}s^3 + \frac{L^4}{1680}s^4} \tag{4.18}$$

The tunable parameter vector, $\rho := [\rho_0 \quad \rho_1 \quad L]^T$. Initial parameter vector, ρ^0, is set as $\rho^0 = [2 \quad 2 \quad 3]^T$ and the optimal parameters obtained after optimization is $\rho^* = [1.0013 \quad 1.3045 \quad 6.9325]^T$. So the actual delay time of 7 seconds is estimated by the Pade approximation as $L = 6.9325$ seconds.

In Laguerre approximations method for the time-delay system with FRIT, the minimum phase part is defined the same as in (4.17) and the the non-minimum phase part (time-delay part) with Laguerre expansions of order $M = 6$ is described as

$$\tilde{P}_{n(Laguerre)}(\eta, a) = \sum_{i=1}^{M} \eta_i \frac{\sqrt{2a}}{s+a} \left[\frac{s-a}{s+a}\right]^{i-1} \tag{4.19}$$

The tunable parameter vector, $\rho := [\eta_1 \ \ \eta_2.....\eta_5 \ \ a \ \ \rho_0 \ \ \rho_1]^T$. Initial parameter vector, ρ^0, is set as $\rho^0 = [0.6 \ \ 0.3 \ \ 0.3 \ \ 0.2 \ \ 0.2 \ \ 3 \ \ 2 \ \ 2]^T$ and the optimal parameters obtained after optimization is $\rho^* = [-0.0075 \ \ -0.5578 \ \ 0.2210 \ \ -1.2596 \ \ -0.1950 \ \ 1.4078 \ \ 1.0049 \ \ 0.7103]^T$.

The simulation results of three methods are compared in Fig. 4.6 for the set point tracking and in Fig. 4.7 for the model estimation of time-delay system. According to the simulation results and optimal values obtained after optimization, the proposed method of time-delay system with Kautz expansions can give the satisfactory results.

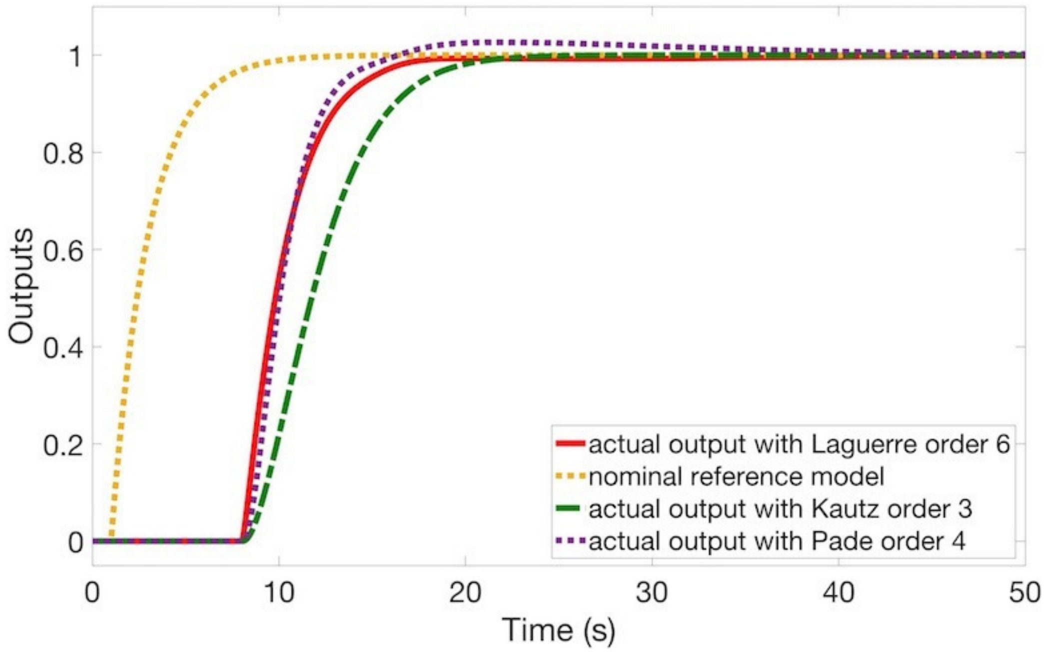

Figure 4.6: Optimal outputs with Laguerre order 6 (solid-line), Kautz order 3 (dash-dot line) and Pade order 4 (dotted line) compared with the nominal reference model

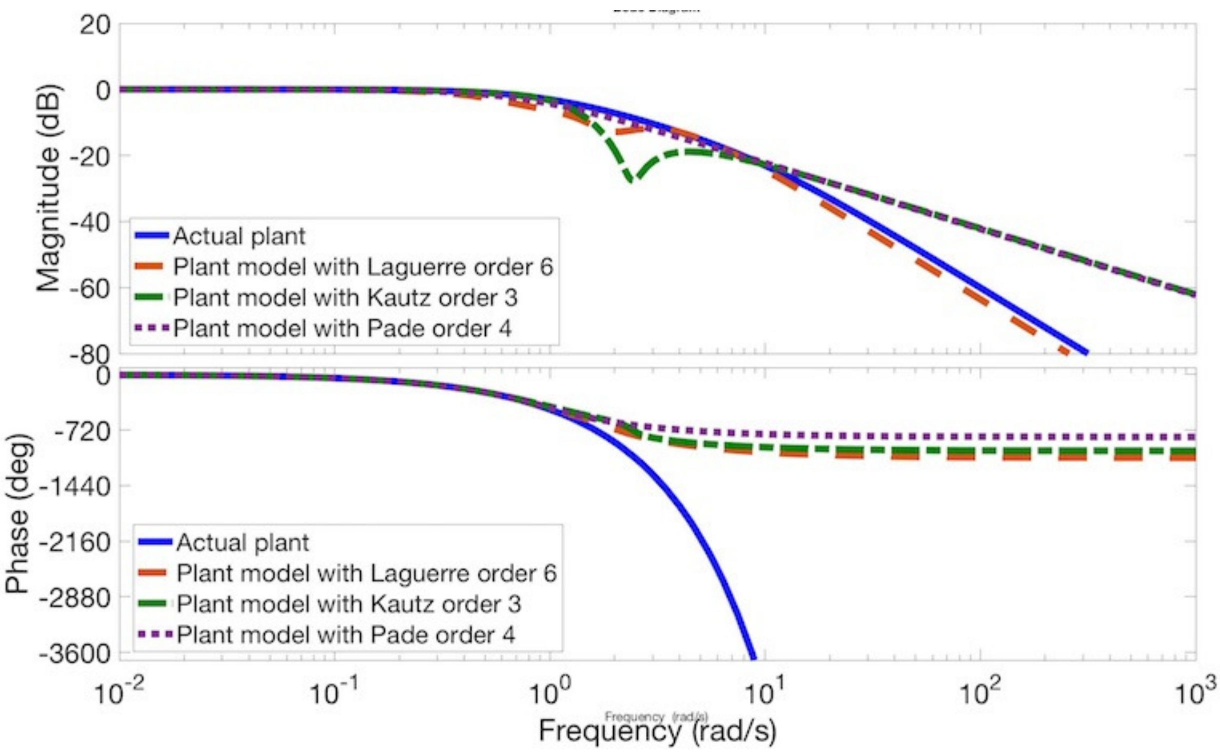

Figure 4.7: Frequency characteristics of plant (solid line) and plant model with Laguerre order 6 (dashed line), Kautz order 3 (dashed-dot line) and Pade order 4 (dotted line), with optimal parameters

4.7 Summary

In this chapter, FRIT of feedforward controller with Kautz expansion in 2DoF control structure for linear time-delay system is proposed. With Kautz expansion, time-delay is not explicit parameter for the plant model compared with Pade approximations. The linear time-delay system is approximate with the proposed method. Comparison with the well-known Pade approximations and Laguerre expansions, and the proposed method is also done. Ideal noise-free system is considered in this chapter. Inherent feature of noise in measured input and output data and approximation of systems with large time constant are further investigations of our current research work.

Chapter 5

Positioning Control and Model Estimation of the Vibrating System

5.1 Introduction

Positioning is one of the most important control techniques in factory automations; such as flexible robot arms, precision machineries, transport machineries and so on. Vibrations cannot be avoided in these apparatuses and many researchers pay their attentions to positioning control of vibrating systems. In [45, 46, 47], the positioning control and vibration suppression have been studied. All of these research works are model-based approaches and a mathematical model of the process needs to be built or identified before the controllers are designed. In contrast to these research works, this chapter shows data-driven approach with the fictitious reference iterative tuning (FRIT) for positioning control and the model estimation of vibration system.

Using Kautz expansions in 2DoF-FRIT control structure, the proposed method of chapter 3 is applied in a practical system to show its applicability and effectiveness. The vibrating system of [52] is considered as the practical application for this chapter.

In [52], the authors proposed a method for the sensorless parameter estimation of an electromagnetic transducer. With that method, the parameters of the mechanical, electromechanical coupling, and electrical system models are simultaneously estimated without using the position, velocity or acceleration sensors. For more details, the readers are referred to original paper and its references. In this chapter, the vibrating system of [52] is used for different purpose, especially for positioning control and estimating the mathematical model of the system using the actual parameter values of [52] .

5.2 Problem formulation

A plant to be addressed in this chapter is a single-input, single-output, linear time invariant system. It is assumed that the information of the system, i.e., P, is unknown except its natural frequency. The 2DOF control system with tunable feedforward controller is addressed. The cost function is defined by

$$J(\rho) = \|y(\rho) - T_d(\rho)r\|^2 \tag{5.1}$$

The cost function is minimized to achieve the optimal parameter for the desired output and an approximate model of the plant using one-shot experimental input and output data. System disturbance is not considered in this chapter.

The truncated Kautz series is used to parametrize the controller and approximate the vibrating system and the parametrized plant model is described as

$$\tilde{P}(\eta, b, c) = \frac{\sqrt{2b}}{s^2 + bs + c}\left[\sum_{i=1}^{M} \eta_{2i-1} s \left(\frac{s^2 - bs + c}{s^2 + bs + c}\right)^{i-1} + \eta_{2i}\sqrt{c}\left(\frac{s^2 - bs + c}{s^2 + bs + c}\right)^{i-1}\right] \tag{5.2}$$

5.3 Unknown plant Model

The schematic of a simple mass-spring-damper system coupled to electromagnetic transducer as shown in Fig.5.1.

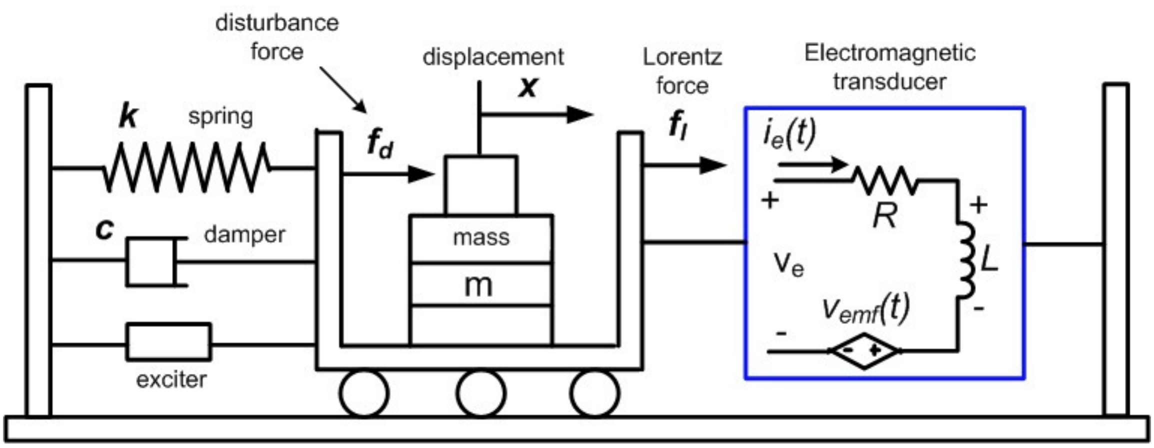

Figure 5.1: Schematic of mass-spring-damper system coupled to electromagnetic transducer (It is simplified diagram of the vibrating control system in [52])

In this system, the electromagnetic transducer is used as an actuator for the vibrating control. An electrical system of the electromagnetic transducer is modeled by the series connection of the inductor, L [H], internal resistance in the coil, R [Ω], and motional electromotive force, $v_{emf}(t)$ (as shown in the blue box of Fig. 5.1). The differential equations of the system are obtained as

$$m\frac{d^2x(t)}{dt^2} + c\frac{dx}{dt} + kx(t) = f_d(t) + f_l(t) \tag{5.3}$$

$$L\frac{di_e(t)}{dt} + Ri(t) = v_e(t) - v_{emf}(t) \tag{5.4}$$

where m [kg] is the mass, c [Ns/m] is the damping coefficient, k [N/m] is the spring constant, $x(t)$ [m] is the displacement of the mass-spring-damper system, $f_l(t)$ [N] is the Lorentz force generated from the electromagnetic transducer, and $f_d(t)$ [N] is the disturbance force, $v_e(t)$ [V] is the voltage across the electromagnetic transducer. The motional electromotive force, $v_{emf}(t)$, and Lorentz force, $f_l(t)$, are described as

$$v_{emf}(t) = \phi\frac{dx(t)}{dt} \tag{5.5}$$

$$f_l(t) = \phi i_e(t) \tag{5.6}$$

where ϕ [N/A or Vs/m] is the electromechanical coupling coefficient and $i_e(t)$ [A] is the current flowing through the electromagnetic transducer. The effect of the disturbance force, $f_d(t)$, caused by the exciter is neglected. The purpose of this research work is to control the displacement, $x(t)$, of mass-spring-damper system by changing the voltage across the electromagnetic transducer, $v_e(t)$. Substituting (5.5) and (5.6), in (5.4) and (5.3), respectively, and taking Laplace transform, (5.3) and (5.4) become

$$(ms^2 + cs + k)X(s) = \phi I_e(s) \tag{5.7}$$

$$(R + Ls)I_e(s) + \phi sX(s) = V_e(s) \tag{5.8}$$

Rearranging (5.7) and (5.8), the transfer function of the vibrating system is obtained as

$$P(s) = \frac{X(s)}{V_e(s)} = \frac{\frac{\phi}{m}}{(R + Ls)(s^2 + \frac{c}{m}s + \frac{k}{m}) + \frac{\phi^2}{m}s} \tag{5.9}$$

5.4 Positioning Control

The coefficient values of (5.9) are $L = 0.786$ mH, $R = 2.57\ \Omega$, $c = 1.92$ Ns/m, $k = 4.47 \times 10^3$ N/m, $m = 1.73$ kg and $\phi = 2.51$ N/A. Damping factor ζ and natural frequency ω are $\zeta = \frac{c}{\sqrt{4mk}}$ and $\omega = \sqrt{\frac{k}{m}}$, respectively.

By substituting these values in (5.9), the transfer function of the system becomes

$$P = \frac{1.451}{7.86e^{-4}s^3 + 2.5708s^2 + 8.5247s + 6640.4} \tag{5.10}$$

(5.10) is used as an unknown plant for the proposed method expect the natural frequency of the system ($\omega = 50.8\ rad/s$) is assumed to be known.

Nominal reference model and the feedback controller are defined as

$$T_{d0} = \frac{1}{0.1s+1} \tag{5.11}$$

$$C_{fb} = \frac{500}{s} \tag{5.12}$$

The model order, M, is considered as 2 and the polynomial, N', is considered as $(s+\rho_{nn})^{2M}$. The initial parameter vector ρ^0 is set as $\rho^0 = [0.02\ \ 0.01\ \ 0.01\ \ 5\ \ 7]^T$. Using these initial values, $C_{ff}(\rho^0)$ and $T_d(\rho^0)$ are implemented in 2DoF system and then the initial experiment is performed. Fig. 5.2 shows the step responses of desired and actual closed loop transfer function, $T_d(\rho)$ and $T_{ry}(\rho)$ respectively. In Fig. 5.3 and 5.4, initial input, u^0, and initial output, y^0, are illustrated. Using initial input and output data, u^0 and y^0, minimization of (5.1) has been done by off-line optimization. CMA-Evolution Strategy [34] is used as an off-line non-linear optimization. As a result, the optimal parameter vector is obtained as $\rho^* = [-0.0001\ \ 0.0001\ \ 0.004\ \ 4.4895\ \ 6.8303]^T$. The optimal input, u^*, and optimal output, y^* are illustrated in Fig. 5.3 and 5.4, respectively.

Then final experiment is performed again using the optimal parameters obtained from off-line optimization. Step responses of desired and actual closed loop transfer functions, $T_d(\rho^*)$ and $T_{ry}(\rho^*)$, with optimal parameters are shown in Fig. 5.5. It can clearly be seen that set point tracking has been done very well with the proposed method and it implies that the desired output can be achieved by using ρ^*.

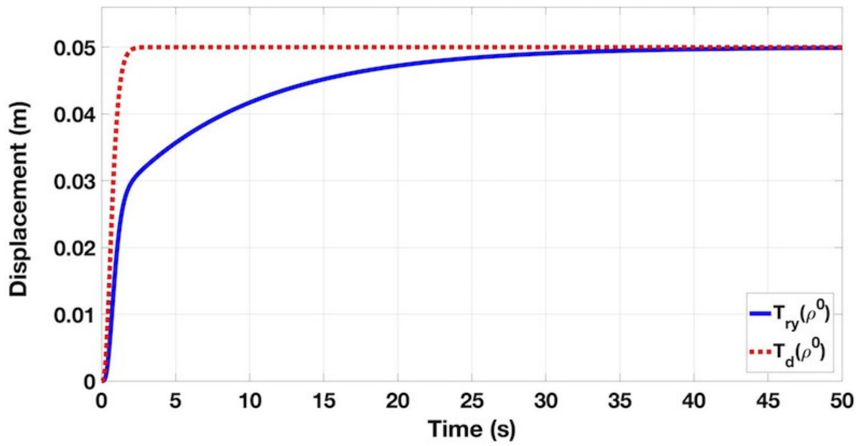

Figure 5.2: Step responses of the actual closed loop transfer function, T_{ry} (solid line), and the desired closed loop transfer function, T_d (dash-dot line), with initial parameters

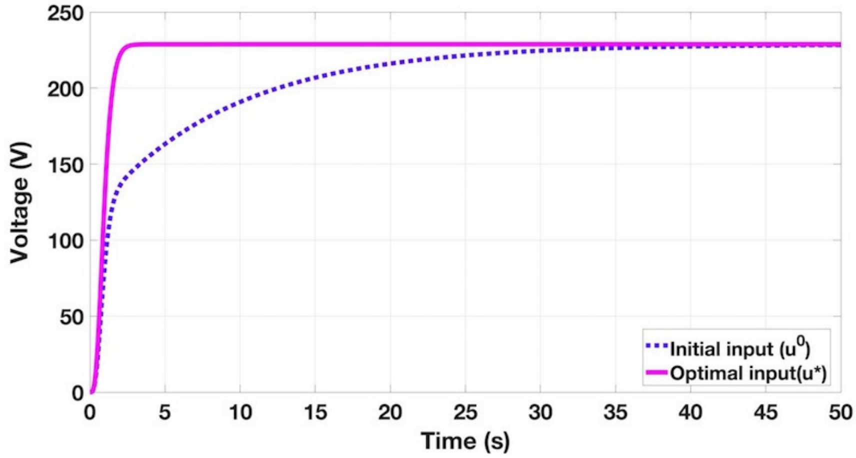

Figure 5.3: Initial input (dash-dot line) after initial experiment and optimal input (solid line) after optimization

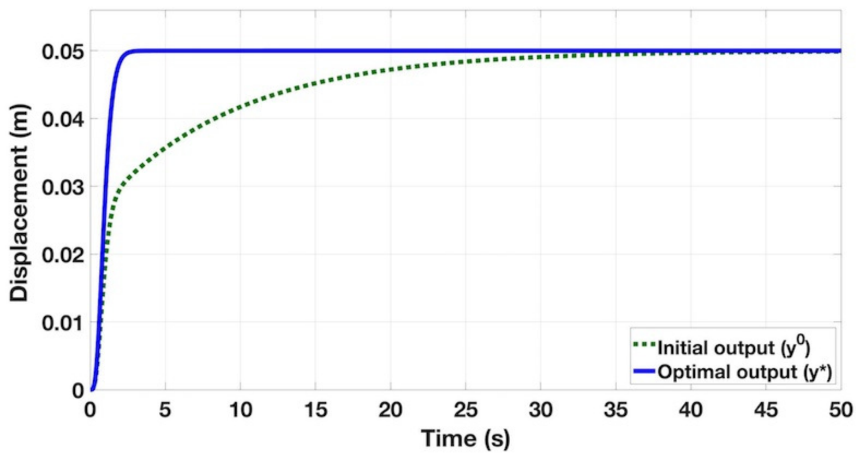

Figure 5.4: Initial output (dash-dot line) after initial experiment and optimal output (solid line) after optimization

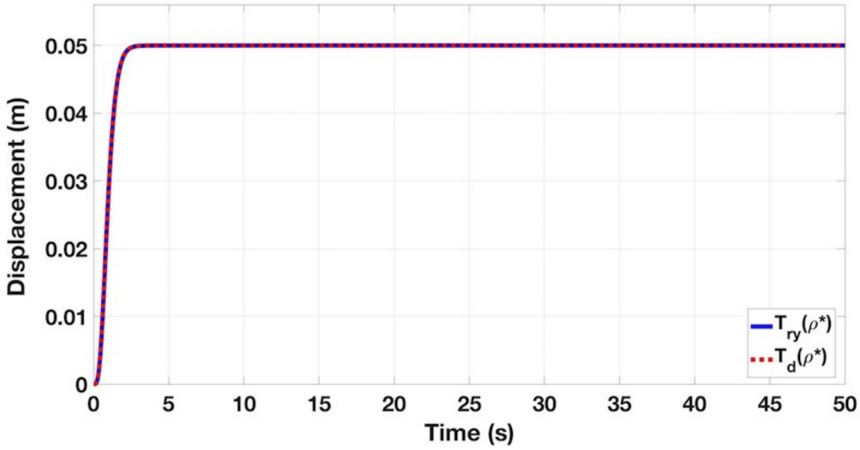

Figure 5.5: Step responses of the actual closed loop transfer function, T_{ry} (solid line), and the desired closed loop transfer function, T_d (dash-dot line) with optimal parameters

5.5 Estimation of vibrating system

Kautz poles are functions of frequencies and damping factors. In this research, the same set of poles are used for the expansions (i.e same b and c in all expansions). Fig. 5.6 and 5.7 show the step responses and frequency responses of plant and plant model with initial parameters.

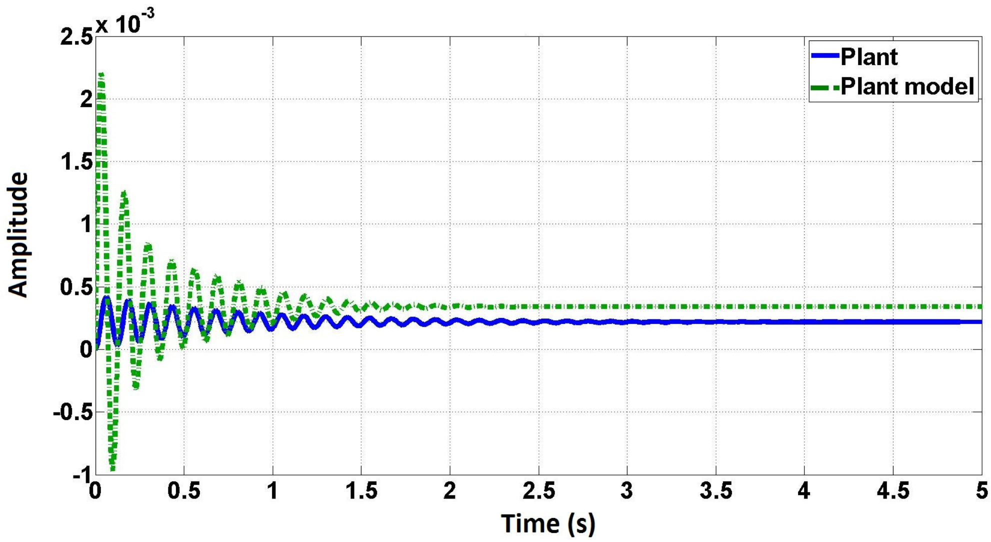

Figure 5.6: Step responses of plant (solid line) and plant model (dash-dot line) with initial parameters

After optimization, the step responses and frequency characteristics of the plant and plant model with optimal parameters can be seen in Fig. 5.8 and Fig. 5.9, respectively.

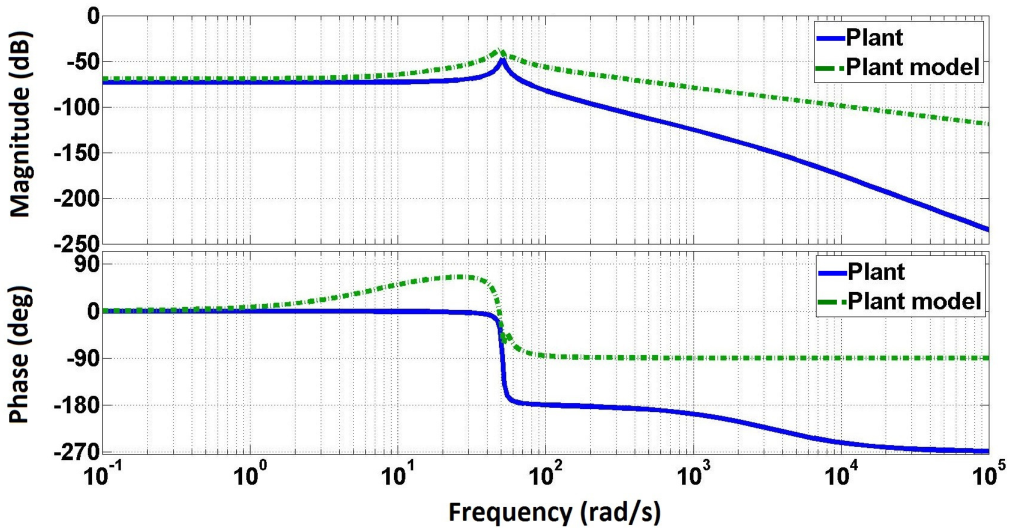

Figure 5.7: Frequency responses of plant (solid line) and plant model (dash-dot line) with initial parameters

From these simulation results, the approximation of plant with our proposed method is also done very well.

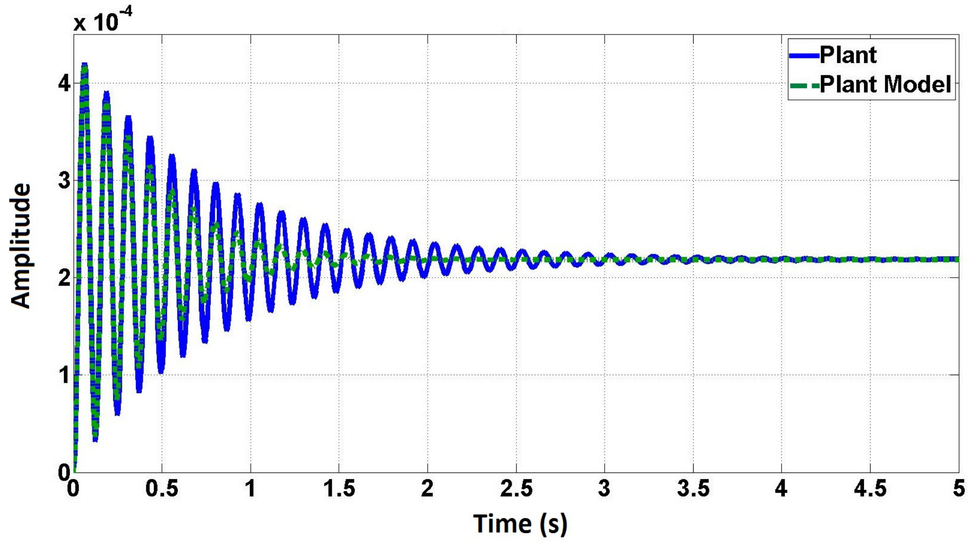

Figure 5.8: Step responses of plant (solid line) and plant model (dash-dot line) with optimal parameters

Damping factor of actual plant is 0.01 and approximated damping factor is 0.067. Fig. 5.10 show the peak values of gain (in dB) of actual plant and estimated plant model. By looking this figure, the results of estimation of vibrating plant is acceptable even though damping factor cannot be exactly estimated.

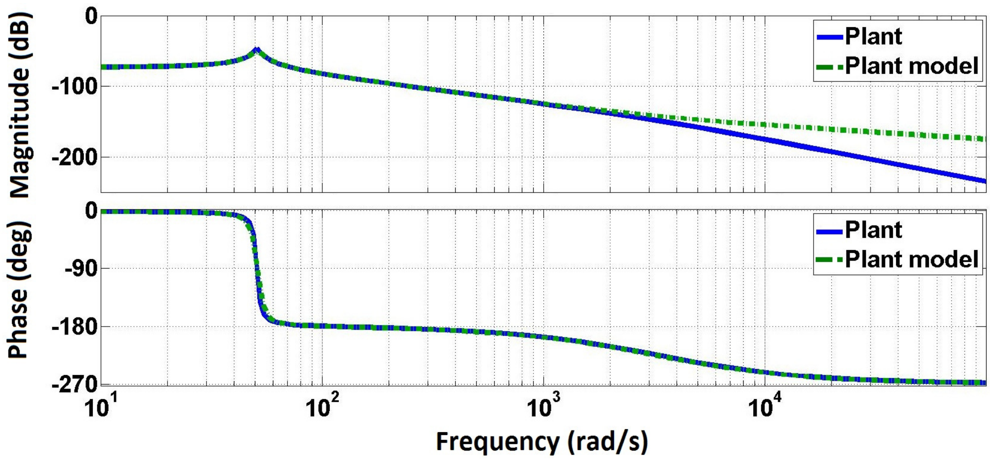

Figure 5.9: Frequency responses of plant (solid line) and plant model (dash-dot line) with optimal parameters

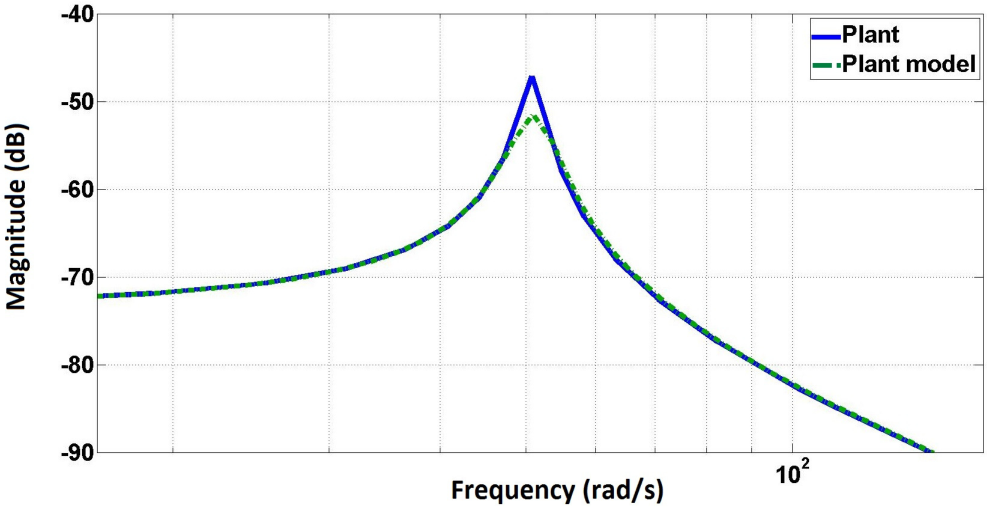

Figure 5.10: The gain characteristics of plant (solid line) and plant model (dash-dot line) to show the peak values of them

5.6 Summary

This chapter shows one of the application area of our proposed method. According to simulation results, positioning control and estimation of the vibration system are done well. Natural frequency of the system is assumed to be known and considered as constant in this research and the next step is to check the results if the natural frequency vary. For further study, the selection of T_d and design of N' are needed to be considered in details for the specific high frequency cases. Selection of the initial parameters and the effects of the disturbance are also needed to clarified.

Chapter 6

Conclusions and Future Work

This research work proposes a new method related to the parametrization of data-driven controller with the special orthonormal basis functions, Kautz expansions. Feedback controller of FRIT in IMC control structure and the feedforward controller of FRIT in 2DoF control structure as well as the desired closed loop transfer function are parameterized with the truncated Kautz series. Basically, the proposed method aims to control and estimate the systems with resonant poles simultaneously, using one-shot experimental input and output data without using a mathematical model of system. The proposed method is also applicable to the non-minimum phase systems, the systems with time-delay and the minimum phase systems as well.

For the non-minimum phase systems, the proposed method can estimate the number of unstable zeros. For the time-delay systems, the lumped part and the time delay part are constructed together as a parameterized lumped transfer functions using Kautz expansions. The effectiveness of Kautz expansions for the poorly damped system from the set point tracking and model estimation points of view is compared with the Laguerre expansions. Our proposed method with the reduced-order Kautz series can give better results than Laguerre series. In the model estimation and control of time-delay systems, the well-known time delay approximations methods; Pade approximations and the truncated Laguerre series are compared with our proposed method. Although our proposed method for time-delay system is not superior than Pade and Laguerre approximations, it is still applicable for time-delay system according to the simulation results. As many studies has been done for controlling the time-delay system with FRIT, the comparisons of these studies and the current approach is also done in the plant model design, the reference model design and the controller design. Even though the experimental data are assumed as noise-free data, the effects of measurement noise in the output data is also checked and simulated. The validity of the proposed method is also tested with the actual parameters of the vibrating system and the satisfactory results are obtained.

The major contribution of the research work is that the controllers and the desired reference model parameterized with small model order Kautz expansion can be applied to the non-minimum phase system and the time-delay system as well as the processes with oscillatory behaviors. To get the desired set point tracking and to approximate the plant model with one single set of measured input output data, FRIT in IMC structure and FRIT in 2DoF structure are used. The current approach is used in the continuous systems but it is applicable to the discrete systems also.

There are many research directions for the future. The problem of choosing an appropriate nominal reference model T_{d0} is still unsolved. So far, it is chosen by the experience of the designer. In addition, the design of the stable polynomial N' needs to be considered. In chapter 2, we consider $N'(\rho_d) = \rho_{d_{2M}} s^{2M} + \rho_{d_{2M-1}} s^{2M-1} + ... + \rho_{d_1} s + 1$. We found that fixed polynomial N' can give better simulation results. But for the high frequency, we need to use $N' = (s + \rho_n)^{2M}$ due to the steady state error constraint. So more analysis are needed to be studied for N'. Furthermore, the appropriate selection of Kautz model order is needed to be considered in future. So far, the current work is applicable for stable, linear time invariant (LTI) systems with single input, single output (SISO) and the input, output data are assumed as noise free. For the noisy data, we need some modifications in our proposed methods. I/O data with measurement noise are also left to study in the future. As other data-driven methods, we still need the stability analysis that will be further part of our research.

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Journal Paper

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Conference Paper

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