A study on RTD-A controller for Multiple Input Multiple Output system and an application example

Du Bin, Chu Jizheng, Cao Xi
School of Information Science and Technology
Beijing University of Chemical Technology
15 Beisanhuan East Road, Chaoyang District, Beijing 100029
P.R. China
caoxi@mail.buct.edu.cn www.buct.edu.cn

Abstract: RTD-A (Robustness Tracking Disturbance rejection-global Aggressiveness) controller, proposed by Babatunde A. Ogunnaike, is suitable for single input single output system (SISO). On the basis of it, a new RTD-A controller for Multiple Input Multiple Output system (MIMO) is illustrated and the global optimal control solution is also discussed in this paper. Simulation results prove that compared with IMC-PID (Internal Model Control), this new algorithm has good performances in set-point tracking, disturbance rejection and robustness.

Key words: IMC-PID; RTD-A Controller; Multiple Input Multiple Output System (MIMO); Robustness

1. Introduction

Nowadays, PID controller is still the most widely used industrial controllers. It was formatted and developed in the year 1915-1940, with a simple structure, robust in the model error, and other characters. According to surveys, more than 90% process controls using traditional PID form all over the world [1-2]. Due to its structural limitations, the relationship between the controller performance indicators and the setting parameters is not illustrative under the situation of non-linear or dead-time control objects, making controller tuning quite complex. The afterwards compound PID control methods, such as the Internal Model PID, the Neural Network PID and the Expert PID, do have improvements on the control parameter tuning methods, but not address to the inherent flaws of the traditional PID because they share the same fundamentals. [3] It was reported that 80% of the industry controllers were not tuning well. On the other hand, more and more attentions has been paid on the development of new structure regulators, for examples, the Fuzzy Control, the State Feedback and Observation Control, and the Model Predictive Control which is quite popular recently.[4-6] All these new achieves good control performance, but also has complex structure and expensive cost. Moreover, they need expert knowledge to tune the parameters, which is much more difficult compared with the traditional one, and that is the major roadblock for the extension activities of these new regulators. Therefore, it is very important to develop kind of controller which has excellent performance with relatively simple structure. The all-around single variable RTD-A robust controller purposed by Ogunnaike [7] has clear parameter setting meaning with strong robustness and easy to implement. The whole control performance indexes can be obtained and tuned at the same time, which cannot be done using the traditional PID controllers. In this paper, based on the work of Ogunnaike, a new RTD-A controller structure for multivariable systems is deduced and the existence proof of the optimal control solution is given out. At the end of this paper, this new algorithm got verified using the strong coupled system of binary fractionating tower.

2. Introduction of SISO RTD-A controller

There is only brief principle introduction for RTD controller. Its theoretical analysis please sees reference [7], and all parameters have the same meaning.

2.1 First order plus delay model

$$g(s)=\frac{Ke^{-\alpha s}}{\tau s+1} \qquad \text{Eq.1}$$

The first order model with time delay proper represents process control objects. Its discrete model is:

$$y(k+1) = ay(k) + bu(k-m); \quad k = 0,1,2,...$$

Eq.2

Where: $a = e^{-\Delta t/\tau}$, $b = K(1-e^{-\Delta t/\tau})$

Delay time step: $m = round(\alpha/\Delta t)$

Sampling time: Δt

2.2 Output prediction

After delay time *m*, the output prediction of model Eq.2 is:

$$y(k+m+1) = a^{m+1}y(k) + b\mu(k,m) + bu(k)$$

Eq.3

$$\mu(k,m) = \sum_{i=1}^{m} a^i u(k-i)$$ Eq.4

According to Eq.3, the prediction of *N* time steps from current time *k*. Suppose the future input is:

$$u(k+i) = u(k) \quad i = 1,...,N$$

Eq.5

Then the prediction output of *N* time steps is:

$$y(k+m+i) = a^{m+i}y(k) + a^{i-1}b\mu(k,m) + b\eta_i u(k)$$

Eq.6

Where: $\eta_i = \frac{1-a^i}{1-a}, \quad 1 \leqslant i \leqslant N$

In actual prediction, various disturbances should be taken into account in Eq.6, which made the prediction more accurate.

2.3 Error prediction update

The deviation $e(k)$ between the real data $y(k)$ obtained from the control object and the model output $y(k)$ is the accumulation of all kinds of errors and disturbances.

$$e(k) = y(k) - y(k)$$ Eq.7

Take consider of real process control object:

$$y(k+1) = a^0 y(k) + b^0 u(k-m^0) + \delta_S(k) + \delta_D(k) + n(k)$$

Eq.8

And a^0, b^0, m^0 represent the true unknown parameters in the FOPDT model. δ_S is the high order nonlinear dynamic disturbance. δ_D is the disturbance that doesn't include in the model. And n represents random disturbance.

2.4 Model error prediction

In reference [7], the error predictions for the current time *k* and future time *N* are:

$$\hat{e}_D(k) = \theta_R \hat{e}_D(k-1) + (1-\theta_R)e(k)$$

Eq.9

$$\hat{e}_D(k+j|k) = \hat{e}_D(k) + \left(\frac{1-\theta_D}{\theta_D}\right)[1-(1-\theta_D)^j]\nabla\hat{e}_D(k)$$

Eq.10

θ_R and θ_D are the regulator parameters. Adds Eq.9 and Eq.10 into Eq.6, then the output prediction with errors update will be:

$$y(k+\mathrm{m}+i)=a^{m+i}y(k)$$
$$+a^{i-1}b\mu(k,m)+b\eta_i u(k)$$
$$+\hat{e}_D(k+m+i|k)$$

Eq.11

2.5 The calculation of control input $u(k)$

According to the output prediction, optimization function for the control object is:

$$J(u(k))$$
$$=\min_{u(k)}\sum_{i=1}^{N}(y^*(k+i)-y(k+m+i))^2$$

Eq.12

Where: $y^*(k+i)$ is the set value trajectory, and its update formula is:

$$y^*(k+i)=\theta_T^i y^*(k)+(1-\theta_T^i)y_d(k)$$

Eq.13

y_d is the ideal set point. θ_T is the regulator parameter, N is the prediction step. Based on the Least Square theory, the optimal solution of Eq.12 after derivation is:

$$u(k)=\frac{1}{b}\frac{\sum_{i=1}^{N}\eta_i\varphi_i(k)}{\sum_{i=1}^{N}\eta_i^2} \qquad \text{Eq.14}$$

At each simple time *k*, after the update of model output prediction, the optimal control input $u(k)$ will be set into the control system.

3 Deduction of MIMO RTD-A controller

Following is the detail deduction of MIMO RTD-A controller based on a DIDO system (Double inputs and double outputs system).

3.1 RTD-A controller for DIDO system

Aim at the coupling system shown in Fig.1, the control performance indexes of each single-loop are integrated as $J(u(k))$ by the proposed multi-variable RTD-A controller, which leads to an global optimization function $J(u_1(k),u_2(k),\ldots u_n(k))$, whose best solution will be given out.

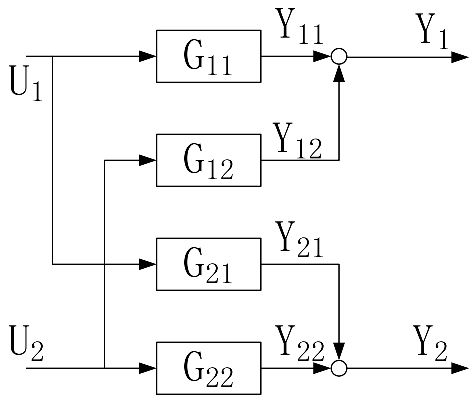

Fig.1 Block of double couple system

For a general single-variable RTD-A controller, the coupling effect between systems only be considered as outside disturbance. But in the multi-variable situation, this coupling effect will be separated from the predicted disturbance $\hat{e}_D(k+m+i|k)$, namely

$$\hat{e}_D(k+m+i|k)$$
$$=\hat{e}_{D1}(k+m+i|k)+\hat{e}_{D2}(k+m+i|k)$$

Eq.15

In Eq.5, $\hat{e}_{D1}$ is the update part of all other respects except coupling effect, so the error updates formula (Eq.10) of single-variable is still effective. $\hat{e}_{D2}$ is the disturbance caused by coupling. It is a function of u which represents other loops' control effects. $\hat{e}_{D2}$ is very useful to solve the global optimization control. For the above double-variable system, $\boldsymbol{Y_{12}}$ and $\boldsymbol{Y_{21}}$ represent the disturbances caused by system coupling, and their transfer functions are $\boldsymbol{G_{12}}$ and $\boldsymbol{G_{21}}$. According to Eq.6, there are:

$$Y_{12}(k+m_{12}+i)=a_{12}^{m_{12}+i}y_{12}(k)+a_{12}^{i-1}b_{12}\mu_{12}(k,m_{12})+b_{12}\eta_{12,i}u_2(k)$$
Eq.16

$$Y_{21}(k+m_{21}+i)=a_{21}^{m_{21}+i}y_{21}(k)-a_{21}^{i-1}b_{21}\mu_{21}(k,m_{21})-b_{21}\eta_{21,i}u_1(k)$$
Eq.17

Notice that a_{ij}, b_{ij} and m_{ij} ($1\leqslant i,j\leqslant 2$) are the discrete parameters corresponding to the transfer function G_{ij}.

In these equations, there is no error update because it is a part of error disturbance. The main challenge is to separate the control efforts of u_1 and u_2. The global optimal function is:

$$\begin{aligned}
\min J(u_1,u_2) &= min\sum_{i=1}^{N}(e_{1i}^2+e_{2i}^2)\\
&= min\sum_{i=1}^{N}\{[Y_1^*(k+i)-Y_1(k+m_1+i)]^2+[Y_2^*(k+i)-Y_2(k+m_2+i)]^2\}\\
&= min\sum_{i=1}^{N}\{[Y_1^*(k+i)-Y_{11}(k+m_{11}+i)-Y_{12}(k+m_{12}+i)]^2\\
&\quad+[Y_2^*(k+i)-Y_{21}(k+m_{21}+i)-Y_{22}(k+m_{22}+i)]^2\}\\
&= min\{\sum_{i=1}^{N}[Y_1^*(k+i)-a_{11}^{m_{11}+i}y_{11}(k)-a_{11}^{i-1}b_{11}\mu_{11}(k,m_{11})\\
&\quad-b_{11}\eta_{11,i}u_1(k)-\hat{e}_{11,D}(k+m_{11}+i\,|\,k)\\
&\quad-a_{12}^{m_{12}+i}y_{12}(k)-a_{12}^{i-1}b_{12}\mu_{12}(k,m_{12})-b_{12}\eta_{12,i}u_2(k)]^2\\
&\quad+\sum_{i=1}^{N}[Y_2^*(k+i)-a_{22}^{m_{22}+i}y_{22}(k)-a_{22}^{i-1}b_{22}\mu_{22}(k,m_{22})\\
&\quad-b_{22}\eta_{22,i}u_2(k)-\hat{e}_{22,D}(k+m_{22}+i\,|\,k)\\
&\quad-a_{21}^{m_{21}+i}\widehat{y_{21}(k)}-a_{21}^{i-1}b_{21}\mu_{21}(k,m_{21})-b_{21}\eta_{21,i}u_1(k)]^2\}\\
&= min\sum_{i=1}^{N}([\varphi_1(k)-b_{11}\eta_{11,i}u_1(k)-b_{12}\eta_{12,i}u_2(k)]^2\\
&\quad+[\varphi_2(k)-b_{21}\eta_{21,i}u_1(k)-b_{22}\eta_{22,i}u_2(k)]^2)
\end{aligned}$$

$$\begin{aligned}
\varphi_1(k) &= Y_1^*(k+i)-a_{11}^{m_{11}+i}y_{11}(k)\\
&\quad-a_{11}^{i-1}b_{11}\mu_{11}(k,m_{11})-\hat{e}_{11,D}(k+m_{11}+i\,|\,k)\\
&\quad-a_{12}^{m_{12}+i}y_{12}(k)-a_{12}^{i-1}b_{12}\mu_{12}(k,m_{12})
\end{aligned}$$

$$\begin{aligned}
\varphi_2(k) &= Y_2^*(k+i)-a_{22}^{m_{22}+i}y_{22}(k)\\
&\quad-a_{22}^{i-1}b_{22}\mu_{22}(k,m_{22})-\hat{e}_{22,D}(k+m_{22}+i\,|\,k)\\
&\quad-a_{21}^{m_{21}+i}y_{21}(k)-a_{21}^{i-1}b_{21}\mu_{21}(k,m_{21})
\end{aligned}$$

Eq.18

The derivations of u_1 and u_2 are:

$$\begin{aligned}
\frac{\partial J(u_1,u_2)}{\partial u_1} &= 2\sum_{i=1}^{N}\{[\overbrace{-b_{11}\eta_{11,i}\varphi_1(k)-b_{21}\eta_{21,i}\varphi_2(k)}^{q_1}]\\
&\quad+[\overbrace{b_{11}^2\eta_{11,i}^2+b_{21}^2\eta_{21,i}^2}^{r_{11}}]u_1(k)\\
&\quad+[\overbrace{b_{11}b_{12}\eta_{11,i}\eta_{12,i}+b_{21}b_{22}\eta_{21,i}\eta_{22,i}}^{r_{12}}]u_2(k)\}\\
&= 0
\end{aligned}$$

$$\begin{aligned}
\frac{\partial J(u_1,u_2)}{\partial u_2} &= 2\sum_{i=1}^{N}\{[\overbrace{-b_{12}\eta_{12,i}\varphi_1(k)-b_{22}\eta_{22,i}\varphi_2(k)}^{q_2}]\\
&\quad+[\overbrace{b_{11}b_{12}\eta_{11,i}\eta_{12,i}+b_{21}b_{22}\eta_{21,i}\eta_{22,i}}^{r_{21}}]u_1(k)\\
&\quad+[\overbrace{b_{12}^2\eta_{12,i}^2+b_{22}^2\eta_{22,i}^2}^{r_{22}}]u_2(k)\}\\
&= 0
\end{aligned}$$

Eq.19

After reorganization, the global optimal function u is:

$$\overbrace{\begin{bmatrix} r_{11} & r_{12} \\ r_{21} & r_{22} \end{bmatrix}}^{R}\begin{bmatrix} u_1 \\ u_2 \end{bmatrix}=\begin{bmatrix} q_1 \\ q_2 \end{bmatrix} \qquad \text{Eq.20}$$
$$\Rightarrow Ru=q \Rightarrow u=R^{-1}q$$

Eq.20 has solution only when matrix R is invertible, which means $|R| \neq 0$.

$$\begin{aligned} |R| &= r_{11}r_{22} - r_{12}r_{21} \\ &= \overbrace{b_{11}^2 b_{12}^2 \sum_{i=1}^{N} \eta_{11,i}^2 \sum_{i=1}^{N} \eta_{12,i}^2}^{\alpha 1} \\ &+ \overbrace{b_{21}^2 b_{22}^2 \sum_{i=1}^{N} \eta_{21,i}^2 \sum_{i=1}^{N} \eta_{22,i}^2}^{\gamma 1} \\ &- \overbrace{b_{11}^2 b_{12}^2 [\sum_{i=1}^{N} \eta_{11,i}\eta_{12,i}]^2}^{\alpha 2} \\ &- \overbrace{b_{21}^2 b_{22}^2 [\sum_{i=1}^{N} \eta_{21,i}\eta_{22,i}]^2}^{\gamma 2} \\ &- \overbrace{2b_{11}b_{12}b_{21}b_{22} \sum_{i=1}^{N} \eta_{11,i}\eta_{12,i} \sum_{i=1}^{N} \eta_{21,i}\eta_{22,i}}^{\beta 2} \\ &= (\alpha_1 - \alpha_2) + (\beta_1 - \beta_2) + (\gamma_1 - \gamma_2) \end{aligned}$$

Eq. 21

Lemma 1: according to energy inequality:

$$[\sum_{i=1}^{N} x_i y_i]^2 \leqslant \sum_{i=1}^{N} x_i^2 \sum_{i=1}^{N} y_i^2 \qquad \text{Eq.22}$$

It can be deducted that

$$\alpha_1 - \alpha_2 \geqslant 0,\ \gamma_1 - \gamma_2 \geqslant 0$$

Form the identical inequality

$$a^2 + b^2 \geqslant 2ab$$

$$\begin{aligned} \Rightarrow \beta_1 &= b_{11}^2 b_{22}^2 \sum_{i=1}^{N} \eta_{11,i}^2 \sum_{i=1}^{N} \eta_{22,i}^2 \\ &+ b_{12}^2 b_{21}^2 \sum_{i=1}^{N} \eta_{12,i}^2 \sum_{i=1}^{N} \eta_{21,i}^2 \\ &\geqslant 2b_{11}b_{12}b_{21}b_{22} \\ &\bullet [\sum_{i=1}^{N} \eta_{11,i}^2 \sum_{i=1}^{N} \eta_{12,i}^2]^{1/2} [\sum_{i=1}^{N} \eta_{21,i}^2 \sum_{i=1}^{N} \eta_{22,i}^2]^{1/2} \end{aligned}$$

energy inequality

$$\begin{aligned} \Rightarrow \quad &\geqslant 2b_{11}b_{12}b_{21}b_{22} \\ &\bullet \sum_{i=1}^{N} \eta_{11,i}\eta_{12,i} \sum_{i=1}^{N} \eta_{21,i}\eta_{22,i} \end{aligned}$$

Eq. 24

So $\beta_1 - \beta_2 \geqslant 0$ is true, and

$$\begin{aligned} |R| &= r_{11}r_{22} - r_{12}r_{21} \\ &= (\alpha_1 - \alpha_2) + (\beta_1 - \beta_2) + (\gamma_1 - \gamma_2) \\ &\geqslant 0 \end{aligned}$$

Eq.25

As a conclusion, Eq.20 has no solution only if

$$\begin{cases} \eta_{11} = \eta_{12} \qquad (\alpha_1 - \alpha_2 \equiv 0) \\ \eta_{21} = \eta_{22} \qquad (\gamma_1 - \gamma_2 \equiv 0) \\ b_{11}^2 b_{22}^2 \sum_{i=1}^{N} \eta_{11,i}^2 \sum_{i=1}^{N} \eta_{22,i}^2 \\ \quad = b_{12}^2 b_{21}^2 \sum_{i=1}^{N} \eta_{12,i}^2 \sum_{i=1}^{N} \eta_{21,i}^2 \\ \quad (\beta_1 - \beta_2 \equiv 0) \end{cases}$$

Eq.26

It is a very harsh requirement of Eq.26, hence there is no need to worry about the situation of no solution in reality. That means equation $u=R^{-1}q$ mostly always has solution.

3.2 RTD-A controller for general multi-input/output system

It is similar to deduct RTD-A controller for general multi-input/output system ($n\times n$, $n\geqslant 3$). The global optimal function is:

$$\begin{aligned}
&\min J(u_1,u_2,...u_n) \\
&= min\sum_{i=1}^{N}(e_{1i}^2+e_{2i}^2+...e_{ni}^2) \\
&= min\sum_{i=1}^{N}\{(Y_1^*-Y_1)^2+\ldots(Y_n^*-Y_n)^2\} \\
&= min\sum_{i=1}^{N}\{(f_1(u_1,u_2,...u_n)^2 \\
&\quad +\ldots f_n(u_1,u_2,...u_n)^2\}
\end{aligned}$$

Eq.27

In Eq.27, $u_1,u_2,...u_n$ are inputs, Y_n^* is the set point, Y_n is model output. $f_n(u_1,u_2,...u_n)$ is a function of error between output prediction and set point of each path under input u_n. Base on the principle of least square, let the partial derivative of $u_1,u_2,...u_n$ equate to zero, and the optimal control input will be:

$$\overbrace{\begin{bmatrix} r_{11} & \cdots & r_{1n} \\ \cdots & \cdots & \cdots \\ r_{n1} & \cdots & r_{nn} \end{bmatrix}}^{R_{n\times n}}\begin{bmatrix} u_1 \\ \vdots \\ u_n \end{bmatrix}=\begin{bmatrix} q_1 \\ \vdots \\ q_n \end{bmatrix}$$
$$\Rightarrow R_{n\times n}u=q$$
$$\Rightarrow u=R_{n\times n}{}^{-1}q$$

Eq.28

4 Double variables complete decoupling internal model PID (IMC-PID)

The principle of this ideal decoupling control is that add a compensator $F(s)$ before the multi-variance system so that the product of $F(s)G(s)$ is a 2 x 2 diagonal matrix ($G_{11}(s)$ and $G_{22}(s)$ keep constant), namely:

$$\begin{bmatrix} F_{11}(s) & F_{12}(s) \\ F_{21}(s) & F_{22}(s) \end{bmatrix}\begin{bmatrix} G_{11}(s) & G_{12}(s) \\ G_{21}(s) & G_{22}(s) \end{bmatrix}$$
$$=\begin{bmatrix} G_{11}(s) & 0 \\ 0 & G_{22}(s) \end{bmatrix}$$
$$\Rightarrow \begin{bmatrix} F_{11}(s) & F_{12}(s) \\ F_{21}(s) & F_{22}(s) \end{bmatrix}$$
$$=\begin{bmatrix} G_{11}(s) & 0 \\ 0 & G_{22}(s) \end{bmatrix}\begin{bmatrix} G_{11}(s) & G_{12}(s) \\ G_{21}(s) & G_{22}(s) \end{bmatrix}^{-1}$$

Eq.29

The precondition of complete decoupling is that the transfer function matrix ***G*** is invertible. After decoupling, parameter tuning can be done following internal model PID tuning rules of single loop.

A general PID controller for the first order plus delay process model is:

$$G_{\text{PID}}=K_c\left[1+\frac{1}{T_i s}+\frac{T_d s}{T_f s+1}\right] \qquad \text{Eq.30}$$

Its internal model PID tunings are:

$$T_f=\frac{(\lambda\delta-\gamma_2\alpha)\alpha}{\lambda+(\delta-\gamma_1)\alpha} \qquad \text{Eq.31}$$

$$K_c=\frac{\tau+\delta\alpha-T_f}{K(\lambda+(\delta-\gamma_1)\alpha)} \qquad \text{Eq.32}$$

$$T_i = \tau + \delta\alpha - T_f \qquad \text{Eq.33}$$

$$T_d = \frac{\tau\delta\alpha}{\tau + \delta\alpha} - T_f \qquad \text{Eq.34}$$

And $\gamma_1 = -0.6143, \gamma_2 = 0.1247, \delta = 0.3866$. The detailed information is in reference [8].

5 Simulations of DIDO RTD-A Controller

5.1 Illustration of Simulation Object

The DIDO model of Distillation Column is from reference [10].

$$\begin{bmatrix} Y_1 \\ Y_2 \end{bmatrix} = \begin{bmatrix} G_{11} & G_{12} \\ G_{21} & G_{22} \end{bmatrix} \begin{bmatrix} U_1 \\ U_2 \end{bmatrix} = \begin{bmatrix} \dfrac{-0.14e^{-120s}}{1200s+1} & \dfrac{0.6e^{-220s}}{840s+1} \\ \dfrac{-0.04e^{-80s}}{700s+1} & \dfrac{0.4e^{-70s}}{400s+1} \end{bmatrix} \begin{bmatrix} U_1 \\ U_2 \end{bmatrix} \qquad \text{Eq.35}$$

G_{11}, G_{22} are the main path transfer functions; G_{12}, G_{21} are the disturbance path transfer functions. All of them are first order plus large delay. The unit of delay time is second. The controlled variables are Y_1 and Y_2 which represent the temperatures of the tower and its bottom. U_1, U_2 are manipulated variable.

For more realistic, there is 20% negative deviation between model parameter K, τ and the actual object value. In this way, the simulation model is more appropriate to the industry applications, and the comparisons on regulator performance are more persuasive.

5.2 Simulations on set point tracking

Sample time in these simulations is $\triangle t$ =10 s. the results are illustrated in Fig.2 and Fig.3.

(1) According to Eq.31-34, internal model PID tunings are:

Top: $\lambda = 50$, K_c = -52.2, T_d = 41.7, T_i = 1243.3, T_f = 3.1

Bottom: $\lambda = 40$, K_c = 9.6, T_d = 22.5, T_i = 423.9, T_f = 4.3。

(2) SISO RTD-A controller tunings are:

Top: $\theta_R = 0.5$, $\theta_T = 0.1$, $\theta_D = 0.1$, $\theta_A = 0.15$

Bottom: $\theta_R = 0.6$, $\theta_T = 0.1$, $\theta_D = 0.1$, $\theta_A = 0.15$

(3) DIDO RTD-A controller tunings are:

Top: $\theta_R = 0.5$, $\theta_T = 0.1$, $\theta_D = 0.1$, $\theta_A = 0.1$

Bottom: $\theta_R = 0.6$, $\theta_T = 0.1$, $\theta_D = 0.1$, $\theta_A = 0.1$

5.3 Simulations of disturbance suppression

Based on mismatch model, the white disturbance with Mean 0 and Variance 1 is added into the system. The compare of complete decoupling IMC-PID and DIDO RTD-A is given out in Fig.4 and Fig.5. Tunings are the same as section 5.2.

The simulations showed that even under the situation of model mismatch, all the three kinds of regulators could track the set point and meet certain control requirements. Among them, IMC-PID and SISO RTD-A controller had large overshoots during the tracking process, especially the IMC-PID got oscillations in strong disturbances. The reason for overshoots in SISO RTD-A controller is that it cannot overcome the disturbance caused by coupling in MIMO system. After all, it was originally designed for single variable system control. In contrast, the DIDO RTD-A controller proposed here had much better performances which had small tracking overshoot, effective anti-interference and strong robustness. This new algorithm not only eliminates coupling effects from its derivation, but also achieves a global optimal solution, and the control process is quite satisfactory.

5.4 Simulations of discontinuities

Sometimes, the set point needs change from one to another. A common reason for it is the fluctuation of incoming raw material. In this situation, the main target is a smooth transition to the new steady-state.

The change in transfer function is rare, but has obviously effects on the whole process. This may happen when work condition has an unexpected shift. For example, solid reactive residues are frequently and randomly adhered to the Higee's packing-disk which leads to serious vibration problems. In practice, the solution on this problem is "cleaning downtime". Although this approach can solve the vibration issue, it definitely affects the industry continuity.

In Fig.6, the normalized temperature set point of the top was changed from 0.8 to 0.2 at time $t = \frac{500}{60}$, while the set point of the bottom kept the same (set point = 0.6). Due to the coupling effect, the temperature of the bottom also changed, but the shift was very small, as shown in Fig.7.

Fig.8 and Fig.9 illustrated that at time $t = \frac{500}{60}$, the transfer function of the top changed, but the bottom had no change. In detail as follow:

$$G_1 = \begin{cases} \dfrac{-0.14}{1200s+1} e^{-120s} & 0 \leqslant t < 500s \\ \dfrac{-0.3}{1500s+1} e^{-120s} & t > 500s \end{cases}$$

There was an adjustment process after the change in the top's output. And it is very hard to observe the affection on the bottom's output in Fig.9.

As figures shown, the simulations confirmed that the new algorithm can be self adapting to these discontinuities. Not only the production efficiency will be highly enhanced, but the whole process flow will benefit.

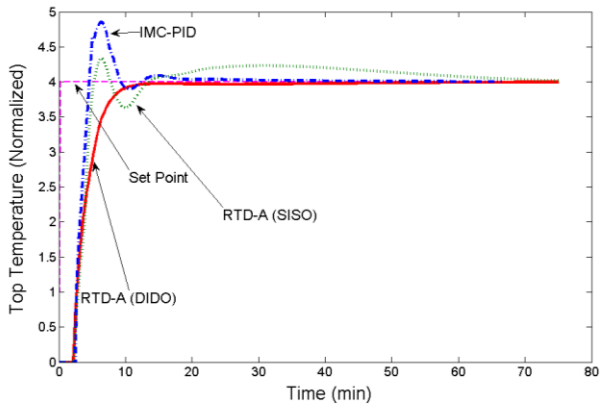

Fig.2 Set point tracking of top temperature

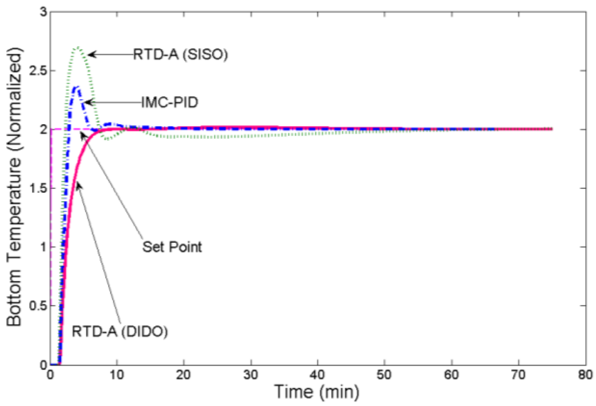

Fig.3 Set point tracking of bottom temperature

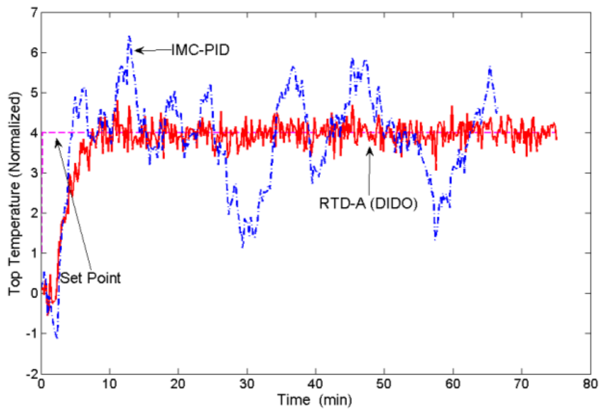

Fig.4 Disturbance rejection of top temperature

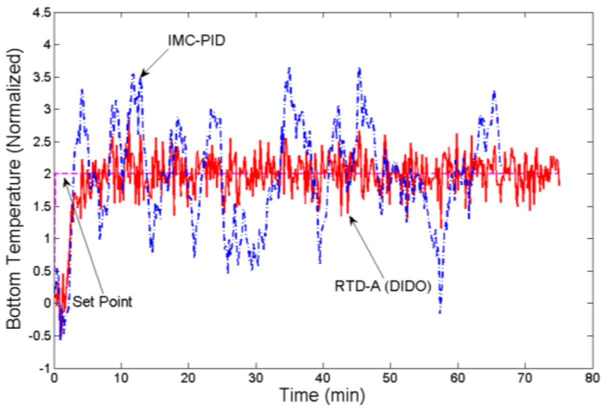

Fig.5 Disturbance rejection of bottom temperature

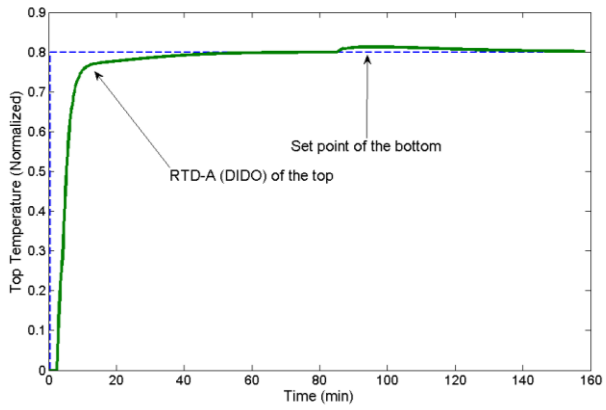

Fig.8 Discontinuity of transfer function (Top)

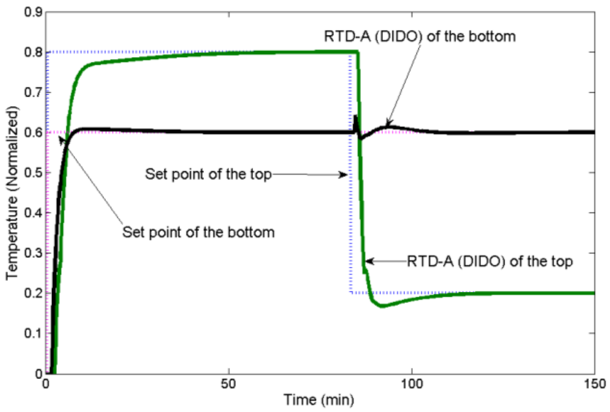

Fig.6 Discontinuity of set point change (Top)

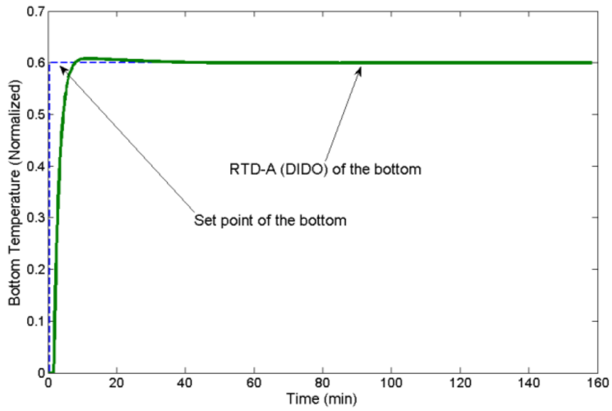

Fig.9 Discontinuity of transfer function (Bottom)

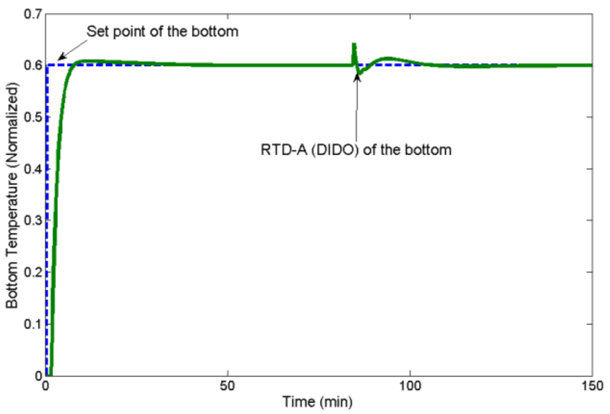

Fig.7 Discontinuity of transfer function (Bottom)

6 Conclusions

Based on SISO RTD-A controller, a MIMO RTD-A controller is proposed in this paper and the existence condition of global optimal solution for multivariable systems are also given out. The correctness and validity of this new control algorithm are verified by the simulation comparisons of SISO RTD-A control, IMC-PID control and itself. The realization of RTD-A control algorithm is simple, and its parameter tuning is very convenient. Although the application prospect of RTD-A controller is quite positive, its research still limited to certain models and parameter optimization is equivocal. That's all focus of the future study.

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