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RESEARCH ARTICLE

Noniterative Data-Driven Gain-Scheduled Controller Design Based on Fictitious Reference Signal

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ABSTRACT This paper proposes a noniterative direct data-driven gain-scheduled control. Gain-scheduled proportional–integral–derivative (PID) control is one of the most popular approaches for nonlinear systems. However, compared to fixed PID, gain-scheduled PID has considerably more scheduler parameters and requires time to tune them, which is the problem in conventional methods that include hand-tuning and model-based control design. To solve these problems, a noniterative data-driven tuning method for a gain-scheduled controller with polynomials via tuning approach using a fictitious reference signal is proposed. The proposed method enables tuning of the parameters from one-shot data obtained from a test without the system model to be controlled. To verify this method, the numerical simulation for two types of nonlinear systems is conducted. Therefore, the proposed method enables the parameters of the gain-scheduled controller to realize high tracking performance.

INDEX TERMS Data-driven control, model-free control, parameter tuning, PID control.

I. INTRODUCTION

The most popular feedback controller is proportional-integral-derivative (PID) control which is the most widely used in industry [1], [2] - it is used in >90% of feedback systems [3]. This is because PID control has a simple structure and is intuitively easy to understand. Fixed PID control can achieve the good performance for strongly linear systems; however, for nonlinear systems, it is difficult to obtain the control performance expected by the designer. One of the most popular approaches for a nonlinear system is a gain-scheduled control which provides the desired control performance by changing controller gains according to scheduling parameters which are the states of the targeted system and external environment. In general, the design of the gain-scheduled controller needs an identified linear-parameter variant (LPV) model of the system to be controlled. However, the model-based control design approach may not be appropriate because industrial systems are complex, and obtaining accurate system models to be controlled is difficult. From this background, in industry, a look-up table (LUT)-based gain-scheduled PID control with trial-and-error tuning is often employed [4], [5], [6]. However, it is required to tune a number of control parameters to obtain the desired control performance. Time-invariant normal PID controller has only three tunable parameters, while gain-scheduled control requires numerous tuning parameters and much time for parameter tuning. This requirement poses a problem for industrial applications, such as automobile systems [7].

In the past decade, data-driven (DD) or model-free controller design approaches that do not involve system identification or controlled plant models have attracted attention [8], [9]. In particular, direct data-driven control approach features that tunable controller parameters are optimized from one-shot time series input/output data. Examples of such methods are the VRFT (virtual reference feedback tuning) [10], [11] using a virtual signal and FRIT (fictitious reference feedback tuning) [12], [13] using fictitious reference signals [14]. Additionally, an approach in which the target

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system model is not used has been employed in industrial systems, e.g., process systems and automotive systems [7], [15], [16], [17], [18], [19], [20].

Although most of the DD control schemes assume linear control systems, industrial systems have many complex nonlinear systems. Thus, there is a need for DD control for nonlinear systems. Some prior studies explored DD control for nonlinear systems, for example, DD-PID [21], DD-FRIT [22], [23], FRIT for feedback linearization [24], application of VRFT to LPV system [17], [25], [26], VRFT for Q-learning [27], VRFT for gain-scheduled PID control considering sparsity [28], automatic tuning method of LUT by VRFT [6], and MFC design by VRFT [29]. We compared these methods for nonlinear systems. DD-PID, DD-FRIT, and VRFT-Q-learning require high storage capacity and computational cost, which leads to difficulties in implementation on mass-produced controllers. For FRIT using feedback linearization, the model structure should be known in advance, and the commonly used PID controller parameters cannot be directly obtained. LPV-VRFT [25], sparse-VRFT-GS-PID control [28], and MFC-VRFT [29] were proposed as methods with low computational load. Although the VRFT approaches are attractive, the prefilter design remains a challenge. For example, rigorous prefilter design requires system identification [11]. Furthermore, the noise is amplified as the virtual reference signal is calculated from the inverse function of the reference model. Hence, the control parameters that realize model matching may not be obtained.

To overcome some of these challenges, we propose a DD design method for a gain-scheduled controller. The proposed method (FRIT-GS) employs the FRIT approach using a fictitious reference signal. The gain-scheduled controller used in this paper consists of a velocity form of time-variant PID controller and a gain scheduler expressed as a polynomial. The polynomial is represented by tunable weighting coefficients and scheduling parameters. Next, we derived the objective function for optimizing the gain scheduler parameters based on FRIT framework. The proposed method is a data-driven approach that does not require a model to be controlled, and thus does not require system identification and trial-and-error parameter tuning.

The contributions and advantages in this study are summarized as follows:

- Contributions: (i) We extend the standard data-driven control, i.e., FRIT [13], to optimize the gain-scheduled controller parameters from one-shot data without knowing the plant model under noisy conditions. The data-driven method that uses a fictitious reference signal to optimize the gain-scheduled controller has not been examined in previous studies. (ii) To verify the effectiveness of the proposed method, we perform a numerical simulation for nonlinear systems and compare the simulation results obtained using the proposed method with those obtained using the conventional method.
- Advantages: (i) The plant model and trial-and-error design are not required; only the one-shot time-series data are needed, which makes designing the gain-scheduled controller easy. (ii) Compared to the DD-PID, DD-FRIT, and VRFT for Q-learning, the calculation cost related to the proposed method is low. (iii) Compared to the VRFT approach, which is one of the most popular data-driven approaches, the proposed method is more robust to noise.

The direct data-driven tuning for the gain-scheduled controller has been proposed [17], [25], [26], [28]. However, the optimized parameters obtained by VRFT approach are affected by the noise due to the calculation of virtual reference signal which is VRFT's key concept. This is a motivation to adopt the fictitious reference signal in the proposed method. In numerical examples, the proposed method is compared with VRFT approach. The results reveal that the proposed method is less sensitive to noise than the VRFT approach.

The structure of remainder of this paper is as follows. Section II describes preliminary information, including problem setting and FRIT. In section III, we propose a noniterative data-driven design method for a gain-scheduled controller. Section IV presents the numerical simulation. By performing simulations on two nonlinear systems, the effectiveness of the proposed method will be verified. In the proposed method, the parameters are optimized to obtain the desired response by changing the PID gain corresponding to the characteristic variation of the system to be controlled. Additionally, the FRIT-GS (proposed) and VRFT-GS (conventional) methods are compared. Section V describes the conclusion.

II. PRELIMINARY

Here, we describe the problem formulation and FRIT.

A. PROBLEM FORMULATION

The gain-scheduled control illustrated in Fig. 1 is considered in the form of a block diagram, where $r \in R$ is the set-point; $y \in R$ is the plant output; $u \in R$ is the control input; $e(= r - y) \in R$ is the error between the set-point and the plant output; $\rho(t) \in R^m$ is a time-variant controller parameter; $t \in Z$ is the discrete time; $p \in R^{n_p}$ is the scheduling parameter which is the measurable state inputted into the gain scheduler; $C(q, \rho)$ is the controller given as $u = C(q, \rho)\, e$, where q is a shift operator defined by $y(t+1) := qy(t)$; $\rho \in R^{n_m}$ is the time-variant controller parameter; $f(p, w)$ is the scheduling function; $w \in R^{n_w}$ is the tunable gain scheduler parameter. The controlled object P is a nonlinear single-input single-output system, which is described as

$$y(t+1) = f_p\left(y(t), \ldots, y\left(t - n_y\right), u(t), \ldots, u\left(t - n_u\right)\right) \tag{1}$$

where $f_p(\cdot)$ is a nonlinear function which is unknown. Here n_u and n_y are the orders of the input and output, respectively, which are unknown. It is assumed that Eq. (1) is a stable system and it is possible to linearize the system at any equilibrium point. This assumption is satisfied in many industrial systems such as automobile systems. One of the scheduling parameter candidates is the plant states. In general, designing a gain-scheduled controller requires linearizing a nonlinear system. Our aim is to design a gain-scheduled controller without system identification and linearization.

The gain-scheduled controller is given as

$$C(q,\rho) = \rho^T \psi(q) = f(p,w)^T \psi(q) \tag{2}$$

with

$$\begin{aligned} \rho &= \left[\,\rho_1\ \rho_2\ \cdots\ \rho_m\,\right]^T \\ f(p,w) &= \left[f_1(p,w^{\rho_1})\ f_2(p,w^{\rho_2})\ \cdots\ f_m(p,w^{\rho_m})\,\right]^T \\ \psi(q) &= \left[\,\psi_1(q)\ \psi_2(q)\ \cdots\ \psi_m(q)\,\right]^T \\ w &= \left[\,(w^{\rho_1})^T\ (w^{\rho_2})^T\ \cdots\ (w^{\rho_m})^T\,\right]^T \end{aligned} \tag{3}$$

where $\rho \in R^{n_m}$ consisting of $\rho_j \in R$ is a time-variant controller parameter vector; f: $R^{n_p} \times R^{n_w} \rightarrow R^{n_m}$ consisting of f_j: $R^{n_p} \times R^{n_l} \rightarrow R$ is a vector-valued function of the scheduling function for ρ_j; $\psi(q) \in R^{n_m}$ consisting of $\psi_j(q)$ are a rational function vector; $w \in R^{n_w}$ consisting of $w^{\rho_j} \in R^{n_l}$ is the overall parameter vector. $w^{\rho_j} \in R^{n_l}$ is the tuning parameter vector for ρ_j. Here, $n_w = n_m n_l$. In Eqs. (2) and (3), the gain scheduler f: $p \times w \longmapsto \rho$ consists of the scheduling parameters $p \in R^{n_p}$ and the tuning parameters $w \in R^{n_w}$. If the tuning parameters w is determined, the controller parameters (gains) are determined according to the scheduling parameters using the gain scheduler. The detailed settings of the rational function vector $\psi(q)$ are described in Section III.

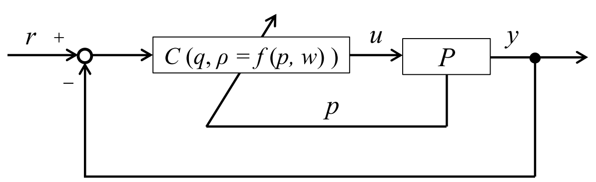

FIGURE 1. Gain-scheduled feedback system.

Similar to previous studies on DD controls, the model-referenced control is considered. Fig. 2 shows a model-referenced gain-scheduled control. We aim to tune the scheduler parameters directly such that the following objective function is minimized:

$$J_{MR}(w) = \frac{1}{N}\sum_{t=1}^{N}\left(y(t,w) - M_d(q)\,r(t)\right)^2. \tag{4}$$

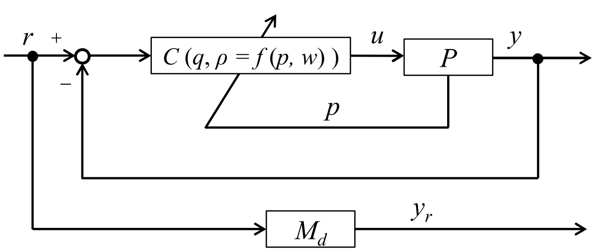

FIGURE 2. Gain-scheduled feedback system with reference model.

This objective function represents that the optimized parameters w are obtained such that the closed-loop characteristics from the set-point value r to the output y matched a reference model M_d defined by a user.

B. FRIT [13]

FRIT is a data-driven design method to tune the parameters of a feedback controller directly from a set of plant input/output data so that the closed-loop system matches the user-defined reference model. Namely, FRIT is a model-free model matching control system design method that minimize the following objective function:

$$J_{MR}(\rho) = \frac{1}{N}\sum_{t=1}^{N}\left(y(t,\rho) - M_d(q)\,r(t)\right)^2 \tag{5}$$

That is, the objective is to make the plant output similar to the response of the reference model. Fig. 3 shows the structure of FRIT. We describe the FRIT procedure using this figure. First, a closed-loop test is conducted with the initial controller parameters that make the system stable, and the input and output time series data $D = \{u_0(t), y_0(t) : t = 1, \ldots, N\}$ are obtained. In the FRIT approach, the fictitious reference signal [14] obtained using the initial input-output time series data is the key element and is calculated as

$$r_f(\rho,t) = C^{-1}(\rho)\,u_0(t) + y_0(t), \tag{6}$$

where C^{-1} is an inverse function of the controller, r_f is a fictitious reference signal, and u_0 and y_0 are initial input/output time series data. Thus, the objective function of FRIT is given as

$$J_{FRIT}(\rho) = \frac{1}{N}\sum_{t=1}^{N}\left(y_0(t) - M_d(q)\,r_f(\rho,t)\right)^2. \tag{7}$$

We obtain the optimized parameters by minimizing this objective function.

Remark 1. A comparison of Eqs. (5) and (7) shows that y and r are replaced by y_0 and r_f, respectively. Thus, FRIT is easier to understand intuitively than other DD approaches [30].

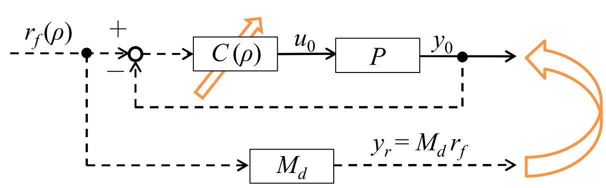

FIGURE 3. FRIT concept.

III. PROPOSED METHOD

A. GAIN-SCHEDULED PID CONTROL

The proposed gain-scheduled PID control, which consists of the velocity form of PID controller and PID gain scheduler, is described here.

1) VELOCITY FORM OF PID CONTROLLER

In the position form of PID controller, if the gain changes abruptly, the control input will change over time, causing disturbances in the system. Thus, we adopt the velocity form of PID the control law which has the advantage that it is not necessary to reset the integral term and that the control input does not change abruptly despite a sudden change in gain. Thus, velocity form is suitable for gain-scheduled control. The block diagram of the velocity from of PID control is shown in Fig. 4. $\Delta = 1-q^{-1}$ is the difference operator; q^{-1} is the backward shift operator such that $q^{-1}y(t) := y(t-1)$. An integrator is located just before the control input and can reduce the time variation of the control input. Furthermore, the integrator is located after the integral gain K_i, and the differential gain K_d is located after the differentiator. When the orders are reversed, it is not preferable due to the large time variation of the input during switching [31]. The control input of the velocity form of PID control is given by

$$u(t) = u(t-1) + C_v(q,\rho)\,e(t) \tag{8}$$

with

$$\begin{aligned} C_v(q,\rho) &= K(t)\psi(q) \\ K(t) &= \left[K_p(t)\ K_i(t)\ K_d(t)\right]^T \\ \psi(q) &= \left[1-q^{-1}\ 1\ (1-q^{-1})^2\right]^T \end{aligned} \tag{9}$$

where $K_p(t)$, $K_i(t)$, and $K_d(t)$ are the proportional, integral, and derivative gains, respectively.

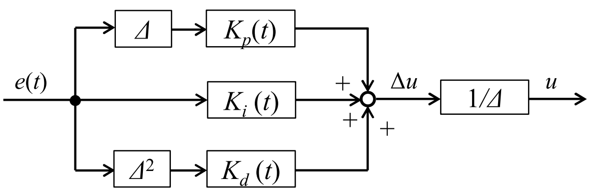

FIGURE 4. Velocity form of the PID controller.

2) PID GAIN SCHEDULER

We adopt a polynomial as the gain scheduler. Implementation of the other methods such as database control [21], just-in-time method [32], and neural networks [33] in mass-produced controllers has been difficult due to limitations in computational cost and ROM capacity. In addition, LUTs are popular gain scheduler approaches in industry, especially in automotive control. However, LUTs require more ROM space and tuning parameters. Additionally, there is concern that LUT-based gain scheduler control, which is designed for each operating point, may cause system instability due to sudden fluctuations in PID gains. Therefore, we express the scheduling function as a polynomial shown in Eq. (10). As a result, the number of parameters to be stored is reduced, and since the gain changes continuously, there is less likelihood of abrupt changes in the gain.

$$\begin{aligned} K_j(p) &= \left(w^{\rho_j}\right)^T p_{sf}(p) \\ w^{\rho_j} &= \left[w_1^{\rho_j}\ w_2^{\rho_j}\ \cdots\ w_l^{\rho_j}\right]^T \\ p_{sf}(p) &= [1\ p_1\ p_1^2\ \cdots\ p_1^{n_\sigma} \\ &\quad 1\ \ p_2\ \ p_2^2\ \ \cdots\ \ p_2^{n_\sigma}\ \ \cdots \\ &\quad \cdots\ 1\ p_{n_p}\ p_{n_p}^2\ \cdots\ p_{n_p}^{n_\sigma}]^T \end{aligned} \tag{10}$$

where $K_j(p) \in R$ is the PID gain scheduler (scheduling function); $p_i \in R$ is the scheduling parameter where $i \in \{1, 2, \ldots, n_p\}$; $p_{sf} \in R^{n_l(=n_p(n_\sigma+1))}$ is the basis function vector composed of the scheduling parameters; $w^{\rho_j} \in R^{n_l}$ is the weighting coefficient vector for each PID gain and acts a tuning parameter. The scheduling parameters are generally state variables including the position and the velocity of the control system, and signals from the external environment, such as temperature.

Remark 2. The basis function vector $p_{sf}(p)$ is designed by selecting the scheduling parameters p_i and the order for p_i. The scheduling parameters are generally set to plant sates. For specific examples, refer to the simulation studies described below.

B. THE OBJECTIVE FUNCTION OF THE PROPOSED METHOD

An objective function was derived to obtain optimal values for the weighting coefficients of the gain scheduling function. From the standard FRIT objective function (Eqs. (7), (8), and (9)) and PID gain scheduler (Eq. (10)), the objective function for gain-scheduled PID control using FRIT (GS-PID-FRIT) is given by

$$J(w) = \frac{1}{N}\sum_{t=1}^{N}\left(y_0(t) - M_d(q)r_f(w;t,u_0,y_0,p_0)\right)^2 \tag{11}$$

with

$$r_f(w;t,u_0,y_0,p_0) = C_v^{-1}(w;t,p_0)\,\Delta u_0 + y_0(t) \tag{12}$$

$$C_v^{-1}(w;t,p_0) = \frac{1}{c_0(p_0) + c_1(p_0)z^{-1} + c_2(p_0)z^{-2}} \tag{13}$$

where

$$\begin{aligned} c_0(p_0) &= K_p(p_0) + K_i(p_0) + K_d(p_0) \\ c_1(p_0) &= -(K_p(p_0) + K_d(p_0)) \\ c_2(p_0) &= K_d(p_0). \end{aligned} \tag{14}$$

Remark 3. By introducing the fictitious reference signal (12), the objective function (11) is composed of the initial data $D=\{u_0(t), y_0(t), p_0(t): t=1,\ldots,N\}$. Thus, the optimized parameters are obtained without the need for repeated tests and system identification of the controlled object. In other words, a noniterative direct data-driven tuning is built.

C. ALGORITHM

We summarize the algorithm for the direct noniterative DD tuning via FRIT approach, which tunes the weighting coefficients of the gain scheduler (scheduling function).

Step 1: Acquire a set of data $D = \{u_0(t),\ y_0(t),\ p_0(t):\ t = 1, \ldots, N\}$ by a closed-loop test.

Step 2: Set the reference model M_d and design scheduling functions Eq. (10).

Step 3: Obtain the weighting coefficients w of the scheduling function to minimize the objective function Eq. (11) by nonlinear optimization.

Remark 4. After optimizing the weighting coefficients w using the above algorithm, the controller is implemented using the PID controller and scheduler shown in Eqs. (8)–(10).

Remark 5. Although the FRIT approach also allows data collection in open-loop tests, most literature on FRIT assumes a closed-loop test. This is because open-loop test may be difficult in industrial systems. The closed-loop test requires some kind of the initial PID gain; however, this is a rare when the characteristics of the system model to be controlled are not known at all, so some initial gain can be obtained. Therefore, a closed-loop test is conducted for simulation studies.

Remark 6. The proposed method does not guarantee the stability of a closed-loop system. However, this is a general problem including VRFT and FRIT approaches which are the representative and popular DD tuning method. In practical situations, a simple control design is required rather than ensuring stability [34]. Also, the stability assurance based on Lyapunov and the small gain theorem may lead to a conservative performance. It is noted that model free adaptive control (MFAC) [35], [36], [37] and noniterative correlation-based tuning (NCbT) [38] are known to ensure the closed-loop stability. However, MFAC is not parameter tuning type data-driven control which includes the proposed method, and there are some design parameters tuned by the user. Thus, the proposed method for controller tuning and MFAC are different approach. NCbT which is data-driven tuning type method can guarantee the closed-loop stability for LTI controller, but the literature [25] points out NCbT approach cannot extend LPV controller.

Remark 7. We compared the proposed method with VRFT-GS, in which the objective function is a convex function. To design the prefilter strictly, the controlled object model should be identified. Furthermore, the computation of the virtual reference signal requires the inverse function of the reference model, thereby amplifying noise. To solve this problem, application of the instrumental variable method can be considered; however, this method will increase the number of tests [11], [39] and the variance of the estimated values. In contrast, since FRIT does not require an inverse function of the reference model, such problems do not occur. In the next section, we compare the effects of noise on FRIT and VRFT approaches via simulation studies. Further, VRFT evaluates the input and FRIT evaluates the output, so that it is remarked that FRIT is easier to understand intuitively [30].

IV. NUMERICAL SIMULATION

To verify the proposed method, numerical simulation is conducted. The controlled objects are two nonlinear systems. The first is a spring–mass system represented by the LPV system, which is often used in industries. Another system is the Hammerstein model [40], which consists of a linear dynamical system and a static nonlinear map. These systems are extensively used for modeling nonlinear systems [41] and verifying the efficacy of the DD controls [21], [22], [23]. The simulation is implemented using a PC (CPU: core i5-8250U 1.6 GHz; RAM: 16GB). MATLAB/Simulink (2021a) is used as the programming language and ode 5 (Dormand-Prince) is employed as the solver. The optimization method uses the Nelder-Mead Simplex Method.

A. APPLICATION TO SYSTEM 1

The proposed method was applied to a LPV spring–mass system, wherein the system parameters vary with the plant output. The sampling period in Simulink is set to 1 ms.

1) SYSTEM DESCRIPTION

The plant, reference model, and gain-scheduled controller used in this section were described as follows: the plant was a spring–mass system with time-varying parameters (Fig. 5), where y, m, c, and k, and represent the system response (displacement), the mass, damping coefficient, and spring stiffness, respectively. These parameters vary with the response of the system. The plant used in the simulation was the system obtained by discretizing the following equation of motion:

$$m(y,t)\frac{d^2y(t)}{dt^2} + c(y,t)\frac{dy(t)}{dt} + k(y,t)\,y(t) = u(t) + v(t) \tag{15}$$

with

$$\begin{aligned} m(y,t) &= 1 + 0.2y(t) \\ k(y,t) &= 5 + 2y(t) + y^2(t) \\ c(y,t) &= 2 + 0.5y(t) \end{aligned} \tag{16}$$

where v is the white noise. The set-point is given by

$$r(t) = \begin{cases} 0.75\ (0 < t \le 10) \\ 2.5\ (10 < t \le 25) \\ 1.5\ (25 < t \le 40) \\ 0.5\ (40 < t \le 50). \end{cases} \tag{17}$$

The reference model with no-overshoot whose time constant is 1 s is given as

$$\begin{aligned} M_d(q) &= \mathrm{c2d}(M_d(s)) \\ M_d(s) &= \frac{1}{s+1} \end{aligned} \tag{18}$$

where c2d is an operator that is transferred from a continuous system to a discrete one. The sampling period of controller is set to 50 ms. The gain scheduler was based on Eq. (10). The scheduling parameter and the basis function are given as

$$p(t) = y(t),$$
$$p_{sf}(p(t)) = \left[\, 1 \;\; p(t) \;\; p^2(t) \,\right]. \tag{19}$$

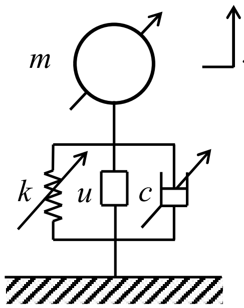

FIGURE 5. Time-varying spring–mass system.

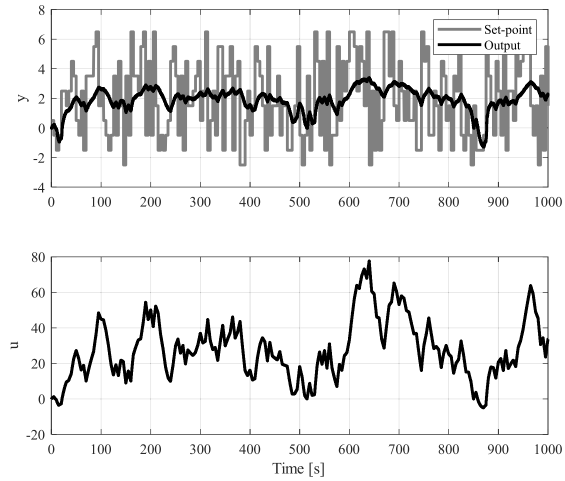

FIGURE 6. Initial input and output data in a closed-loop test for a spring–mass system. The variance of the white noise v is set to 1×10^{-4}. u: control input; y: plant output.

2) RESULTS

Fig. 6 shows the initial input/output time-series data when the closed-loop test was conducted. A random signal was used as the set-point value, and the input/output data at that time were measured. Let v be white noise with a variance of 1×10^{-4}. The gain scheduler parameters were optimized from these data. The calculation times for optimization using FRIT and FRIT-GS were 6.97 s and 29.5 s, respectively. Fig. 7 shows the input/output time-series data with the optimized gain scheduler parameters. For comparison, the fixed PID gain obtained by the standard FRIT is shown in the figure. The optimized PID gains were $K_p = 2.5234$, $K_i = 1.0586$, and $K_d = -1.2163$. The figure shows the output, input, proportional gain, integral gain, and derivative gain (consecutively from the top). The cost value of FRIT-fixed and FRIT-GS are 1.1220×10^{-2} and 1.4401×10^{-3}, respectively. A comparison of the standard FRIT and FRIT-GS shows that FRIT-GS has higher followability because the PID gain varies appropriately with the plant state, and the desired effect is obtained.

Next, we compare the proposed method and VRFT-based gain-scheduled control (VRFT-GS). For VRFT-GS, refer to Appendix and previous literature [7], [28]. The prefilter, which is a design parameter of VRFT-GS, is set to $L = M_d(1 - M_d)$ as proposed in the previous study [11]. For a clearer comparison, the variance of the white noise v is set to 0.01. Fig. 8 shows the initial input/output data when the closed-loop test is conducted under v of 0.05. The optimized parameters are obtained from these time-series data. The calculation times for optimization using VRFT-GS and FRIT-GS were 0.121 s and 26.2 s, respectively. Fig. 9 shows the results of comparison between FRIT-GS and VRFT-GS. The cost values of FRIT-fixed, FRIT-GS, and VRFT-GS are 1.6569×10^{-2}, 1.3331×10^{-2}, and 1.8167×10^{-1}, respectively. The figure shows that while VRFT-GS has a shorter calculation time than FRIT-GS, FRIT-GS has a better tracking performance than VRFT-GS even when the noise is loud.

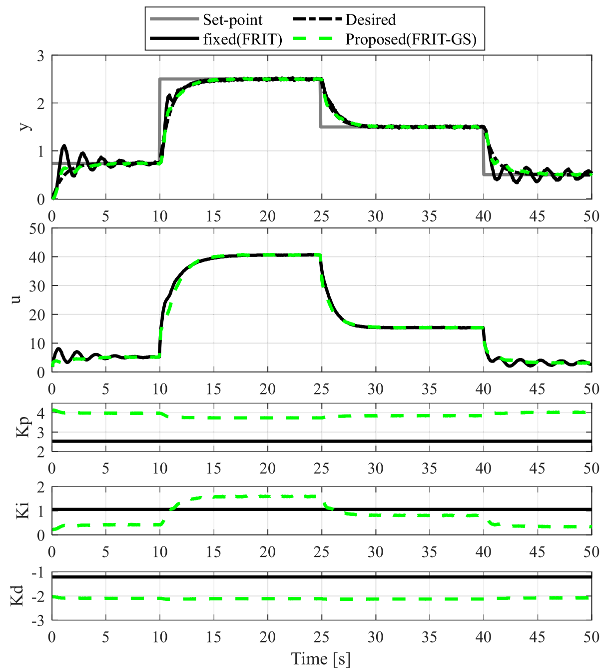

FIGURE 7. Signal trajectory after tuning with the proposed method and fixed PID gain for the spring–mass system. The desired and proposed lines almost overlap. u: control input; y: plant output; K_p: proportional gain; K_i: integral gain; K_d: derivative gain.

We also examined the control performance under colored noise because the noise is often difficult to capture accurately. The pink noise was set as the noise v. Fig. 10 depicts the power spectrum of the pink noise. The noise level was the almost same as that in Fig. 8. The initial data were measured under the noise, and the controller parameters are optimized. Fig. 11 shows the closed-loop test results of FRIT-GS and VRFT-GS. The cost values of FRIT-GS and VRFT-GS were 2.5797×10^{-2} and 5.2397×10^{-1}, respectively. The results show that the proposed method achieved a satisfactory tracking performance under the colored and white noises.

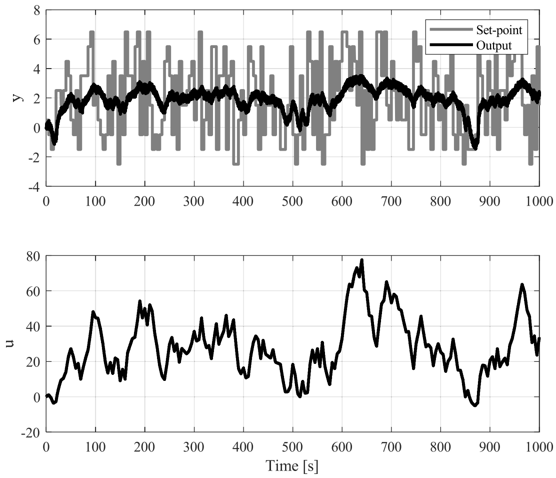

FIGURE 8. Initial input and output data in a closed-loop test for a spring–mass system. The variance of the white noise v is set to 0.01. u: control input; y: plant output.

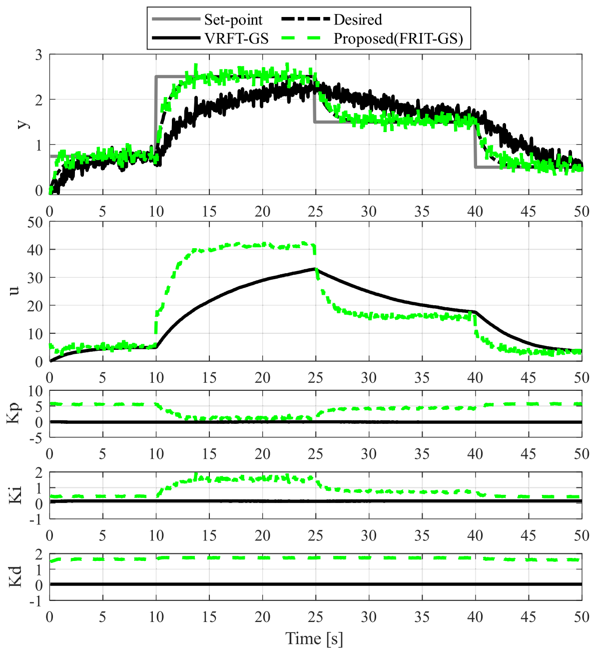

FIGURE 9. Signal trajectory after FRIT-GS and VRFT-GS tuning in a noisy spring–mass system. The desired and proposed lines almost overlap. u: control input; y: plant output; K_p: proportional gain; K_i: integral gain; K_d: derivative gain.

Moreover, the tracking performance under brown noise was almost similar to that shown in Fig. 11.

Remark 8. The simulation results shown in Figs. 6 and 7, verify the effectiveness of the proposed method by comparing the fixed PID controller and the proposed data-driven gain-scheduled controller in the presence of low noise. The proposed method shows better tracking performance than the fixed PID controller.

Remark 9. The simulation results shown in Figs. 8–11 confirm the effectiveness of the proposed method by comparing it to the VRFT approach, which is a state-of-the-art data-driven

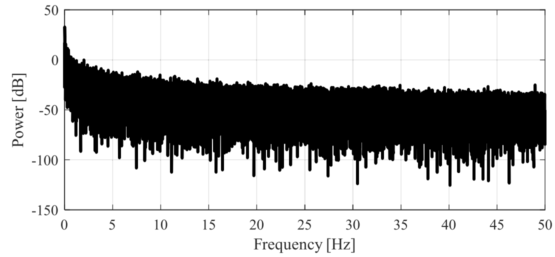

FIGURE 10. Power spectrum of the pink noise used in the spring-mass system simulation.

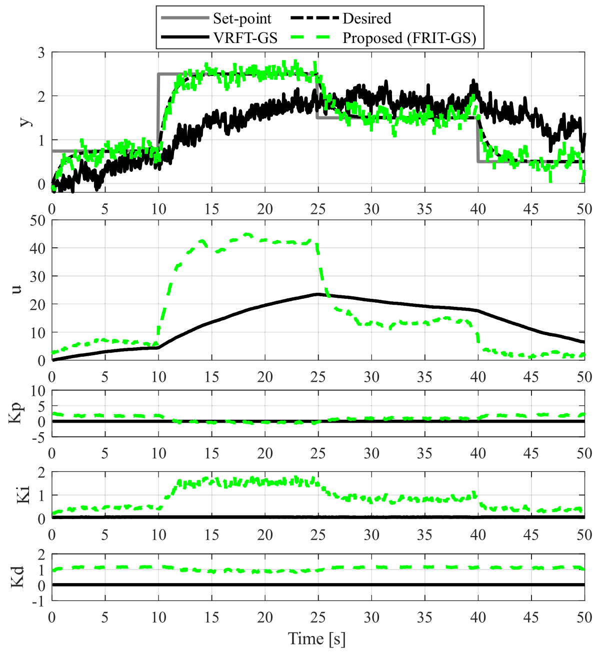

FIGURE 11. Signal trajectory after FRIT-GS and VRFT-GS tuning in a colored noisy spring–mass system. The desired and proposed lines almost overlap. u: control input; y: plant output; K_p: proportional gain; K_i: integral gain; K_d: derivative gain.

control method, under high white/colored noise conditions. The proposed method outperforms the VRFT approach in terms of the tracking performance.

B. APPLICATION TO SYSTEM 2

We adopted the Hammerstein model, which is widely used to describe nonlinear systems, as the controlled object using a system formulation identical to that in previous works [21], [22], [23]. The sampling period in Simulink is set to 1 s.

1) SYSTEM FORMULATION

The Hammerstein model [40] is given as

$$\begin{aligned} y(t) &= 0.6y(t-1) - 0.1y(t-2) + 1.2x(t-1) \\ &\quad - 0.1x(t-2) + v(t) \\ x(t) &= 1.5u(t) - 1.5u^2(t) + 1.5u^3(t) \end{aligned} \tag{20}$$

where v is the white noise. Fig. 12 shows the static characteristics of the controlled object. The sampling period of controller is set to 1 s in this simulation including the controller. The set-point is given by

$$r(t) = \begin{cases} 1.0\ (0 < t \leq 100) \\ 3.5\ (100 < t \leq 200) \\ 2.0\ (200 < t \leq 300) \\ 0.5\ (300 < t \leq 400) \end{cases} \tag{21}$$

The user-defined reference model is set to

$$M_d\left(q^{-1}\right) = \frac{0.399q^{-1}}{1 - 0.736q^{-1} + 0.135q^{-2}}. \tag{22}$$

The gain scheduler adopts Eq. (10), and the scheduling parameter and basis function are given by

$$\begin{aligned} p\,(t) &= y\,(t)\,, \\ p_{sf}\,(p(t)) &= \left[\,1\ p(t)\ p^2(t)\,\right]. \end{aligned} \tag{23}$$

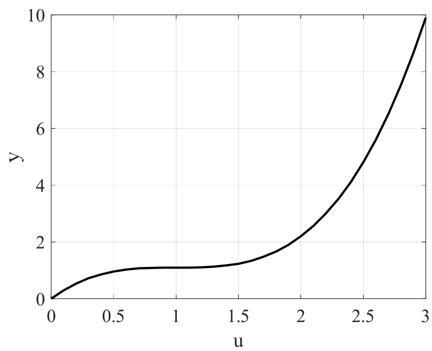

FIGURE 12. Static characteristics of the Hammerstein model. *u*: control input; *y*: plant output.

2) RESULTS

Fig. 13 shows the initial input/output time-series data when the closed-loop test was conducted. The target was assigned a random signal, and the input/output data were measured. The variance of the white noise v was set to 1×10^{-3}. As the feedback controller, a fixed PID controller was used with the optimized PID gains (CHR method): $K_p = 0.059$, $K_i = 0.058$, and $K_d = 0.0038$ [21]. Fig. 14 shows the time series data with the optimized gain scheduler parameters which were obtained from these input/output data. The calculation times for optimization using FRIT and FRIT-GS were 3.48 s and 14.2 s, respectively. The output, input, proportional gain, integral gain, and differential gain are plotted (from top to bottom). For comparison, the time series data with the fixed PID gains optimized by CHR and FRIT methods are shown here. Here, the PID gains optimized by FRIT were $K_p = -0.0401$, $K_i = 0.2740$, and $K_d = 0.1047$. The cost values of CHR, FRIT-fixed, and FRIT-GS are 1.4908×10^{-1}, 1.7330×10^{-2}, and 7.0564×10^{-3}, respectively. The fixed PID control tuned by standard FRIT cannot follow the desired value. The figure confirms that the PID gain via the proposed method varies with the plant state, and the output follows the desired response.

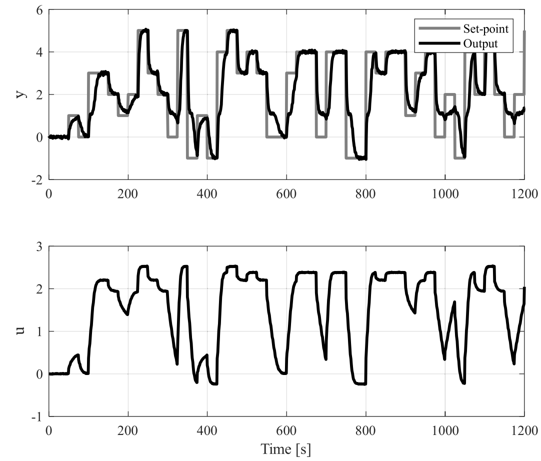

FIGURE 13. Initial input and output data under the closed-loop test when the variance of the white noise v is set to 1×10^{-3}. *u*: control input; *y*: plant output.

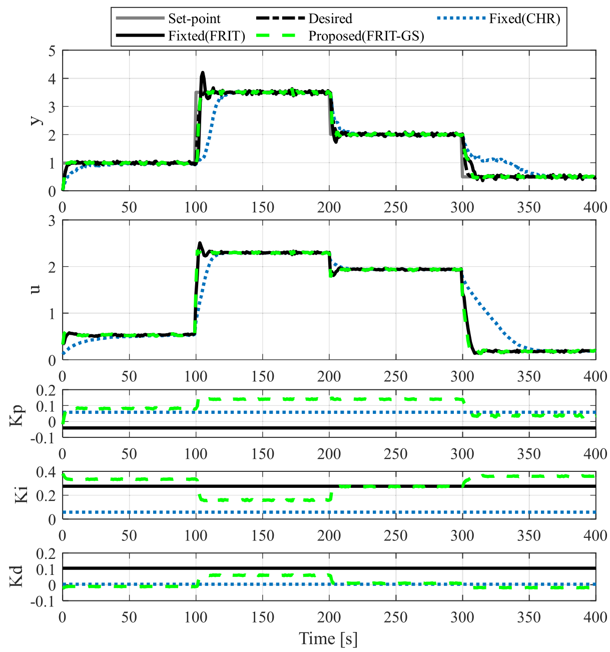

FIGURE 14. Signal trajectory after tuning with the proposed and conventional methods for the Hammerstein model. The desired and proposed lines almost overlap. *u*: control input; *y*: plant output; K_p: proportional gain; K_i: integral gain; K_d: derivative gain.

Next, we compare the proposed method and VRFT-based gain-scheduled control (VRFT-GS). The prefilter—the design parameter of VRFT-GS—is set to $L = M_d(1 - M_d)$ as proposed in previous studies [11]. To further clarify the comparison, the variance of the white noise v is set to 0.05. Fig. 15 shows the initial input/output data when the closed-loop test is conducted under v of 0.05. The optimized parameters are obtained from these time-series data. The calculation times for optimization using VRFT-GS and FRIT-GS were 0.301s and 16.7 s, respectively. Fig. 16 shows the closed-loop test results of FRIT-GS and VRFT-GS. The cost values of FRIT-fixed, FRIT-GS, and VRFT-GS are 8.6676×10^{-2},

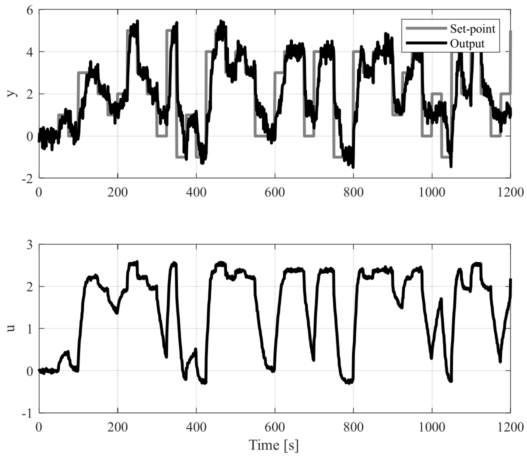

FIGURE 15. Initial input and output data under the closed-loop test when the variance of the white noise v is set to 0.05. u: control input; y: plant output.

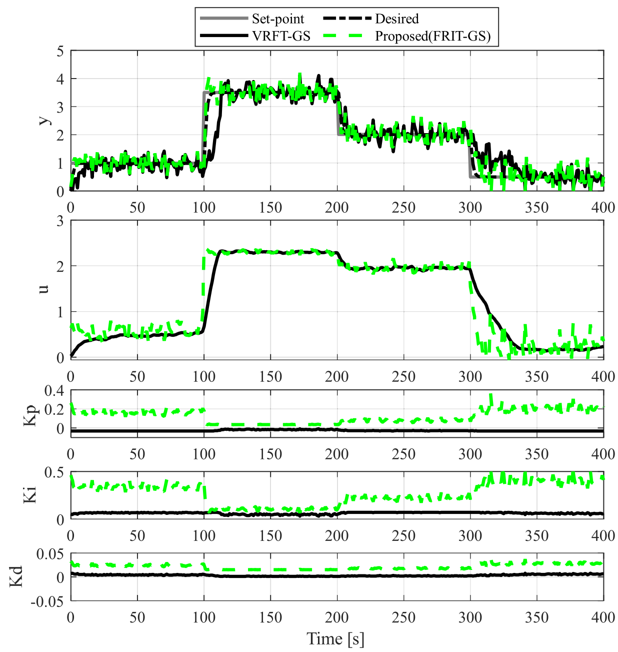

FIGURE 16. Signal trajectory after tuning with FRIT-GS and VRFT-GS in a noisy Hammerstein model. The desired and proposed lines almost overlap. u: control input; y: plant output; K_p: proportional gain; K_i: integral gain; K_d: derivative gain.

8.4334×10^{-2}, and 1.8267×10^{-1}, respectively. According to the figure, while VRFT-GS has a shorter calculation time than FRIT-GS, FRIT-GS has a higher tracking performance than VRFT-GS even when the noise is high.

We also examined the control performance under colored noise because the noise is often difficult to accurately capture. The pink noise was set as the noise v. Fig. 17 illustrates the power spectrum of pink noise. The noise level was similar to that in Fig. 15. The initial data were measured under the noise, and the controller parameters were then optimized. Fig. 18 shows the closed-loop test results of FRIT-GS and VRFT-GS.

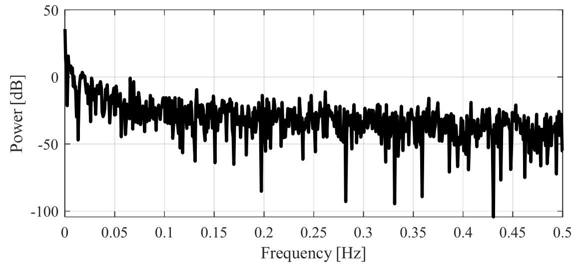

FIGURE 17. Power spectrum of the pink noise used in the Hammerstein model simulation.

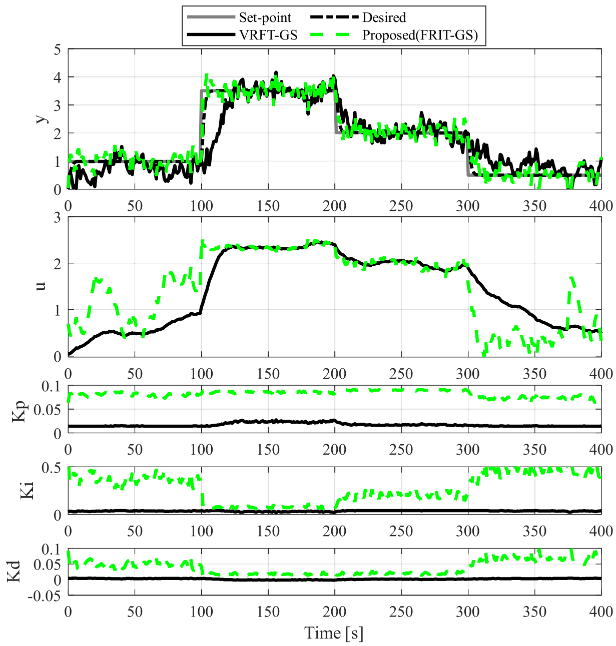

FIGURE 18. Signal trajectory after FRIT-GS and VRFT-GS tuning in a colored noisy Hammerstein model. The desired and proposed lines almost overlap. u: control input; y: plant output; K_p: proportional gain; K_i: integral gain; K_d: derivative gain.

The cost values of FRIT-GS and VRFT-GS were 7.7257×10^{-2} and 2.7962×10^{-1}, respectively. The results show that the proposed method achieved a satisfactory tracking performance under the colored and white noises. The tracking performance under brown noise was almost similar to that shown in Fig. 18.

Remark 10. The simulation results shown in Figs. 13 and 14 confirm the effectiveness of the proposed method by comparing the fixed PID controller to the proposed data-driven gain-scheduled controller under low noise conditions. The proposed method shows better tracking performance than fixed PID controller.

Remark 11. The simulation results shown in Figs. 15–18 confirm the effectiveness of the proposed method by comparing it to the VRFT approach, which is a state-of-the-art data-driven control, under high noise conditions. The proposed method shows better tracking performance compared to the VRFT approach.

C. DISCUSSION

The simulation results for two nonlinear systems confirmed that FRIT-GS (the proposed method) has better tracking performance than the conventional FRIT. In other words, by using the scheduling parameters optimized by FRIT-GS, the PID gains changed appropriately according to the state of the plant; therefore, the actual response follows the desired response generated by the reference model. In addition, FRIT-GS and VRFT-GS were compared under loud white and colored noises. Moreover, a correlation exists between the initial input and output data because the data was obtained through the closed-loop test. The results showed that FRIT-GS realized satisfactory high tracking performance, but VRFT-GS could not follow the desired response because of the noise. This shortcoming of VRFT-GS is attributed to the virtual reference signal used in VRFT. This virtual reference signal is obtained by multiplying the output signal obtained in the initial data by the inverse function of the reference model (see Eq. (24) shown in appendix). Then, the output noise increases because the inverse function of the reference model has high-pass characteristics. Hence, the VRFT approach could not obtain suitable parameters. Thus, we demonstrated that the proposed method (FRIT-GS) can realize higher control performance than fixed PID control and provide good results even in a noisy environment. The optimization time of proposed method was $\sim$30 s, which is considered to be a practically reasonable time.

V. CONCLUSION

This paper proposed a noniterative DD design method for a gain-scheduled PID controller without system identification via an approach using a fictitious reference signal. In this method, the gain scheduler (scheduling function) adopts polynomial function, and the tunable weighting factors of the gain scheduler are obtained based on the FRIT framework. The proposed method made it possible to directly design a gain-scheduled PID controller without obtaining a controlled plant model from one-shot data. To confirm the effectiveness of this method, the numerical simulation for two types of nonlinear systems was conducted. Thus, we confirmed that the tunable parameters of the gain scheduler can be optimized without knowing the system model to be controlled. In addition, high tracking performance was achieved even in a noisy environment. The proposed method features rapid automatic parameter tuning without trial and error. The future work will include theoretical and application extensions of the proposed method. We aim to achieve theoretical stability which is guaranteed by incorporating the method presented in [42] and [43]. For the application extensions, we plan to apply the proposed design method to nonlinear industrial systems such as automobile systems, which include powertrains [18], drivetrains [7], and vehicle dynamics controls [17], [44]. Moreover, we aim to extend the proposed design method to highly more complex systems, including an event-triggered multiagent control [45] and an uncertain networked system [46].

APPENDIX

A. VRFT [11]

Herein, the VRFT is briefly explained. Firstly, the virtual reference signal is expressed as:

$$r_v(t) = M_d^{-1} y_0(t). \tag{24}$$

Using $r_v(t)$, the VRFT objective function is expressed as:

$$J_{VR}(\rho) = \frac{1}{N}\sum_{t=1}^{N}\left(u_0(t) - u_v(t)\right)^2, \tag{25}$$

where

$$u_v(t) = C(\rho, z)\left(r_v(t) - y_0(t)\right). \tag{26}$$

By adding the prefilter L, we can express the VRFT objective function as

$$J_{VR}(\rho) = \frac{1}{N}\sum_{t=1}^{N}\left(u_L(t) - C(\rho, q)\, e_L(t)\right)^2 \tag{27}$$

with

$$u_L(t) = Lu_0(t),\ e_L(t) = L\left(r_v(t) - y_0(t)\right). \tag{28}$$

B. VRFT-GS

Here, we describe the VRFT for gain-scheduled controller [7], [28]. FRIT-GS was compared with VRFT-GS (Section IV). The objective function of VRFT-GS is given as:

$$J(w) = \frac{1}{N}\sum_{t=1}^{N}\left(d(t) - w^T\xi(t)\right)^2 \tag{29}$$

with

$$\begin{aligned} d(t) &= L\Delta u(t) \\ \xi(t) &= X\left(M_d^{-1}(q) - I\right)Ly(t). \end{aligned} \tag{30}$$

Here,

$$w = \left[\, w_p\ w_i\ w_d \,\right]^T \tag{31}$$

$$X = \left[\, p_{sf}^T\psi_1(q)\ p_{sf}^T\psi_2(q)\ p_{sf}^T\psi_3(q) \,\right]^T \tag{32}$$

where ψ_i is the $i-$ th element of the vector ψ, as shown in Eq. (9). Since the objective function is convex, the least-squares (LS) method provides the optimal solution:

$$w^* = \left(\Xi^T\Xi\right)^{-1}\Xi^T D \tag{33}$$

with

$$\Xi = \left[\, \xi(1)\ \xi(2)\ \cdots\ \xi(N) \,\right]^T \tag{34}$$

$$D = \left[\, d(1)\ d(2)\ \cdots\ d(N) \,\right]^T \tag{35}$$

LIST OF SYMBOLS

Symbol	Description
C	Controller
P	Controlled object (plant)
M_d	Reference model
C^{-1}	Inverse function of the controller
L	Prefilter
t	Time
q	Shift operator
$\Delta(= 1 - q^{-1})$	Difference operator
s	Laplace operator
r	Set-point signal
y	Plant output signal
u	Control input signal
$e(= r - y)$	Error between set-point and plant-output
ρ	Controller parameter vector
p	Scheduling parameter vector
p_{sf}	Basis function vector
f_p	Nonlinear map
n_u	The order of control input
n_y	The order of plant output
f	Scheduling function
w	Tunable gain scheduler parameter vector
ψ	Rational function vector
J	Objective function
N	Data length
n_w	The number of overall tunable parameters
n_p	The number of scheduling parameters
n_m	The number of controller parameters
n_l	The number of tunable parameters for ρ_j
r_f	Fictitious reference signal
u_0	Initial input signal
y_0	Initial output signal
r_v	Virtual reference signal
u_v	Virtual control input signal
K	PID gain vector
K_p	Proportional gain
K_i	Integral gain
K_d	Derivative gain

REFERENCES

[1] F. Shahni, W. Yu, and B. Young, "Rapid estimation of PID minimum variance," *ISA Trans.*, vol. 86, pp. 227–237, Mar. 2019.

[2] H. Zhang, W. Assawinchaichote, and Y. Shi, "New PID parameter autotuning for nonlinear systems based on a modified monkey–multiagent DRL algorithm," *IEEE Access*, vol. 9, pp. 78799–78811, 2021.

[3] K. J. Åström and T. Hägglund, "The future of PID control," *Control Eng. Pract.*, vol. 9, no. 11, pp. 1163–1175, 2001.

[4] E. B. Ondes, I. Bayezit, I. Poergye, and A. Hafsi, "Model-based 2-D look-up table calibration tool development," in *Proc. 11th Asian Control Conf. (ASCC)*, Gold Coast, QLD, Australia, Dec. 2017, pp. 1011–1016.

[5] C. Guardiola, B. Pla, D. Blanco-Rodriguez, and P. Cabrera, "A learning algorithm concept for updating look-up tables for automotive applications," *Math. Comput. Model.*, vol. 57, nos. 7–8, pp. 1979–1989, Apr. 2013.

[6] S. Yahagi and I. Kajiwara, "Direct data-driven tuning of look-up tables for feedback control systems," *IEEE Control Syst. Lett.*, vol. 6, pp. 2966–2971, 2022.

[7] S. Yahagi and I. Kajiwara, "Direct tuning of gain-scheduled controller for electro-pneumatic clutch position control," *Adv. Mech. Eng.*, vol. 13, no. 7, pp. 1–12, 2021.

[8] Z.-S. Hou and Z. Wang, "From model-based control to data-driven control: Survey, classification and perspective," *Inf. Sci.*, vol. 235, pp. 3–35, Jun. 2013.

[9] K. Prag, M. Woolway, and T. Celik, "Toward data-driven optimal control: A systematic review of the landscape," *IEEE Access*, vol. 10, pp. 32190–32212, 2022.

[10] G. O. Guardabassi and S. M. Savaresi, "Virtual reference direct design method: An off-line approach to data-based control system design," *IEEE Trans. Autom. Control*, vol. 45, no. 5, pp. 954–959, May 2000.

[11] M. C. Campi, A. Lecchini, and S. M. Savaresi, "Virtual reference feedback tuning: A direct method for the design of feedback controllers," *Automatica*, vol. 38, no. 8, pp. 1137–1146, 2002.

[12] S. Soma, O. Kaneko, and T. Fujii, "A new method of controller parameter tuning based on input-output data—Fictitious reference iterative tuning (FRIT)," *IFAC Proc. Volumes*, vol. 37, no. 12, pp. 789–794, Aug. 2004.

[13] O. Kaneko, "Data-driven controller tuning: FRIT approach," *IFAC Proc. Volumes*, vol. 46, no. 11, pp. 326–336, 2013.

[14] M. G. Safonov and T.-C. Tsao, "The unfalsified control concept: A direct path from experiment to controller," in *Feedback Control, Nonlinear Systems, and Complexity*. Berlin, Germany: Springer-Verlag, 1995, pp. 196–214.

[15] M. Nakamoto, "An application of the virtual reference feedback tuning method to a multivariable process control," *IFAC Proc. Volumes*, vol. 38, no. 1, pp. 237–242, 2005.

[16] M. Kano and M. Ogawa, "The state of the art in chemical process control in japan: Good practice and questionnaire survey," *J. Process Control*, vol. 20, no. 9, pp. 969–982, Oct. 2010.

[17] S. Formentin, G. Panzani, and S. M. Savaresi, "VRFT for LPV systems: Theory and braking control application," in *Robust Control and Linear Parameter Varying Approaches*. Berlin, Germany: Springer-Verlag, 2013, pp. 289–309.

[18] T. E. Passenbrunner, S. Formentin, S. M. Savaresi, and L. D. Re, "Direct multivariable controller tuning for internal combustion engine test benches," *Control Eng. Pract.*, vol. 29, pp. 115–122, Aug. 2014.

[19] T. Kinoshita, Y. Ohnishi, T. Yamamoto, and S. L. Shah, "Design of a data-oriented performance driven control system based on the generalized minimum variance control law," *Ind. Eng. Chem. Res.*, vol. 58, no. 26, pp. 11440–11451, Jul. 2019.

[20] S. Yahagi, I. Kajiwara, and T. Shimozawa, "Slip control during inertia phase of clutch-to-clutch shift using model-free self-tuning proportional-integral-derivative control," *Proc. Inst. Mech. Eng. D, J. Automobile Eng.*, vol. 234, no. 9, pp. 2279–2290, Aug. 2020.

[21] T. Yamamoto, K. Takao, and T. Yamada, "Design of a data-driven PID controller," *IEEE Trans. Control Syst. Technol.*, vol. 17, no. 1, pp. 29–39, Jan. 2009.

[22] S. Wakitani, Y. Ohnishi, and T. Yamamoto, "Design of FRIT-based nonlinear PID control systems," *J. Soc. Instrum. Control Eng.*, vol. 52, no. 10, pp. 885–891, 2013.

[23] S. Wakitani, K. Nishida, M. Nakamoto, and T. Yamamoto, "Design of a data-driven PID controller using operating data," *IFAC Proc. Volumes*, vol. 46, no. 11, pp. 587–592, 2013.

[24] F. Tsukui and S. Masuda, "Data-driven control parameter tuning using feedback linearization," *IEEJ Trans. Electron., Inf. Syst.*, vol. 137, no. 7, pp. 891–897, 2017.

[25] S. Formentin, D. Piga, R. Tóth, and S. M. Savaresi, "Direct learning of LPV controllers from data," *Automatica*, vol. 65, pp. 98–110, Mar. 2016.

[26] S. Formentin and S. M. Savaresi, "Virtual reference feedback tuning for linear parameter-varying systems," *IFAC Proc. Volumes*, vol. 44, no. 1, pp. 10219–10224, Jan. 2011.

[27] M.-B. Radac, R.-E. Precup, and R.-C. Roman, "Data-driven model reference control of MIMO vertical tank systems with model-free VRFT and *Q*-learning," *ISA Trans.*, vol. 73, pp. 227–238, Feb. 2018.

[28] S. Yahagi and I. Kajiwara, "Direct tuning method of gain-scheduled controllers with the sparse polynomials function," *Asian J. Control*, vol. 24, no. 5, pp. 2111–2126, Sep. 2022.

[29] S. Yahagi and I. Kajiwara, "Non-iterative data-driven tuning of model-free control based on an ultra-local model," *IEEE Access*, vol. 10, pp. 72773–72784, 2022.

[30] O. Kaneko, "On basics and future developments of FRIT from viewpoints of tracking for desired responses," *IEEJ Trans. Electron., Inf. Syst.*, vol. 132, no. 6, pp. 816–819, 2012.

[31] M. Saeki and K. Ogawa, "Gain scheduled PID controller design by data-driven loop-shaping method," *IEEJ Trans. Electron., Inf. Syst.*, vol. 131, no. 4, pp. 758–763, 2011.
[32] A. Stenman, F. Gustafsson, and L. Ljung, "Just in time models for dynamical systems," in *Proc. 35th IEEE Conf. Decis. Control*, Dec. 1996, pp. 1115–1120.
[33] C. Bishop, *Pattern Recognition and Machine Learning* (Information Science and Statistics). New York, NY, USA: Springer-Verlag, 2006.
[34] P. Polack, S. Delprat, and B. d'Andréa-Novel, "Brake and velocity model-free control on an actual vehicle," *Control Eng. Pract.*, vol. 92, Nov. 2019, Art. no. 104072.
[35] Z. Hou and S. Jin, "Data-driven model-free adaptive control for a class of MIMO nonlinear discrete-time systems," *IEEE Trans. Neural Netw.*, vol. 22, no. 12, pp. 2137–2188, Dec. 2011.
[36] X. Zhang, H. Ma, X. Zhang, and Y. Li, "Compact model-free adaptive control algorithm for discrete-time nonlinear systems," *IEEE Access*, vol. 7, pp. 141062–141071, 2019.
[37] K. Deng, F. Li, and C. Yang, "A new data-driven model-free adaptive control for discrete-time nonlinear systems," *IEEE Access*, vol. 7, pp. 126224–126233, 2019.
[38] K. van Heusden, A. Karimi, and D. Bonvin, "Data-driven model reference control with asymptotically guaranteed stability," *Int. J. Adapt. Control Signal Process.*, vol. 25, no. 4, pp. 331–351, Apr. 2011.
[39] S. Formentin, S. M. Savaresi, and L. D. Re, "Non-iterative direct data-driven controller tuning for multivariable systems: Theory and application," *IET Control Theory Appl.*, vol. 6, no. 9, pp. 1250–1257, 2012.
[40] L. Zi-Qiang, "On identification of the controlled plants described by the Hammerstein system," *IEEE Trans. Autom. Control*, vol. 39, no. 3, pp. 569–573, Mar. 1994.
[41] H. Tanaka and S. Hazue, "Identification of a Hammerstein model equipped with a static nonlinear odd function," *Trans. Inst. Syst., Control Inf. Eng.*, vol. 20, no. 11, pp. 430–438, 2007.
[42] S. Yahagi and I. Kajiwara, "Direct tuning of the data-driven controller considering closed-loop stability based on a fictitious reference signal," *Meas. Control*, vol. 54, nos. 5–6, pp. 1026–1042, May 2021.
[43] S. Engell, T. Tometzki, and T. Wonghong, "A new approach to adaptive unfalsified control," in *Proc. Eur. Control Conf. (ECC)*, Kos, Greece, Jul. 2007, pp. 1328–1333.
[44] S. Yahagi and M. Suzuki, "Intelligent PI control based on the ultra-local model and Kalman filter for vehicle yaw-rate control," *SICE J. Control, Meas., Syst. Integr.*, pp. 1–10, Feb. 2023, doi: 10.1080/18824889.2023.2174648.
[45] L. Cao, Y. Pan, H. Liang, and T. Huang, "Observer-based dynamic event-triggered control for multiagent systems with time-varying delay," *IEEE Trans. Cybern.*, vol. 53, no. 5, pp. 3376–3387, May 2023, doi: 10.1109/TCYB.2022.3226873.
[46] H. Liang, L. Chen, Y. Pan, and H. Lam, "Fuzzy-based robust precision consensus tracking for uncertain networked systems with cooperative–antagonistic interactions," *IEEE Trans. Fuzzy Syst.*, vol. 31, no. 4, pp. 1362–1376, Apr. 2023.

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