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A METHOD TO DESIGN PID CONTROLLERS USING FRIT-PSO

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Abstract- This paper proposes the Fictitious Reference Iterative Tuning-Particle Swarm Optimization (FRIT-PSO) method to design PID controllers for feedback control systems. The proposed method is an offline PID parameter tuning method. Moreover it is not necessary to derive any mathematical models of objected control systems. The proposed method is demonstrated by comparing with the FRIT method in numerical examples and an experiment.

Index terms*:* PID control, feedback control systems, iterative methods, fictitious reference iterative tuning, particle-swarm optimization, DC motors.

I. INTRODUCTION

Recently it is strongly needed to improve productivity and cost-saving in some process industries, which are chemical process, oil process and steel process and so on. Moreover power systems are one of large-scale plants with PI control[1][2]. In these process control systems, PID controllers are embedded to achieve stability and some performances. The PID controller is described as the following form and only three parameters K_P, K_I, K_D are designed.

$$C(s) = K_P + \frac{K_I}{s} + sK_D. \tag{1}$$

Because the performances of the control system are directly dependent to K_P, K_I, K_D, the design of the PID parameters is very important [3].

Traditionally PID controllers are designed based on dynamical models of the considered systems [4][5]. The models are described as simple transfer functions such as first-order systems with a time-delay. In the papers [6-12], general transfer functions are considered and PID controllers can be designed based on the Bode plots. H-infinity controllers are designed based on the transfer functions of magnetic bearings in the paper [13-15]. Recently PID design methods using optimization techniques have been pointed out [16][17]. However usual process control systems are difficult to derive exact transfer functions of the considered systems.

Therefore data-driven PID design techniques have been focused on [18-22]. In the data-driven PID design method, mathematical models of the considered control systems are not necessary at all although the reference model is one of design parameters. Because the data-driven PID design techniques are based on iterative methods [23-25], the design can be reduced to a problem by using optimization techniques [26][27]. By using only input and output data for the considered control systems, given performance indices which depends on PID parameters are optimized. One of data-driven PID design techniques is FRIT (Fictitious Reference Iterative Tuning) which is proposed in the paper [28][29]. The advantage of FRIT is that PID tuning is offline and possible based on a set of one-shot data. However FRIT has a disadvantage such that local solutions are easy to obtain after PID tuning because the nonlinear and non-convex optimization problem is considered.

In this paper, FRIT and an optimization technique, that is particle swarm optimization (PSO)[30], is applied to data-driven PID design and the FRIT-PSO method is proposed. Firstly the disadvantage of the FRIT is revealed based on the developed networked control system [31][32]. Secondly it is shown that the disadvantage of FRIT is solved by using the proposed FRIT-PSO in the numerical example. Moreover it is demonstrated that FRIT-PSO achieves better performances than FRIT in an experiment. In the experiment, the angular speed control of a DC-motor with Arduino [33] is carried out.

II. OPTIMIZATION PROBLEM IN FRIT

a. *A set of input and output data*

The control system is shown in the Fig. 1. Here assume that the control object is described as *P*(s) in Fig. 1 but the mathematical model of *P*(s) is not known in advance or is not necessary. Since PID gains are design parameters, the PID controller in the equation (1) is described as the following form.

$$C(\rho, s) = \rho_1 + \frac{\rho_2}{s} + s\rho_3,$$
$$\rho = \begin{bmatrix} \rho_1 & \rho_2 & \rho_3 \end{bmatrix}^T = \begin{bmatrix} K_P & K_I & K_D \end{bmatrix}^T.$$

In the figure 1, the reference signal is r, the control input is u and the output is y. A reference model is given as T_d(s) and the error signal between y and T_d(s)r(s) is defined as e. It is assumed that a one-shot data set $\{u_0, y_0\}$ is given in advance by using an initial PID parameter ρ^0. The data u_0 is time series of the control input and y_0 is time series of the output by using ρ^0.

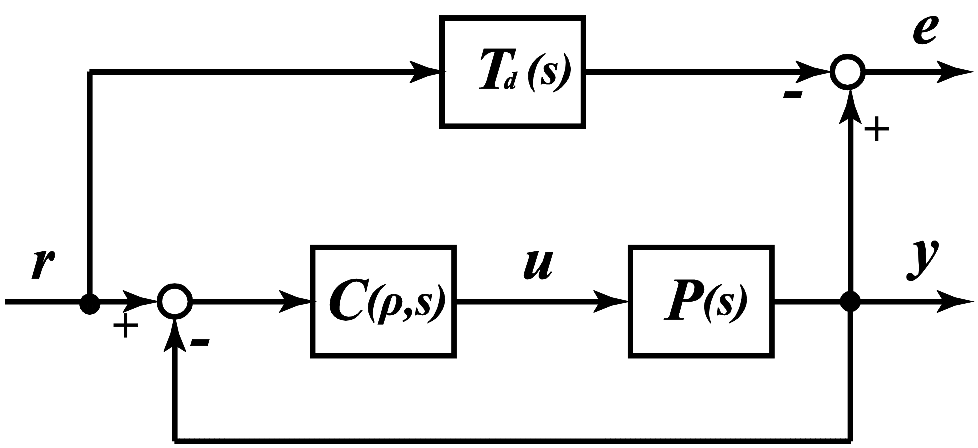


Figure 1. Feedback control systems and reference models

b. *Optimization problem in FRIT*
Since the reference model is given as T_d(s) in Fig. 1, the error signal can be described as

$$e(\rho, s) = y(s) - T_d(s)r(s),$$

and this equation can be described as

$$e(\rho, s) = (T(\rho, s) - T_d(s))r(s),$$

where the transfer function $T(\rho, s)$ from r to y is given as the following equation.

$$T(\rho, s) = \frac{P(s)C(\rho, s)}{1 + P(s)C(\rho, s)}.$$

Here strongly note that $T(\rho, s)$ is not known because P(s) is not known in advance. The main optimization problem is to find the following optimal parameter based on the data set $\{u_0, y_0\}$ only. The quadratic form of the error signal is considered as the performance index because the purpose of the PID design problem is to minimize the error signal.

$$\begin{aligned} \rho^* &= \arg\min_{\rho} J(\rho), \\ J(\rho) &= \int_0^\infty e(\rho, t)^2 dt, \\ e(\rho, t) &= L^{-1}[e(\rho, s)], \end{aligned} \tag{2}$$

where L means the Laplace transform and L^{-1} means the inverse Laplace transform. This optimization problem is difficult to solve.

On the FRIT, the following fictitious reference signal is introduced to solve the optimization problem in the equation (2).

$$\tilde{r}(\rho, s) = C(\rho, s)^{-1} u_0 + y_0.$$

Moreover a new error signal and a new performance index are defined as the following forms.

$$\begin{aligned} \tilde{e}(\rho, s) &= y_0 - T_d(s)\tilde{r}(\rho, s), \\ \tilde{J}(\rho) &= \int_0^\infty \tilde{e}(\rho, t)^2 dt, \\ \tilde{e}(\rho, t) &= L^{-1}[\tilde{e}(\rho, s)]. \end{aligned} \tag{3}$$

Then the fictitious optimization problem is defined as follows,

$$\rho^* = \arg\min_{\rho} \tilde{J}(\rho), \tag{4}$$

instead of the main problem defined in the equation (2).

c. *Gradient method in FRIT*

To compute the optimal solution ρ^* in the equation (4), the iterative method is given as the equation (5). This is same as the steepest descent method [26][27].

$$\rho^{i+1} = \rho^i - \alpha^i R(\rho^i)^{-1} \left.\frac{\partial \widetilde{J}(\rho)}{\partial \rho}\right|_{\rho=\rho^i} \tag{5}$$

where

$$\alpha^i = diag(\gamma_1, \gamma_2, \gamma_3)$$

$$R(\rho^i) = \left(\left.\frac{\partial \widetilde{J}(\rho)}{\partial \rho}\right|_{\rho=\rho^i} \right)^T \left(\left.\frac{\partial \widetilde{J}(\rho)}{\partial \rho}\right|_{\rho=\rho^i} \right), \tag{6}$$

$$\left.\frac{\partial \widetilde{J}(\rho)}{\partial \rho}\right|_{\rho=\rho^i} = 2\int_0^\infty \left.\frac{\partial \widetilde{e}(\rho,t)}{\partial \rho}\right|_{\rho=\rho^i} \widetilde{e}(\rho^i,t)dt, \tag{7}$$

for $\gamma_1 > 0, \gamma_2 > 0, \gamma_3 > 0$. In the equation (7), the partial differential term of the fictitious error signal defined by the equation (3) is same as the next equation

$$L\left[\left.\frac{\partial \widetilde{e}(\rho,t)}{\partial \rho}\right|_{\rho=\rho^i} \right] = \left.\frac{\partial}{\partial \rho}(y_0 - T_d(s)\widetilde{r}(\rho,s))\right|_{\rho=\rho^i},$$

and the calculated result is given as the following equation.

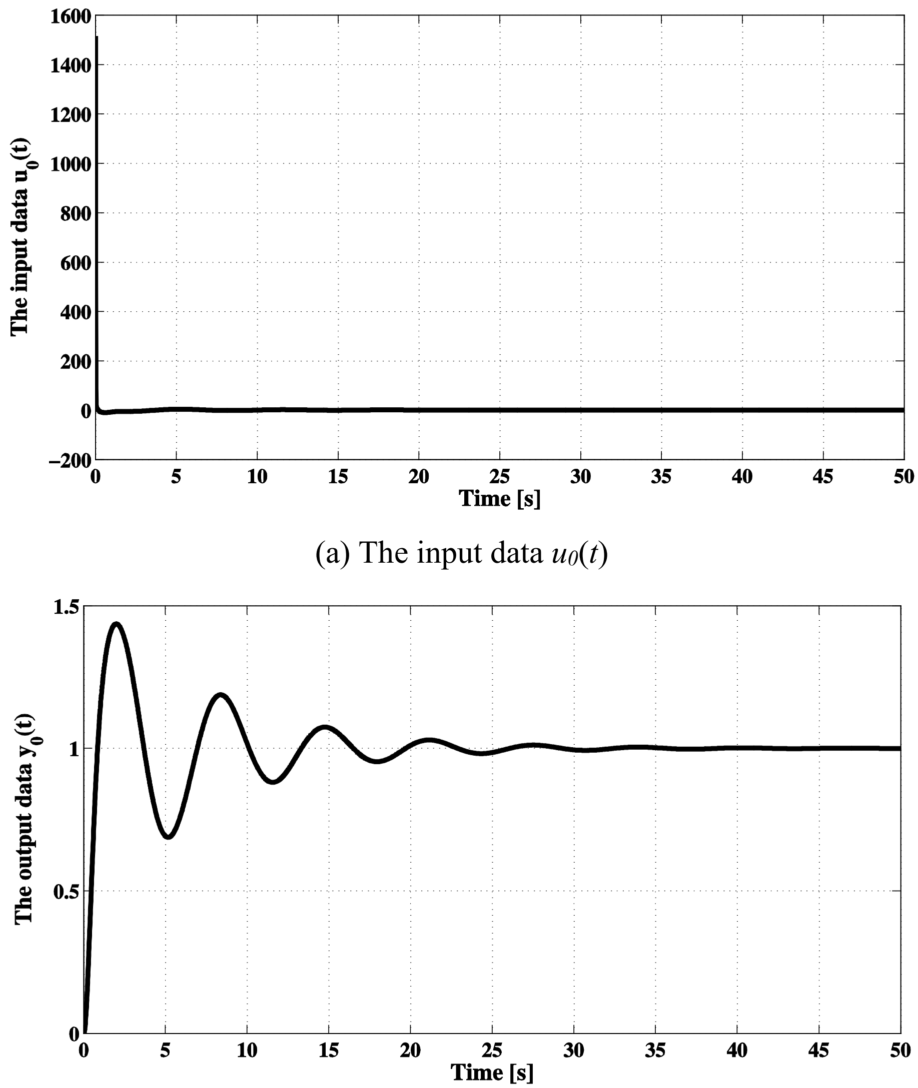
$$L\left[\left.\frac{\partial \widetilde{e}(\rho,t)}{\partial \rho}\right|_{\rho=\rho^i} \right] = T_d(s)\frac{1}{C(\rho^i,s)^2} \left.\frac{\partial C(\rho,s)}{\partial \rho}\right|_{\rho=\rho^i} u_0. \tag{8}$$

It is possible to compute the equation (6) offline because the equations (7) and (8) can be computed offline by using the data set $\{u_0, y_0\}$ and the reference model $T_d(s)$. Thus the iteration in the equation (5) can be computed offline and suboptimal solutions are obtained because the optimization problem in the equation (4) with (3) is nonlinear and non-convex.

d. *Motivated numerical examples*

Now we consider the vehicle system considered in the paper [31][32] and assume that the input and output data $\{u_0, y_0\}$ is obtained in the figure 2 in advance. The figure 2(a) is the input data $u_0(t)$ and the figure 2(b) is the output data $y_0(t)$. The PID parameter is given as $\rho = [15 \quad 15 \quad 15]^T$. Based on the paper [7], we consider the following reference model which is described as the 3-order system to avoid overshoot in the reference response.

$$T_s(s) = \frac{1}{\frac{1}{256}s^3 + \frac{3}{8}s^2 + s + 1} \tag{9}$$



(a) The input data $u_0(t)$

(b) The output data $y_0(t)$

Figure 2. A data set $\{u_0, y_0\}$($\rho = [15 \quad 15 \quad 15]^T$)

The maximum number of iteration of FRIT is 1000 and the gain a^i is given adequately in the equation (5). Then the following PID parameter and the fictitious performance index based on FRIT are obtained.

$$\rho^* = [9.60 \quad 0.93 \quad 9.84]^T, \tilde{J}(\rho^*) = 0.0174.$$

The figure 3 shows the output signals based on FRIT. The black dotted line denotes the reference response, the blue dashed line denotes the output signal before FRIT and the red solid line denotes the output signal after FRIT. We can see that the output signals are improved after FRIT. However it seems that the PID tuning is not enough since the output signal after FRIT is not fitted with the reference response.

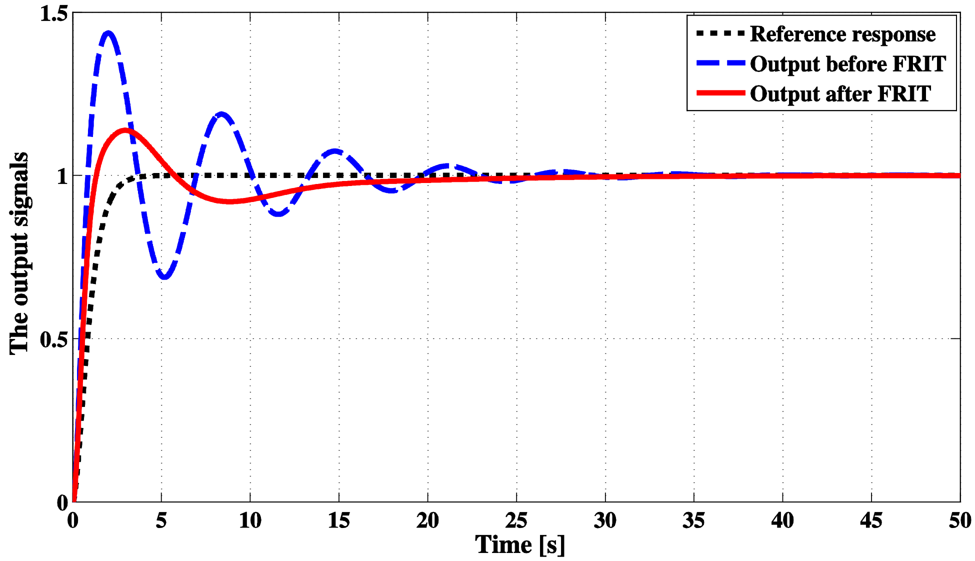


Figure 3. The reference response and the output signals before and after FRIT

The figure 4 shows the output signals applying FRIT in 3 different cases. The black dotted line denotes the reference response. The case 1 means FRIT using $\rho^0 = [15 \quad 15 \quad 15]^T$. The red solid line denotes the output signal in case 1. The case 2 means FRIT using $\rho^0 = [20 \quad 20 \quad 20]^T$. The green dashed line denotes the output signal in case 2 and the following PID parameter and the fictitious performance index are obtained.

$$\rho^* = [9.61 \quad 0.92 \quad 9.80]^T, \tilde{J}(\rho^*) = 0.0174.$$

The case 3 means FRIT using $\rho^0 = [10 \quad 10 \quad 10]^T$. The purple chained line denotes the output signal in case 3 and the following PID parameter and the fictitious performance index are obtained.

$$\rho^* = [9.61 \quad 0.89 \quad 9.54]^T, \tilde{J}(\rho^*) = 0.0174.$$

In each case, the output signals are not enough matched to the reference response. It is difficult to understand which is best. However the values of the performance index in the equation (2) can be computed as follows, Case 1: $J(\rho^*)=0.2088$, Case 2: $J(\rho^*)=0.2089$, Case 3: $J(\rho^*)=0.2110$. It is possible to see that Case 1 is best. This result shows that the PID design using FRIT is highly dependent on the initial PID parameter ρ^0. The figure 5 shows the values of the performance index $\tilde{J}(\rho^i)$ in case 1, case 2 and case 3. The value in case 2 is smaller than those in case 1 and case 3 however the output signal in case 2 does not become better.

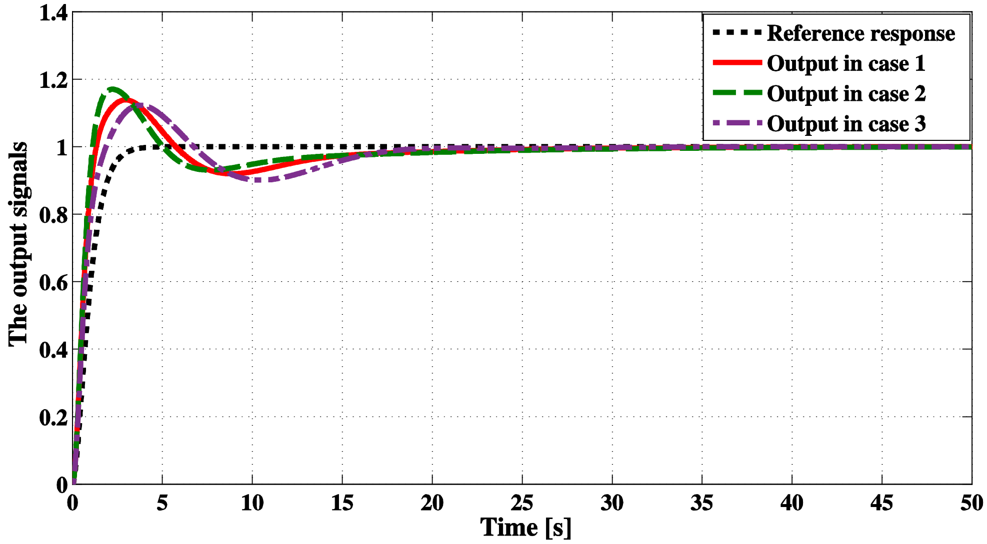


Figure 4. The output signals(Case 1, Case 2 and Case 3)

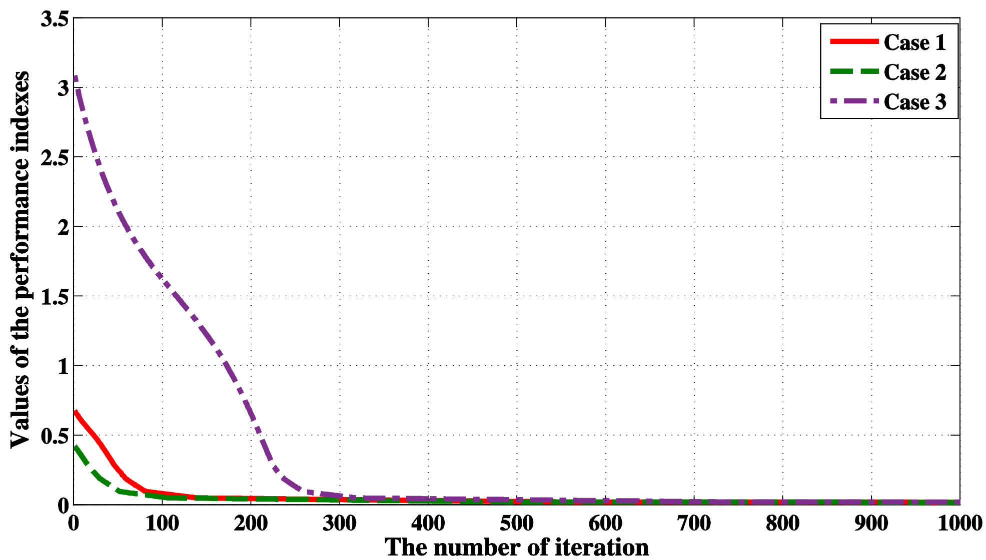


Figure 5. The values of the performance index $\tilde{J}(\rho^i)$ (Case 1, Case 2 and Case 3)

From the figures 4 and 5, we can see that the minimization of the fictitious performance index does not directly influence the minimization of the performance index in the equation (2). Therefore it seems that the optimal solution is difficult to obtain based on FRIT only. Moreover the number of iteration seems large because the values of performance indexes do not become small after the iteration number is large in FRIT. To overcome this problem, we propose the FRIT-PSO approach for the PID controller design by utilizing the advantage of FRIT. The advantage is offline computation of optimal or suboptimal PID parameters.
In this example, the following 4-order system is used to obtain the one-shot data set $\{u_0, y_0\}$.

$$P(s) = \frac{12s+8}{20s^4 + 113s^3 + 147s^2 + 62s + 8}.$$

Because the reference model is given as the 3-order system in the equation (9), the optimization problem becomes nonlinear and non-convex. The above examples show that the suboptimal solutions exist. If the reference model is chosen as the higher order system, the optimization problem may become easy but it seems difficult to obtain the optimal solution by using FRIT.

III. PID DESIGN USING FRIT-PSO

In this section, the FRIT-PSO method is proposed. The optimization problem to design PID controllers is same as the equation (2).

a. *Optimization and Algorithm of FRIT-PSO*

Since the proposed approach is based on PSO, it assumed that the number of particles is n and each particle consists of PID gains. Each particle $\{\rho_1, \rho_2, \cdots, \rho_n\}$ is described as a 3-dimensional vector.

Step 0: Initialization

The initial PID parameter is given as $\rho^0 = [K_P \quad K_I \quad K_D]^T$ and a one-shot data set $\{u_0, y_0\}$ is obtained based on the figure 1. Here assume that the transfer function using ρ^0 is stable. The initial values of particles are assigned as $\{\rho_1(k), \rho_2(k), \cdots, \rho_n(k)\}$ between a suitable range.

Moreover $\{\rho_1(k), \rho_2(k), \cdots, \rho_n(k)\}$ are chosen as uniformly distributed random numbers. The parameter k is the number of iteration for FRIT-PSO and the initial number is given as k=1.

Step 1: Optimization using FRIT

For each particle ($j = 1,2,\cdots,n$), the fictitious reference signals are defined as

$$\tilde{r}(\rho_j(k), s) = C(\rho_j(k), s)^{-1} u_0 + y_0. \tag{10}$$

The error signal and the performance index are also defined as the following forms.

$$\begin{aligned} &\tilde{e}(\rho_j(k), s) = y_0 - T_d(s)\tilde{r}(\rho_j(k), s), \\ &\tilde{J}(\rho_j(k)) = \int_0^\infty \left|\tilde{e}(\rho_j(k), t)\right|^2 dt, \\ &\tilde{e}(\rho_j(k), t) = L^{-1}\left[\tilde{e}(\rho_j(k), s)\right] \end{aligned} \tag{11}$$

The following optimization problems are solved for each particle ($j = 1,2,\cdots,n$) based on the equation (5).

$$\rho_j^*(k) = \arg\min_{\rho_j(k)} \tilde{J}(\rho_j(k)).$$

Step 2: Updating particles based on the PSO algorithm

Step 2-a: Updating the local best and the global best

The parameters $\rho_{jL}(k), \rho_g(k)$ are defined as follows,

$$\rho_{jL}(k) = \arg \min_{\substack{\rho_j^*(m) \\ m=1,2,\cdots,k}} \tilde{J}(\rho_j^*(m))$$

$$\rho_g(k) = \arg \min_{\substack{\rho_{jL}(m) \\ j=1,2,\cdots n \\ m=1,2,\cdots,k}} \tilde{J}(\rho_{jL}(m))$$

where the parameter $\rho_{jL}(k)$ is called as the local best of the jth particle and the parameter $\rho_g(k)$ is called as the global best.

If $\tilde{J}(\rho_j(m), T) < \tilde{J}(\rho_{jL}(k-1))$, then the local best $\rho_{jL}(k)$ is updated as $\rho_{jL}(k) = \rho_l(m)$. Otherwise the local best is not updated and the local best is kept as $\rho_{jL}(k) = \rho_{jL}(k-1)$. Moreover if $\tilde{J}(\rho_{jL}(m)) < \tilde{J}(\rho_g(k-1))$, then the global best $\rho_g(k)$ is updated as $\rho_g(k) = \rho_{lL}(m)$. Otherwise the global best is not updated and the global best is kept as $\rho_g(k) = \rho_g(k-1)$.

Step 2-b: Updating the vector and the position

The vector of the jth particle v_j is updated as follows,

$$v_j(k+1) = c_0 v_j(k) + c_1\psi_1\{\rho_{jL}(k) - \rho_j(k)\} + c_2\psi_2\{\rho_g(k) - \rho_j(k)\}.$$

The parameters ψ_1, ψ_2 are random numbers between 0 to 1. The parameters c_0, c_1, c_2 are the weighting factors for stability and performance of PSO. Since the setting of the parameters is based on the paper [34], the parameters which satisfy the following equation are used,

$$0 \le c_0 < 1, 0 < \frac{c_1 + c_2}{2} < 2c_0 + 2.$$

Then the position of the jth particle ρ_j is updated as follows,

$$\rho_j(k+1) = \rho_j(k) + v_j(k+1),$$

where the position is the PID gain. Thus PID tuning is done by the above equation.

Step 3: Iteration of the PSO algorithm

The iteration of Step 2 is repeated until the iteration number of PSO becomes $k=k_{\max}$. The parameter $k_{\max}$ is called as the maximum iteration number of FRIT-PSO in this paper. For the proposed FRIT-PSO, the following theorems are satisfied.

Theorem 1. For each $\rho_j(k), j = 1,2,\cdots,n, k = 1,2,\cdots,k_{\max}$, $J(\rho_j(k)) = 0$ is satisfied, if and only if $\tilde{J}(\rho_j(k)) = 0$ is satisfied. Moreover the optimal solution is given as

$$\rho^* = \rho_g(k_{\max}).$$

with the minimum performance index $\tilde{J}(\rho^*)$.

Proof: The fictitious reference signal in the equation (10) can be rewritten as

$$\tilde{r}(\rho_j(k), s) = F(\rho_j(k), s)r,$$

$$F(\rho_j(k), s) = \frac{C(\rho_j(k), s)^{-1} C(\rho^0, s)}{1 + C(\rho^0, s)P(\rho^0, s)} + T(\rho^0, s).$$

On the other hand, the equation

$$T(\rho_j(k), s)\tilde{r}(\rho_j(k), s) = \frac{P(s)C(\rho_j(k), s)}{1 + P(s)C(\rho_j(k), s)}\{C(\rho_j(k), s)^{-1}u_0 + y_0\},$$

can be calculated as the following simple form

$$T(\rho_j(k),s)\tilde{r}(\rho_j(k),s) = y_0.$$

Then the error signal $\tilde{e}(\rho_j(k),s)$ in the equation (11) is derived as follows,

$$\begin{aligned}\tilde{e}(\rho_j(k),s) &= T(\rho_j(k),s)\tilde{r}(\rho_j(k),s) - T_d(s)\tilde{r}(\rho_j(k),s),\\ &= F(\rho_j(k),s)(T(\rho_j(k),s) - T_d(s))r,\\ &= F(\rho_j(k),s)e(\rho_j(k),s). \qquad (12)\end{aligned}$$

Here note that $\tilde{e}(\rho_j(k),s) = 0$ is satisfied if $\tilde{J}(\rho_j(k)) = 0$ and $e(\rho_j(k),s) = 0$ is satisfied if $J(\rho_j(k)) = 0$. Thus the equation (11) means that $\tilde{J}(\rho_j(k)) = 0$ is a necessary and sufficient condition for $J(\rho_j(k)) = 0$ because $F(\rho_j(k),s)$ is not zero. Moreover it is obvious that the optimal parameter ρ^* is given as the global best $\rho_g(k_{\max})$ after the FRIT-PSO algorithm.

Theorem 2. For each $\rho_j(k), j = 1,2,\cdots,n, k = 1,2,\cdots,k_{\max}$, there exists a positive scalar $\beta > 0$ which satisfies the following condition.

$$J(\rho_j(k)) \geq \beta\tilde{J}(\rho_j(k)). \qquad (13)$$

Proof : From the equation (12), the following condition is satisfied.

$$\left\|\tilde{e}(\rho_j(k))\right\|_2 \leq \left\|F(\rho_j(k),s)\right\|_\infty \left\|e(\rho_j(k))\right\|_2. \qquad (14)$$

where $\|x\|_2$ is a 2-norm of a signal x(t) and $\|X(s)\|_\infty$ is an infinity-norm of a transfer function. Moreover because

$$\tilde{J}(\rho_j(k)) = \left\|\tilde{e}(\rho_j(k))\right\|_2^2, J(\rho_j(k)) = \left\|e(\rho_j(k))\right\|_2^2,$$

are satisfied, then the inequality (14) can be described as

$$\tilde{J}(\rho_j(k)) \leq \left\|F(\rho_j(k),s)\right\|_\infty^2 J(\rho_j(k))$$

Thus the condition (13) is satisfied for the following positive scalar.

$$\beta = \frac{1}{\left\|F(\rho_j(k),s)\right\|_\infty^2} > 0.$$

b. *A numerical example of FRIT-PSO*

Considering the result of Theorem 2, it is clear that the small value of the fictitious performance index is not equivalent to the small value of the real performance index. Moreover the number of iteration of FRIT $i_{\max}$ can be small because the important problem is how to set the suitable initial PID gains for FRIT. The proposed FRIT-PSO can solve this problem.

Here we demonstrate the proposed approach in comparison with the result shown in the figure 4. The same data set in the previous section is used. The parameters are summarized as follows,

- Data set : $\{u_0, y_0\}$ in the figure 2
- The reference model: the equation (9)
- The number of particles : n=10
- The initial range of particles in FRIT-PSO: $1<K_P<2$, $1<K_I<2$, $10<K_D<20$

  The advantage of the proposed FRIT-PSO method is to be able to select PID gains considering the forecasted information about the gains.
- Parameters of PSO : c_0=0.3, c_1=0.5, c_2=0.5
- The maximum number of iteration in FRIT: $i_{\max}$ =10
- The maximum number of iteration in FRIT-PSO: $k_{\max}$=30

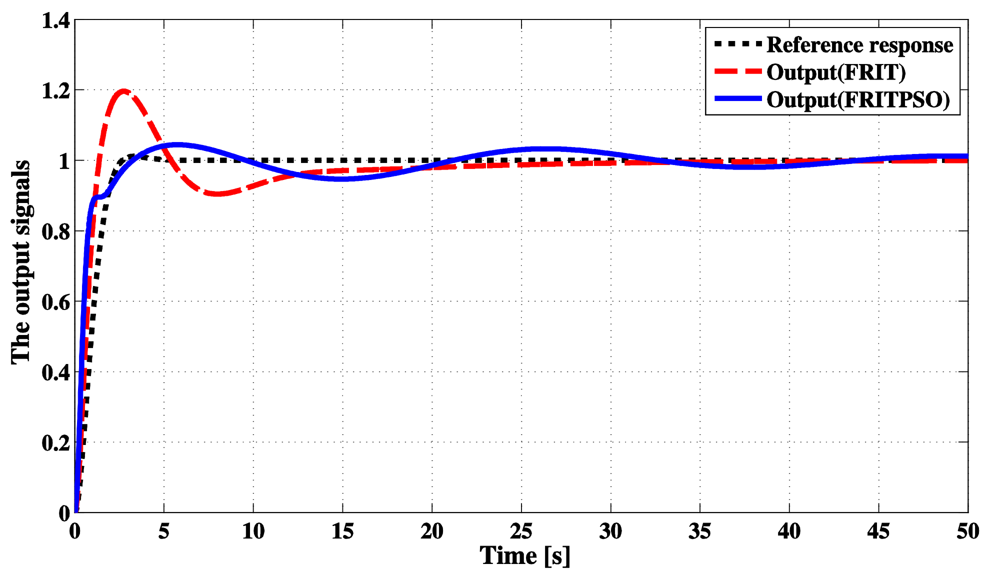


Figure 6. The output signals (FRIT vs FRIT-PSO)

By using the proposed FRIT-PSO, the following PID parameters are obtained.

$$\rho^* = \rho_g(10) = \begin{bmatrix} 3.90 & 1.17 & 18.75 \end{bmatrix}^T, \tilde{J}(\rho^*) = 0.52$$

The output signals are shown in the figure 6. In this figure, the black dotted line denotes the reference response, the red dashed line denotes the output signal using FRIT in case 1 and the blue solid line denotes the output signal using the proposed FRIT-PSO. Moreover the value of the performance index is computed as

$$J(\rho^*) = 0.162 .$$

Thus the proposed FRIT-PSO achieves better performances than FRIT. Moreover the value in Theorem 2 is computed as $\beta = 0.2308$ by using FRIT-PSO. Thus Theorem 2 is satisfied.

The value of the fictitious performance index is shown in Figure 7. The value is decreasing linearly after 5 in the number of iteration. The particle positions before FRIT-PSO and after FRIT-PSO are shown in Figure 8 and Figure 9 respectively. The particles are concentrating at the optimal position which is equal to the global best. This means that all particles can find out the same local best. Moreover this optimal position is beyond the initial area of PID parameters. This figure shows the effectiveness of the proposed FRIT-PSO.

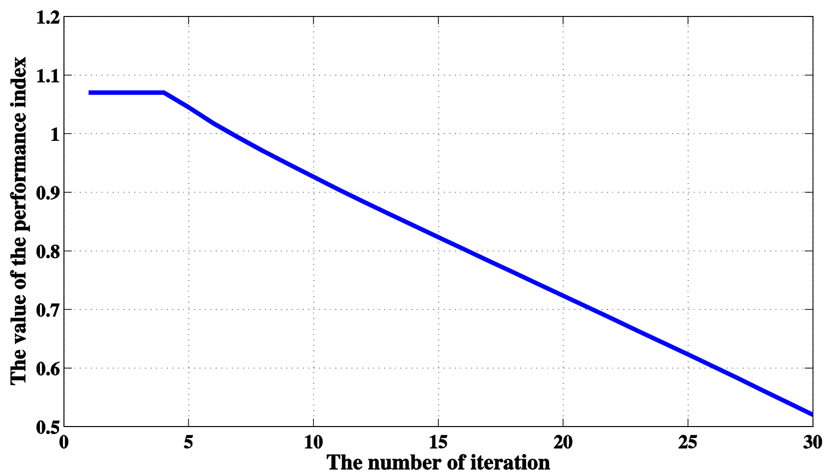


Figure 7. The value of the performance index (FRIT-PSO)

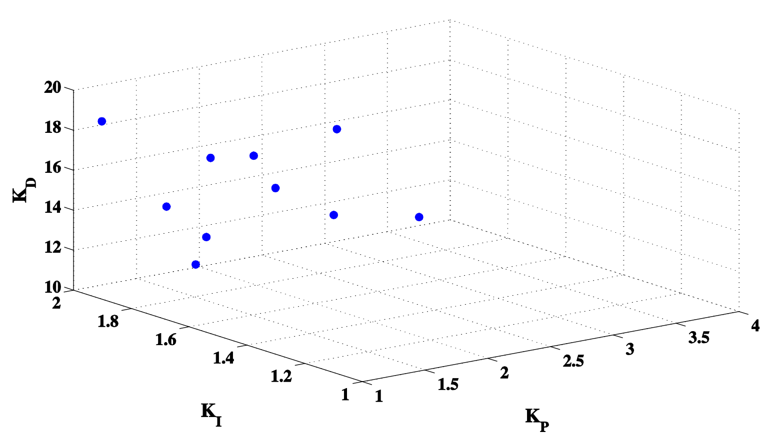


Figure 8. The particle positions before FRIT-PSO

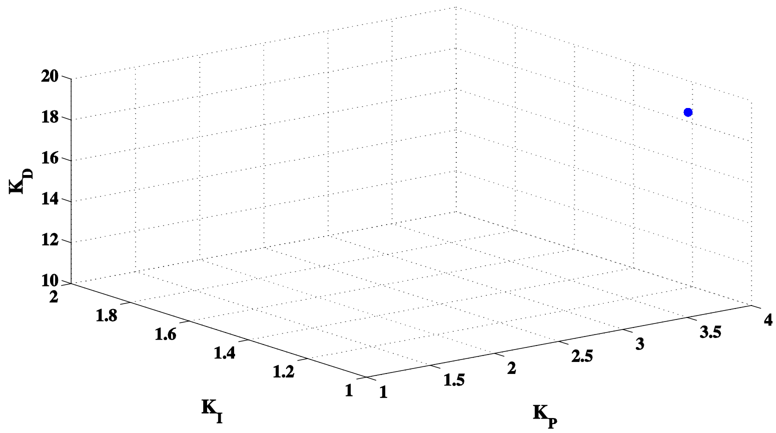


Figure 9. The particle positions after FRIT-PSO

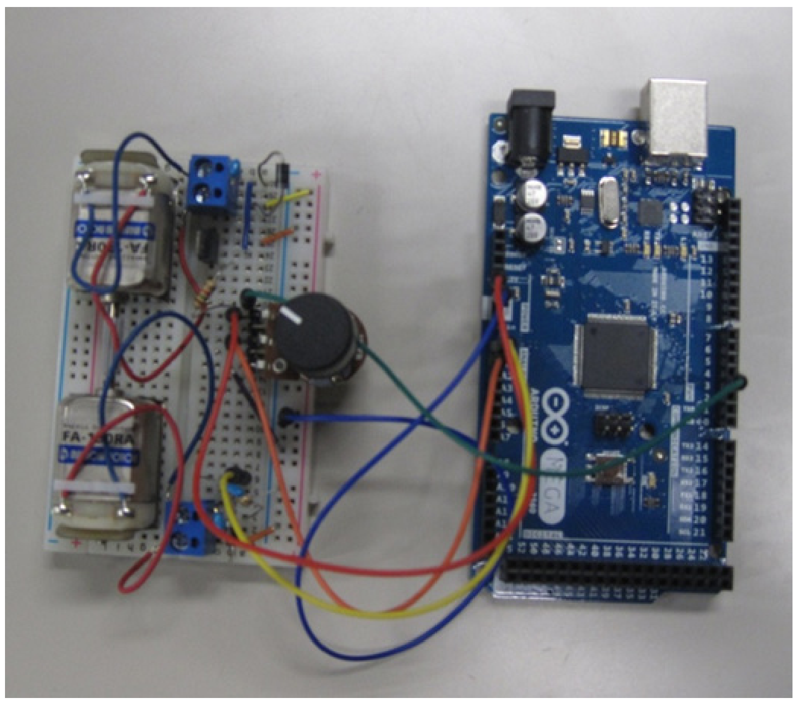
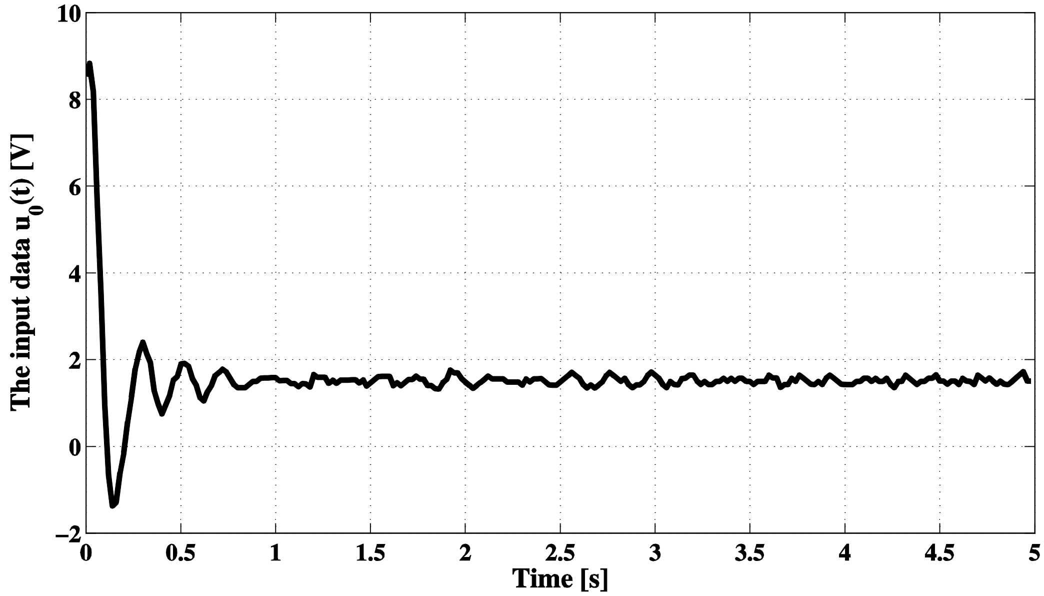


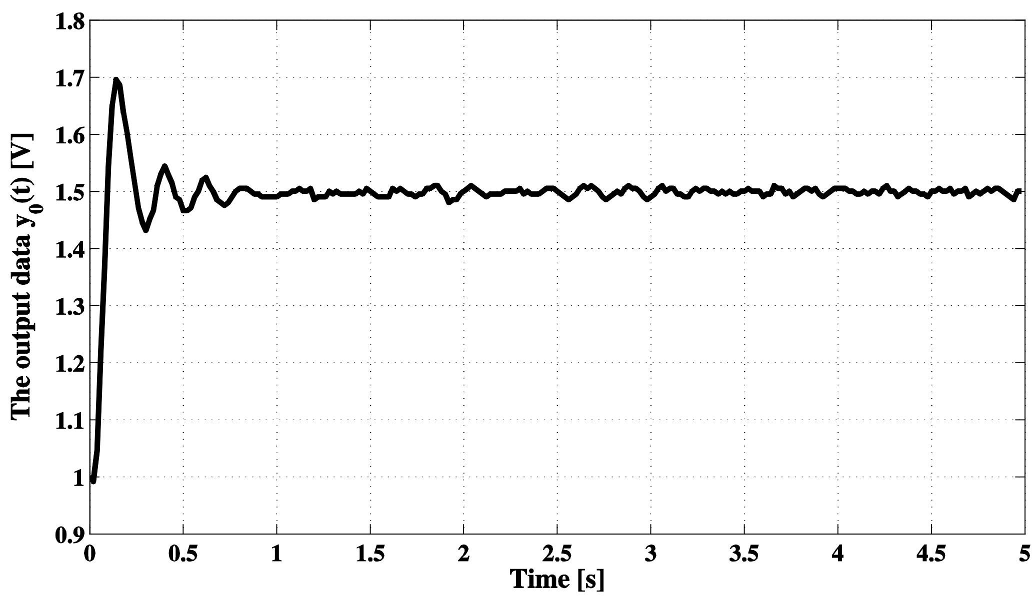
Figure 10. The experimental device

c. *An experimental result of FRIT-PSO*

In this section, the effectiveness of the proposed FRIT-PSO approach is verified based on an experiment. The figure 10 shows the simple experimental device. The input signal is the voltage of a DC motor and the output is the angular velocity of a DC motor. The angular velocity is measured as the voltage of another DC motor. Arduino is also the input-output device to a computer. The purpose of this experiment is to design the optimal PI controller to control the angular velocity by using only the input and output data shown in Figure 11. The PI controller is designed in this experiment because the output signal contains some noises and the D controller, which is a high pass filter, leads to the worse control performance.



(a) The input data $u_0(t)$



(b) The output data $y_0(t)$

Figure 11. A data set $\{u_0, y_0\}(\rho = [15 \quad 15]^T)$

The reference signal is changing from 1.0 [V] to 1.5[V]. The PI controller is given as follows,

$$C(\rho, s) = \rho_1 + \frac{\rho_2}{s},$$
$$\rho = [\rho_1 \quad \rho_2]^T = [K_P \quad K_I]^T.$$

The reference model is the 2-order system described in the following equation.

$$T_s(s) = \frac{4}{s^2 + 4s + 4}$$

The number of particles is 10 and the initial PI gains are given as $0 \le K_P \le 2, 0 \le K_I \le 2$. The number of iteration is 30 in the proposed FRIT-PSO, that is $i_{\max}$=30 and $k_{\max}$=30. On the other hand the number of iteration is 1000 in case of FRIT, that is $i_{\max}$=1000. The parameters of PSO are same as the numerical example. The data set $\{u_0, y_0\}$ is obtained in Figure 11. By using the proposed FRIT-PSO and the traditional FRIT, the designed PI controllers are given as follows,

FRIT-PSO : $\rho^*_{FRIT-PSO} = [0.36 \quad 0.95]^T$,

FRIT : $\rho^*_{FRIT} = [0.05 \quad 1.23]^T$.

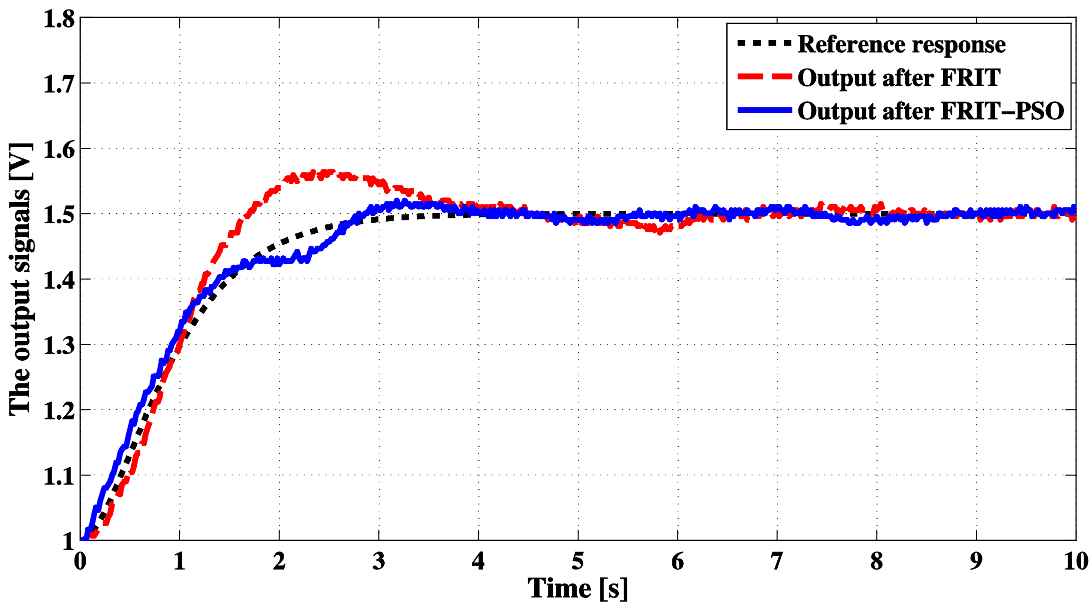


Figure 12. Output signals for experimental results

The experimental result is illustrated in Figure 12. The black dotted line denotes the reference response, the red dashed line denotes the output using FRIT and the blue solid line denotes the output using the proposed FRIT-PSO. The output using FRIT-PSO is well matched to the reference response. The following values of the performance indexes

$$J(\rho^*_{FRIT-PSO}) = 0.022,$$
$$J(\rho^*_{FRIT}) = 0.162.$$

The above values of the performance index also indicates the efficacy of the proposed FRIT-PSO to design the PI controller.

VI. CONCLUSIONS

The FRIT-PSO approach has been proposed for PID tuning. Because the proposed approach is based on FRIT, offline PID tuning is possible. Moreover the proposed approach can avoid to obtain the local solution since the PSO method is also applied. The performance of the proposed FRIT-PSO has been demonstrated by comparing with the FRIT method in the numerical examples and an experiment. Especially the effectiveness of the proposed method has been demonstrated in the experiment based on the angular speed control of a DC-motor. The proposed FRIT-PSO method has achieved better performances than the traditional FRIT method.

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