TELKOMNIKA, Vol. 11, No. 9, September 2013, pp. 5048~5054
ISSN: 2302-4046

Sanitizer Dosing Decoupling Control based on IMC-NN Inverse System

Xie Peizhang*, Zhou Xingpeng
Key Laboratory of Measurement and Control of CSE, School of Automation, Southeast University, Ministry of Education, Nanjing, China, 210096
*Corresponding author, e-mail: xpzseu@gmail.com

Abstract

Multi tunnels multi pools (MTMP) structure is very common in tap-waterworks, MTMP structure sanitizer dosing system is a complicated system with coupling, large time delay and inertial. Internal model control decoupling based on wavelet neural networks inverse system is introduced to solve the problems. First α order inverse system is identified using wavelet neural networks, this inverse system cascades the original system so that pseudo-linearization system can be obtained, and then this MIMO system can be transformed to SISO system with no coupling. In addition time delay and model error can be overcome by internal model control. Practical application shows that the coupling, time delay and inertial of MTMP sanitizer dosing system is overcome, also this method is able to resist the disturbance and improve the robustness.

Keywords: *multi tunnels multi pools, sanitizer dosing system, decoupling, internal model control, inverse system*

Copyright © 2013 Universitas Ahmad Dahlan. All rights reserved.

1. Introduction

Sanitizer dosing is a key process during producing tap-water, as is shown in Figure 1. However the system is a complicated system with coupling, large time delay and large inertial, in addition the precision model is almost impossible to acquire. Also multi tunnels multi pools structure is very common in tap-waterworks, hence coupling is bring to the system.

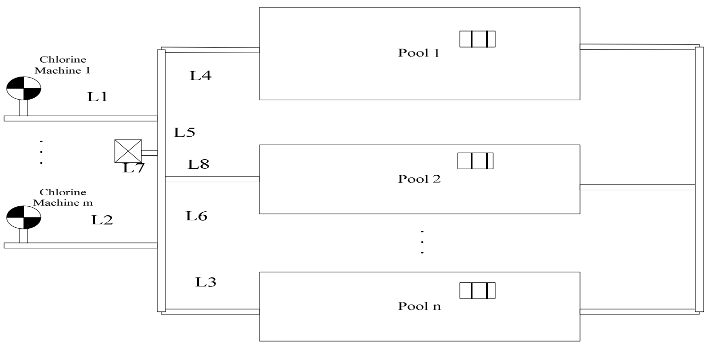

Figure 1. Multi Tunnels Multi Pools Structure Sanitizer Dosing System

There are some papers on decoupling, simplified dynamic or static decoupling matrix methods are widely used in application of multi-variable decouple control, while the precision model is needed and its effect is not satisfactory in high-frequency domain. Recently neural networks method is introduced to decouple control [1-6], in paper [3] double –neuron adaptive predictive decouple algorithm is used to solve a kind of MIMO decouple control system, in paper [4] neural networks and adaptive PID is designed for nonlinear and time-varying MIMO system. Instead of neural networks, support vector machine (SVM) is used to identify the inverse system [7, 8]. The disadvantages of these methods are that time delay and model error do not take into

Received March 7, 2013; Revised June 1, 2013; Accepted June 17, 2013

account, leading to that these methods are not suitable for MTMP structure sanitizer dosing control system. Because of time delay and model error, direct feed-forward control based on pseudo-linearization system using wavelet neural networks inverse system is not suitable. However internal model control is very useful in the field of time-delay and model error control [9-11].

In this paper, because of nonlinear, coupling, precision model can not be acquired; leading to that simplified dynamic or static decoupling matrix control can not be applied. First α order inverse system is identified using wavelet neural networks, after that this inverse system cascades the original system so that pseudo-linearization system can be obtained, this MIMO system will be transformed to SISO system with no coupling, then improved internal model control algorithm is designed for the pseudo-linearization system.

2. Multi Tunnels Multi Pools Structure Sanitizer Dosing System

Liquid chlorine is the common sanitizer, side effects followed the chlorine dosing system, such as chloroform etc. so stable residual-chlorine is very important for tap-waterworks. Chlorine dosing system is a complicated system with multi-models, large time delay, large inertial and nonlinear. Also the multi tunnels multi pools structure brings coupling, so that the precision model is almost impossible to acquire and methods based on precision model can not be applied.

There are some papers about the decay law of residual-chlorine in water [12, 13]. The process can be divided into two parts, one is the rapid process and the other is the slow process. During the rapid process, chlorine injects to the after-filter-water, the consumption of chlorine is very large, it is related to the initial dosage and the amount of NH3. Then during the slow process, the speed of consumption obviously slow down. Based on the theory, combined to the experiment, the approximate model can be acquired.

Without considering coupling, the structure of single tunnel single pool chlorine dosing process model is shown in Figure 2.

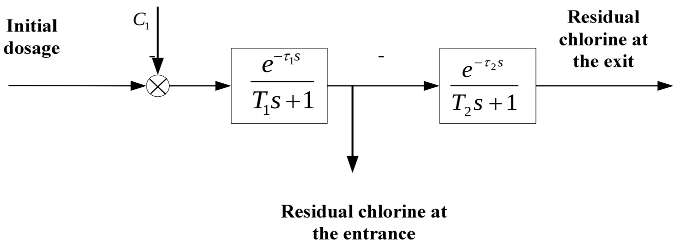

Figure 2. Single Tunnel Single Pool Chlorine Dosing Process Model

C_1 is the difference between initial dosage and the residual-chlorine at 0 minute(actually some seconds later). The model can be treated as first-order inertial model with time-delay approximately. T_1, τ_1, T_2, τ_2 are coefficients of first-order inertial model and coefficients of pure time delay, C_1 and T_1, τ_1, T_2, τ_2 are related to many factors and also they are time-varing.

In this paper, the residual-chlorine at the entrance of pools is the main purpose, so the model of multi tunnels multi pools structure chlorine dosing system as follows:

$$\begin{cases} y_1 = \eta_{11}(X_1 - C_1)\dfrac{e^{-\tau_{11}s}}{T_{11}s+1} + \eta_{21}(X_2 - C_2)\dfrac{e^{-\tau_{21}s}}{T_{21}s+1} + \cdots + \eta_{m1}(X_m - C_m)\dfrac{e^{-\tau_{m1}s}}{T_{m1}s+1} \\ y_2 = \eta_{12}(X_1 - C_1)\dfrac{e^{-\tau_{12}s}}{T_{12}s+1} + \eta_{22}(X_2 - C_2)\dfrac{e^{-\tau_{22}s}}{T_{22}s+1} + \cdots + \eta_{m2}(X_m - C_m)\dfrac{e^{-\tau_{m2}s}}{T_{m2}s+1} \\ \vdots \\ y_n = \eta_{1n}(X_1 - C_1)\dfrac{e^{-\tau_{1n}s}}{T_{1n}s+1} + \eta_{2n}(X_2 - C_2)\dfrac{e^{-\tau_{2n}s}}{T_{2n}s+1} + \cdots + \eta_{mn}(X_m - C_m)\dfrac{e^{-\tau_{mn}s}}{T_{mn}s+1} \end{cases} \quad (1)$$

3. α Order Neural Networks Inverse System

3.1. α Order Inverse System

Definition 1: Σ is a system with p order input $u(t)=(u_1,u_2,\cdots,u_p)^T$ and q order output $u(t)=(y_1,y_2,\cdots,y_p)^T$, suppose Π_α is a q order input and p order output system with mapping function $u=\overline{\theta}\varphi$. Where $\varphi_t=(\varphi_1,\varphi_2,\cdots,\varphi_q)^T$ is a random differential vector that meet the requirement of initial value of system Σ, $u(t)=(u_1,u_2,\cdots,u_p)^T$ is the output vector. If the operator meet the requirement as follows:

$$\theta\overline{\theta}_\alpha\varphi=\theta[\overline{\theta}_\alpha(y_d^\alpha)]=\theta u=y_d$$

Then system Π_α is defined as the α order inverse system of the system Σ.

The inverse system cascades the original system so that pseudo-linearization system can be obtained, this MIMO system can be transformed to SISO system with no coupling, as is shown in Figure 3.

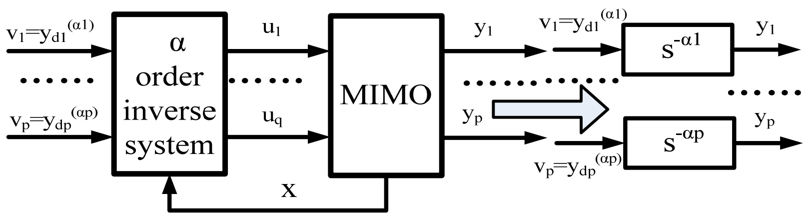

Figure 3. Pseudo-linearization System

The application of direct inverse system control is not very common, because of some fatal weakness such as no feedback, disturbance and etc. Algorithm can be designed based on pseudo-linearization system so that the controller is able to resist the disturbance and improve the robustness.

3.2. Inverse System Using Neural Networks

In order to achieve the inverse system, precision model is required, actually the precision model is impossible to get. Neural networks inverse system is different from any other method based on precision model, basically the neural networks can identify the inverse system if the inverse system exits. The advantage of neural networks inverse system is as follows:

(1) Independent of precision model, only demands a small amount of prior data;

(2) Be able to resist the disturbance and improve the robustness

4. Improved Internal Model Control

Due to the features of the multi tunnels multi pools structure sanitizer dosing system, such as disturbance, time-varying of the parameters, the pseudo-linearization system based on wavelet networks exits model error unavoidable, hence the feed-forward structure system consists of inverse system and original system is short of robustness and cant not resist the disturbance. Besides there exists large time delay and large inertial as well, while internal model control has well robustness and is suitable for time-delay system, improved IMC is proposed to solve the disadvantage of MTMP sanitizer dosing system.

The structure of improved IMC is shown in Figure 4, where G(s) is the control object, $G_m(s)$ is the internal model, $G_{c1}(s)$ is the internal model controller 1, $G_{c2}(s)$ is the internal model controller 2,u is the input of the system, r is the expected output, d is disturbance that can not be observed, y_m is the output of internal model.

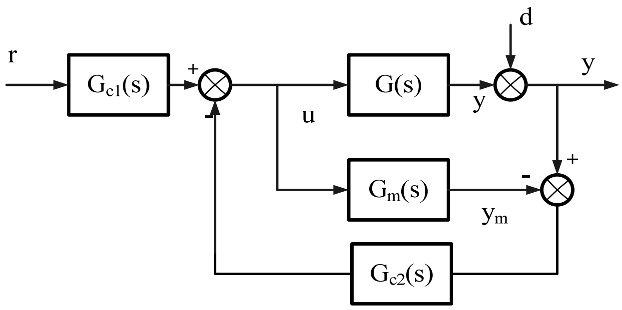

Figure 4. Structure of Improved IMC

$$Y(s)=\frac{G(s)G_{c1}(s)}{1+F_2(s)G_m{}^{-1}(s)[G(s)-G_m(s)]}R(s)+\frac{1-G(s)G_{c2}(s)}{1+F_2(s)G_m{}^{-1}(s)[G(s)-G_m(s)]}D(s) \qquad (2)$$

$F_2(s)=\dfrac{1}{(\lambda s+1)^n}$ is a low-pass filter.

When $G(s)=G_m(s)$, expression (2) can be rewritten as follows:

$$Y(s)=G(s)G_{c1}(s)R(s)+[1-G(s)G_{c2}(s)]D(s) \qquad (3)$$

$G_{c1}(s)$ can adjust the performance of tracking the target, $G_{c2}(s)$ can improve the robustness.

When $G(s)\neq G_m(s)$, besides the disturbance of system, model error is also in the information of feedback, well results also can be obtained via adjusting the controller parameters.

5. Structure of IMC based on Wavelet Neural Networks Inverse System

Steps of designing wavelet neural networks inverse system are as follows:

Step 1: Suppose that the system is consists of 3 inputs and 3 outputs, for each output, $t_i=\min(e^{-\tau_{i1}},e^{-\tau_{i2}},e^{-\tau_{i3}})$, t_i is the time delay. The exist of inverse system can be proved using Interactor algorithm. The order degree of input is 1 and the order degree of output is n_i.

Step 2: Off-line data acquisition; Suppose that N is the number of sample data, T is the sample time, so the number of valid sample data is $C=N-\dfrac{t_i}{T}$, where t_i is the time delay.

Step 3: Training of wavelet neural networks; wavelet neural networks is used to model the inverse system with the data of step 2.

Step 4: wavelet neural networks inverse system cascades the original system so that pseudo-linearization system can be obtained.

Structure of IMC based on wavelet neural networks inverse system is shown in Figure 5. G(z) is the pseudo-linearization system, $G_{mi}(s)$ is the internal model, $G_{ci}(s)$ is the controller.

Design of controller:

Step 1: $G_{mi}(s)$ is the internal model, and the transfer function is $G_{mi}(s)=s^{-n_i}e^{-t_i}$, where n_i is the order degree of output I, t_i is the time delay of output i.

Step 2: Without considering the robustness and restraint, ideal controller is designed without considering the robustness and restraint, $G_{mi}(s)$ can be divided into two parts:

$$G_m(s)=G_{m+}(s)G_{m-}(s)$$

Where $G_{m-}(s)$ is the reversible part and $G_{m+}(s)$ is the irreversible part.
Step 3: Low-pass filter F(s) is introduced to the controller, so that the error of model can be overcome. The expected dynamic property can be obtained through the adjustment of parameters of IMC and structure. Finally the controller can be designed as follows:

$$G_{ci}(s) = F_i(s)G_{m-}^{-}(s)$$

Where $F_i(s) = \frac{1}{(\lambda s+1)^m}$.

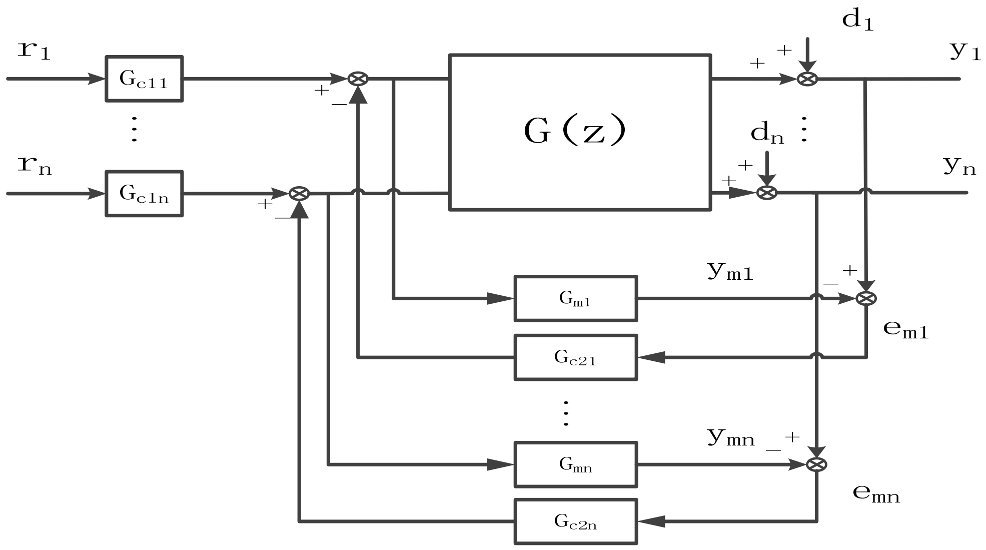

Figure 5. Structure of IMC based on Wavelet Neural Networks Inverse System

6. Case Study

In this paper, the parameters of the case study are shown as follows:
m=3, n=3. $C = [C_1, C_2, C_3]$ is a vector of difference between initial dosage and the residual-chlorine at 0 minute, its value can be obtained by experiments.

$\eta = \begin{bmatrix} \eta_{11} & \eta_{12} & \eta_{13} \\ \eta_{21} & \eta_{22} & \eta_{23} \\ \eta_{31} & \eta_{32} & \eta_{33} \end{bmatrix} = \begin{bmatrix} 0.85 & 0.12 & 0.03 \\ 0.08 & 0.8 & 0.12 \\ 0.07 & 0.08 & 0.85 \end{bmatrix}$ is a matrix of flux ratio into pools from tunnels.

$\tau = \begin{bmatrix} \tau_{11} & \tau_{12} & \tau_{13} \\ \tau_{21} & \tau_{22} & \tau_{23} \\ \tau_{31} & \tau_{32} & \tau_{33} \end{bmatrix} = \begin{bmatrix} 11 & 13 & 16 \\ 13 & 12 & 14 \\ 19 & 17 & 16 \end{bmatrix}$ is a matrix of time delay.

$T = \begin{bmatrix} T_{11} & T_{12} & T_{13} \\ T_{21} & T_{22} & T_{23} \\ T_{31} & T_{32} & T_{33} \end{bmatrix} = \begin{bmatrix} 1.8 & 2.2 & 2.35 \\ 2.05 & 1.6 & 1.95 \\ 2.45 & 2.05 & 1.9 \end{bmatrix}$ is a matrix of parameters of inertial. Sample time T=0.3s, N= 500. $\lambda_1 = 1.8$, $m_1 = 2$, $\lambda_2 = 1.2$, $m_2 = 1$. Expected target value is $y_r = [1,1,1]^T$.

(1) No disturbance

Control effect with no disturbance is shown in Figure 6. Input is square wave with period of 100. The final output is shown as line of dashes.

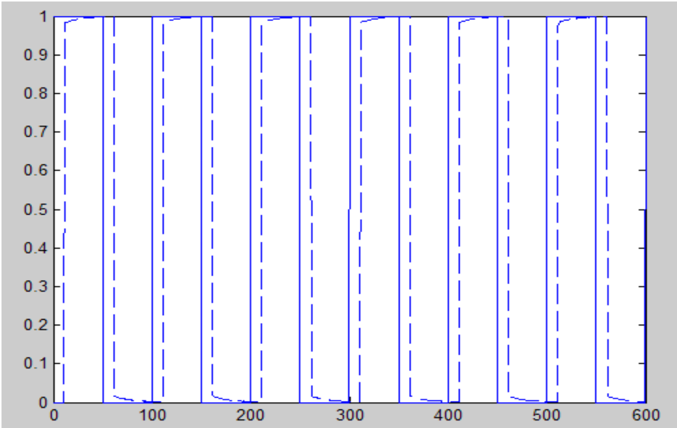

Figure 6. Simulation Results of the Algorithm without Disturbance

(2) With disturbance

Control effect with disturbance is shown in Figure 7. Compared with IMC-PID, IMC-NN inverse system control is more effective to resist the disturbance.

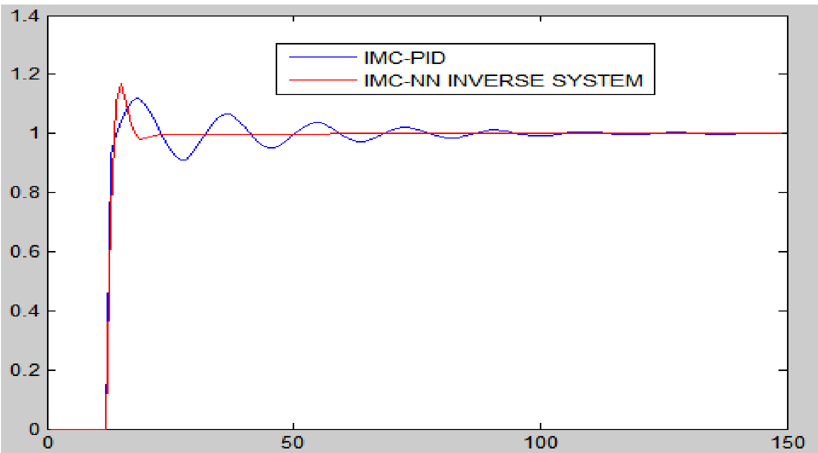

Figure 7. Results with Disturbance

(3) Application of Algorithm in tap-waterworks

Table 1. Comparing with other Algorithm

Month	Unit Consumption without decoupling	Unit Consumption with decoupling	Saving
1-3	1.8328(mg/L)	1.6289(mg/L)	9.46%
3-9	1.7828(mg/L)	1.5731(mg/L)	11.76%
9-12	1.7763(mg/L)	1.5625(mg/L)	12.03%

Due to that the residual-chlorine is stable using the algorithm, and it has the ability to resist the disturbance and improve the robustness, the lower unit consumption of chlorine is obtained as is shown in Table 1.

7. Conclusion

Chlorine dosing system is a complicated system with multi-models, large time delay, large inertial and nonlinear. Also the multi tunnels multi pools structure brings coupling. The paper proposed wavelet neural networks to model the inverse system, after that this inverse system cascades the original system so that pseudo-linearization system can be obtained, then this MIMO system can be transformed to SISO system with no coupling. Due to the model error and time delay, improved IMC is designed to solve these problems. Simulation and application shows that the algorithm has the ability to resist the disturbance and improve the robustness; meanwhile the lower unit consumption of chlorine is obtained.

References

[1] Ehsan Hossaini-asl, Mehdi Shahbazian.Nonlinear dynamic system control using wavelet neural network based on sampling theory. *IEEE International Conference on Systems, Man, and Cybernetics*. 2009; 4502-4507.
[2] Fernando Ornelas-Tellez, Edgar N Sanchez. Neural inverse optimal control for discrete-time uncertain nonlinear systems stabilization. *IEEE World Congress on Computational Intelligence.* 2012; 1-6.
[3] Geng Liang, Guotian Yang. A Kind of MIMO Decouple Control System Based on Double-Neuron Adaptive Predictive And Static Decouple Algorithm. *IEEE Pacific-Asia Workshop on Computational Intelligence and Industrial Application*. 2008; 360-364.
[4] Geng Liang. *A Kind of Fault-tolerant Decouple and Control Algorithms for Non-linear and Time-varying MIMO System Based on Neuron Adaptive PID and Neural network*. Proceedings of the 2007 International Conference on Wavelet Analysis and Pattern Recognition. 2007; 677-682.
[5] Jie Jia LI, Dai Yan LIU, Rui QU. The Strategy of Construction Equipment Energy-Saving Control. *TELKOMNIKA*. 2012; 10(4); 706-712.
[6] Liao Zhong. The Application of Wavelet Neural Network in Adaptive Inverse Control of Hydro-turbine Governing System. *International Conference on Artificial Intelligence and Computational Intelligence.* 2009; 163-166.
[7] Guohai Liu, Lingling Chen. Internal Model Control of Permanent Magnet Synchronous Motor Using Support Vector Machine Generalized Inverse. *IEEE Transaction on Industrial Informatics.* 2013; 9(2): 890-899.
[8] Sun Qiaomei, Ren Guang. SVM Inverse Model-based Heading Control of Unmanned Surface Vehicle. *Information Computing and Telecommunications* (YC-ICT). 2010; 138-141.
[9] Huang Yanwei. Nonlinear Internal Model Control with Inverse Model Based on Extreme Learning Machine. *Electric Information and Control Engineering (ICEICE).* 2011; 2391–2395.
[10] Isabelle Rivals, Léon Personnaz. Nonlinear Internal Model Control Using Neural Networks: Application to Processes with Delay and Design Issues. *IEEE Transactions on Neural Networks*. 2000; 11(1): 80-90.
[11] Gao De-xin. Nonlinear Systems Feedback Linearization Optimal Zero-State Error Control Under Disturbances Compensation. *TELKOMNIKA*. 2012; 10(6): 1349-1356.
[12] Feben D, Taras MJ. Studies on Chlorine Demand Constants. *Journal of American Water Works Association*. 1951; 43(11): 922–932.
[13] Qualls RG, Johnson JD. Kinetics of the Short-term Consumption of Chlorine by Fulvic Acid. *Environmental Science & Technology*. 1983; 17(11): 692-698.