Sanitizer Dosing Decoupling Control based on IMC-NN Inverse System

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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 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

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.

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 account.
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.

\[
\begin{align*}
\eta_{11} (X_1 - C_1) & \frac{e^{-\tau_1 s}}{T_{1s} + 1} + \eta_{21} (X_2 - C_2) \frac{e^{-\tau_2 s}}{T_{2s} + 1} + \cdots + \eta_{n1} (X_n - C_n) \frac{e^{-\tau_n s}}{T_{ns} + 1} \\
\eta_{12} (X_1 - C_1) & \frac{e^{-\tau_1 s}}{T_{1s} + 1} + \eta_{22} (X_2 - C_2) \frac{e^{-\tau_2 s}}{T_{2s} + 1} + \cdots + \eta_{n2} (X_n - C_n) \frac{e^{-\tau_n s}}{T_{ns} + 1} \\
& \vdots \\
\eta_{1n} (X_1 - C_1) & \frac{e^{-\tau_1 s}}{T_{1s} + 1} + \eta_{2n} (X_2 - C_2) \frac{e^{-\tau_2 s}}{T_{2s} + 1} + \cdots + \eta_{nn} (X_n - C_n) \frac{e^{-\tau_n s}}{T_{ns} + 1}
\end{align*}
\]

\( C_1 \) 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. \( T_1, \tau_1, T_2, \tau_2 \) are coefficients of first-order inertial model and coefficients of pure time delay, \( C_1 \) and \( T_1, \tau_1, T_2, \tau_2 \) are related to many factors and also they are time-varying.

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:

\[
\begin{align*}
y_1 &= \eta_{11} (X_1 - C_1) \frac{e^{-\tau_1 s}}{T_{1s} + 1} + \eta_{21} (X_2 - C_2) \frac{e^{-\tau_2 s}}{T_{2s} + 1} + \cdots + \eta_{n1} (X_n - C_n) \frac{e^{-\tau_n s}}{T_{ns} + 1} \\
y_2 &= \eta_{12} (X_1 - C_1) \frac{e^{-\tau_1 s}}{T_{1s} + 1} + \eta_{22} (X_2 - C_2) \frac{e^{-\tau_2 s}}{T_{2s} + 1} + \cdots + \eta_{n2} (X_n - C_n) \frac{e^{-\tau_n s}}{T_{ns} + 1} \\
& \vdots \\
y_n &= \eta_{1n} (X_1 - C_1) \frac{e^{-\tau_1 s}}{T_{1s} + 1} + \eta_{2n} (X_2 - C_2) \frac{e^{-\tau_2 s}}{T_{2s} + 1} + \cdots + \eta_{nn} (X_n - C_n) \frac{e^{-\tau_n s}}{T_{ns} + 1}
\end{align*}
\]
3. \( \alpha \) Order Neural Networks Inverse System

3.1. \( \alpha \) Order Inverse System

Definition 1: \( \Sigma \) is a system with \( p \) order input \( u(t) = (u_1, u_2, \cdots, u_p)^T \) and \( q \) order output \( u(t) = (y_1, y_2, \cdots, y_q)^T \), suppose \( \Pi_\alpha \) is a \( q \) order input and \( p \) order output system with mapping function \( u = \theta \phi \). Where \( \phi = (\phi_1, \phi_2, \cdots, \phi_q)^T \) is a random differential vector that meet the requirement of initial value of system \( \Sigma \), \( u(t) = (u_1, u_2, \cdots, u_p)^T \) is the output vector. If the operator meet the requirement as follows:

\[
\theta \phi = \theta [\phi (y_d)] = \theta u = y_d
\]

Then system \( \Pi_\alpha \) is defined as the \( \alpha \) order inverse system of the system \( \Sigma \).

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.

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 exists. 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.
Sanitizer Dosing Decoupling Control based on IMC-NN Inverse System (Xie Peizhang)

Figure 4. Structure of Improved IMC

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

\[
F_2(s) = \frac{1}{(\lambda s + 1)^n} \text{ is a low-pass filter.}
\]

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

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

\( G_{c1}(s) \) 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, \( t_i = \min(e^{-\tau_t}, e^{-\tau_2}, e^{-\tau_3}) \), \( \tau_t \) 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 \( C = N - \frac{T}{t_i} \), 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, \( G_m(s) \) is the internal model, \( G_{c1}(s) \) is the controller.

Design of controller:

Step 1: \( G_m(s) \) is the internal model, and the transfer function is \( G_m(s) = s^{-n} e^{-t_i} \), 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, \( G_m(s) \) 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 $F_i(s) = \frac{1}{(\lambda s + 1)^m}$.

![Diagram of IMC based on Wavelet Neural Networks Inverse System](image)

**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.
(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.

(3) Application of Algorithm in tap-waterworks

<p>| Table 1. Comparing with other Algorithm |
|-------------------------------|-----------------------------|-----------------------------|----------------------|</p>
<table>
<thead>
<tr>
<th>Month</th>
<th>Unit Consumption without decoupling</th>
<th>Unit Consumption with decoupling</th>
<th>Saving</th>
</tr>
</thead>
<tbody>
<tr>
<td>1-3</td>
<td>1.8328(mg/L)</td>
<td>1.6289(mg/L)</td>
<td>9.46%</td>
</tr>
<tr>
<td>3-9</td>
<td>1.7828(mg/L)</td>
<td>1.5731(mg/L)</td>
<td>11.76%</td>
</tr>
<tr>
<td>9-12</td>
<td>1.7763(mg/L)</td>
<td>1.5625(mg/L)</td>
<td>12.03%</td>
</tr>
</tbody>
</table>

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