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Integrated Data Reconciliation with Generic Model Control for the Steel Pickling Process

Paisan Kittisupakorn† and Pornsiri Kaewpradit

Department of Chemical Engineering, Chulalongkorn University, Bangkok 10330, Thailand
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Abstract−To implement an advanced control algorithm, measurements of process outputs are usually used to determine control action to a process. Nevertheless, measurements of process outputs are often subjected to measuring and signal errors as well as noise. Therefore, in this work, Generic Model Control (GMC), an advanced control technique, with data reconciliation technique has been applied to control the pH of the pickling process consisting of three pickling and three rinsing baths. Here, the data reconciliation problem involves six nodes and fourteen streams. The presence of errors in the data set is determined and identified via measurement test. In addition, the measurement error covariance is initially assumed to be a known variance matrix and is updated every iteration. Simulation results have shown that the reconciled process data give a better view of the true states of the process than raw measuring data. With these reconciled process data, the GMC controller can control the process at a desired set point with great success.

Key words: Data Reconciliation, Generic Model Control, Steel Pickling Process

INTRODUCTION

The accuracy and consistency of process data are the key to efficient operation of chemical plants. The measurements from a physical system are generally noisy and do not verify balance equations. These raw data with undetected biased errors result in false control of the process so that they need to be reconciled to eliminate known errors and measurement noise. The problem of data reconciliation consists of obtaining and estimating the true states that verify balance equations.

Mah et al. [1976] studied the problem of the identification of the source of gross errors and developed a series of rules (based on graph-theoretical results) that enhance the effectiveness of the algorithm search. Data reconciliation problems involving linear models were well studied. Crowe et al. [1983] used a matrix projection method to decompose the problem so that the measured and unmeasured variables can be evaluated sequentially. Later, Crowe [1986] extended this method for problems with bilinear constraints. Various statistical tests have been proposed to detect gross errors [Mah, 1990; Romagnoli, 1983; Romagnoli and Stephanopoulos, 1981]. General reconciliation methods are based on the hypothesis that measurement errors are random Gaussian variables with a known covariance matrix and zero mean. In most practical situations, this matrix is unknown or known approximately [Keller et al., 1992; Valko and Vajda, 1987; Romagnoli, 1983]. Recently, data reconciliation algorithms have been developed for input-output models in linear dynamic systems in which the measurement errors in the input variables are optimally handled in this approach [Kim et al., 1996].

It is well known that most chemical industrial plants cause environmental problems due to usage of chemicals in production lines. Therefore, a model-based control scheme was developed to control dynamic behavior of the process. The control strategy has been applied to chemical process system for control purposes for the past ten years. A new method to handle the constraints on manipulated variables for multivariable unstable processes was proposed by Lee and Park [1991]. Kittisupakorn and Hussain [2000], and Arpornwichanop et al. [2002] presented a model-based control strategy together with extended Kalman Filter (EKF) for reactant concentration control of chemical reactors and for temperature control of batch reactors with exothermic reactions, respectively. Furthermore, nonlinear control algorithms using feedback input-output linearization applied to a lab-scale batch eater-interchange reaction system were discussed by Park and Park [1999]. Generic Model Control (GMC), one of the most popular model-based controllers, is a control algorithm capable of using a non-linear process model directly. In 1989, Lee et al. extended the application of the model based GMC controller to a forced circulation single-stage evaporator. Later, they examined the use of GMC for controlling the level in a surge tank [1991]. Cott and Macchietto [1989], and Kershenbaum and Kittisupakorn [1994] studied the temperature control of an exothermic batch reactor via using a GMC controller. Farrell and Tsai [1995] implemented the GMC algorithm for the batch crystallization process.

The steel pickling process has used concentrated chemicals in production lines, and wastewater released from the process contains hazardous materials and usually causes major environmental problems. Therefore, production scheduling and control of the pickling process are inevitably needed to minimize the amount of hazardous material contained in the released wastewater as well as wastewater itself. A conventional PID controller has normally been used to control the process. However, it is known widely that a PID controller cannot handle non-linearity of the pH control problem and advanced control techniques are required [Cho et al., 1999]. In addition, in reality, the process flow rates of the system are subjected to measurement noise leading to poor control performance of any controller. This work then introduces the application of Generic Model Control (GMC) coupled with steady state data reconciliation to

†To whom correspondence should be addressed.
E-mail: paisan.k@chula.ac.th

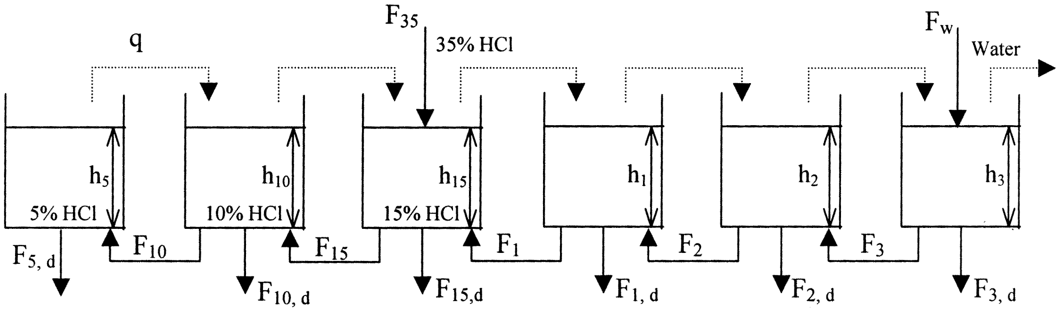

Fig. 1. Pickling process.

control level and pH of the pickling process with respect to measurement noise.

PROCESS AND MATHEMATICAL MODELING

In this research, the pickling process (Fig. 1) consists of two major steps: pickling and rinsing steps. The pickling step is to remove surface oxides (scales) and other contaminants such as dirt out of metals by an immersion of the metals into an aqueous acid solution.

Metals are immersed in pickling baths--5%, 10% and 15% by weight hydrochloric acid (HCl), respectively--to remove scales from metal. The direction of metals is countercurrent to acid stream direction as shown by dotted lines in Fig. 1. The reaction in the baths is

$$FeO + 2HCl \rightarrow FeCl_2 + H_2O$$

Then, metals without scales out of pickling baths are immersed in rinsing baths, which consist of three pure water baths, to rinse acid covering the metals. Similarly, the direction of the metals is opposite to the rinse water flow. Here, the amount of drag-out solution of each bath is assumed to be equal to the amount of drag-in solution.

The objective of this work is to control height and pH (or H+ concentration) of each bath to a desired set point as illustrated in Fig. 2(a) and 2(b). Acid concentrations of the first, second and the last baths are set at 1.37×10^{-3}, 2.74×10^{-3} and 4.11×10^{-3} mole per liter, respectively, by adjusting the acid stream as shown in Fig. 2(a). The pH value of each rinsing bath is controlled at 5.5 (The standard of Department of Industrial Work) as shown in Fig. 2(b).

To develop a mathematical model of the pickling process, it is assumed that whole baths are perfectly mixed and isothermal. Other assumptions made in formulating process models are that the reaction involved is first order, all pH values are measurable and the feed concentration is known. Under these assumptions, the material balances of pickling baths can be written as follows:

Total mass balances (Density is assumed to be constant),

$$A\frac{dh_5}{dt} = F_{10} - F_{5,d} - q \tag{1}$$

$$A\frac{dh_{10}}{dt} = F_{15} - F_{10} - F_{10,d} \tag{2}$$

$$A\frac{dh_{15}}{dt} = F_1 + F_{35} - F_{15} - F_{15,d} \tag{3}$$

Total component balances,

$$Ah_5\frac{dC_5}{dt} = F_{10}(C_{10} - C_5) - Ah_5kC_5 \tag{4}$$

$$Ah_{10}\frac{dC_{10}}{dt} = F_{15}(C_{15} - C_{10}) + q(C_5 - C_{10}) - Ah_{10}kC_{10} \tag{5}$$

$$Ah_{15}\frac{dC_{15}}{dt} = F_1(C_1 - C_{15}) + F_{35}(C_{35} - C_{15}) + q(C_{10} - C_{15}) - Ah_{15}kC_{15} \tag{6}$$

Similarly, with the assumptions above, the material balances of the rinsing baths are as follows:

Total mass balances (Density is assumed to be constant),

$$A\frac{dh_1}{dt} = F_2 - F_1 - F_{1,d} \tag{7}$$

$$A\frac{dh_2}{dt} = F_3 - F_2 - F_{2,d} \tag{8}$$

$$A\frac{dh_3}{dt} = F_w - F_3 - F_{3,d} \tag{9}$$

Total component balances,

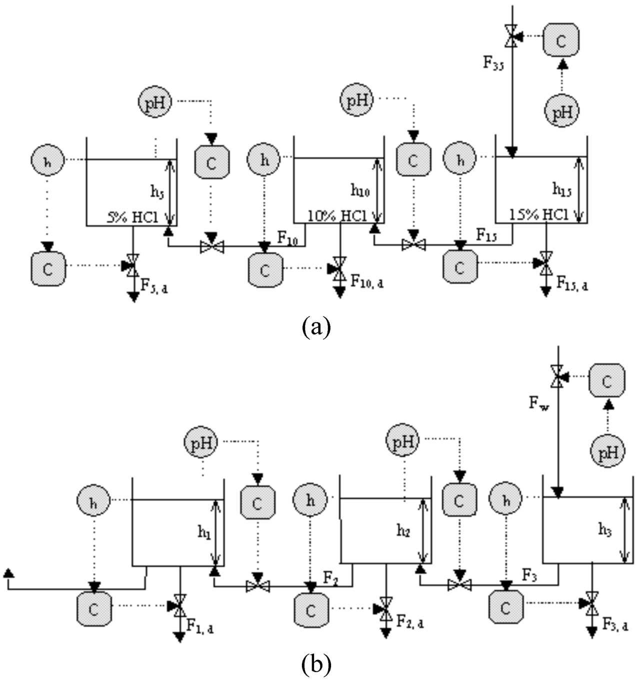

Fig. 2. (a) Flow diagram of pickling bath controls. (b) Flow diagram of rinsing bath controls.

$$Ah_1\frac{dC_1}{dt}=F_2(C_2-C_1)+q(C_{15}-C_1) \tag{10}$$

$$Ah_2\frac{dC_2}{dt}=F_3(C_3-C_2)+q(C_1-C_2) \tag{11}$$

$$Ah_3\frac{dC_3}{dt}=F_w(C_w-C_3)+q(C_2-C_3) \tag{12}$$

Here, it was assumed that all process variables are measurable without noise except process flow rates with measurement noise of ±1% of true values. Therefore, steady state data reconciliation is implemented to reconcile these flow rates, and these reconciled flow rates are then used in the GMC controller to determine control action.

GENERIC MODEL CONTROL (GMC)

Generic Model Control (GMC), an advanced non-linear control technique, uses mathematical models of a plant to determine control action. The process model used can be either linear or non-linear. Here, 12 states need to be controlled as described above. Therefore, 12 manipulated variables are determined based on the GMC control algorithm as shown below:

$$F^k_{5,d}=F^k_{10}-q-A\left[K^1_{5,d}(h_{5,sp}-h^k_5)+\sum_{k=0}^{k}K^2_{5,d}\Delta t(h_{5,sp}-h^k_5)\right] \tag{13}$$

$$F^k_{10,d}=F^k_{15}-F^k_{10}-A\left[K^1_{10,d}(h_{10,sp}-h^k_{10})+\sum_{k=0}^{k}K^2_{10,d}\Delta t(h_{10,sp}-h^k_{10})\right] \tag{14}$$

$$F^k_{15,d}=F_1+F^k_{35}-F^k_{15}-A\left[K^1_{15,d}(h_{15,sp}-h^k_{15})+\sum_{k=0}^{k}K^2_{15,d}\Delta t(h_{15,sp}-h^k_{15})\right] \tag{15}$$

$$F^k_{10}=\frac{Ah^k_5}{(C^k_{10}-C^k_5)}\left[K^1_{10}(C_{5,sp}-C^k_5)+\sum_{k=0}^{k}K^2_{10}\Delta t(C_{5,sp}-C^k_5)+kC^k_5\right] \tag{16}$$

$$F^k_{15}=\frac{Ah^k_{10}}{(C^k_{15}-C^k_{10})}\left[K^1_{15}(C_{10,sp}-C^k_{10})+\sum_{k=0}^{k}K^2_{15}\Delta t(C_{10,sp}-C^k_{10})-\frac{q}{Ah^k_{10}}(C^k_5-C^k_{10})+kC^k_{10}\right] \tag{17}$$

$$F^k_{35}=\frac{Ah^k_{15}}{(C^k_{35}-C^k_{15})}\left[K^1_{35}(C_{15,sp}-C^k_{15})+\sum_{k=0}^{k}K^2_{35}\Delta t(C_{15,sp}-C^k_{15})-\frac{F_1}{Ah^k_{15}}(C^k_1-C^k_{15})-\frac{q}{Ah^k_{15}}(C^k_{10}-C^k_{15})+kC^k_{15}\right] \tag{18}$$

Manipulated variables in rinsing baths are shown as follows:

$$F^k_{1,d}=F^k_2-F^k_1-A\left[K^1_{1,d}(h_{1,sp}-h^k_1)+\sum_{k=0}^{k}K^2_{1,d}\Delta t(h_{1,sp}-h^k_1)\right] \tag{19}$$

$$F^k_{2,d}=F^k_3-F^k_2-A\left[K^1_{2,d}(h_{2,sp}-h^k_2)+\sum_{k=0}^{k}K^2_{2,d}\Delta t(h_{2,sp}-h^k_2)\right] \tag{20}$$

$$F^k_{3,d}=F^k_w-F^k_3-A\left[K^1_{3,d}(h_{3,sp}-h^k_3)+\sum_{k=0}^{k}K^2_{3,d}\Delta t(h_{3,sp}-h^k_3)\right] \tag{21}$$

$$F^k_2=\frac{Ah^k_1}{(C^k_2-C^k_1)}\left[K^1_2(C_{1,sp}-C^k_1)+\sum_{k=0}^{k}K^2_2\Delta t(C_{1,sp}-C^k_1)-\frac{q}{Ah^k_1}(C^k_{15}-C^k_1)\right] \tag{22}$$

$$F^k_3=\frac{Ah^k_2}{(C^k_3-C^k_2)}\left[K^1_3(C_{2,sp}-C^k_2)+\sum_{k=0}^{k}K^2_3\Delta t(C_{2,sp}-C^k_2)-\frac{q}{Ah^k_2}(C^k_1-C^k_2)\right] \tag{23}$$

$$F^k_w=\frac{Ah^k_3}{(C^k_3-C^k_w)}\left[-K^1_w(C_{3,sp}-C^k_3)-\sum_{k=0}^{k}K^2_w\Delta t(C_{w,sp}-C^k_w)+\frac{q}{Ah^k_3}(C^k_2-C^k_3)\right] \tag{24}$$

DATA RECONCILIATION

Since the measurements are subject to errors, material balances are not generally obeyed by the measured values. These values have to be adjusted or reconciled to obtain more accurate estimates of flow rates, which are, at the same time, consistent with the material balances. To formulate this problem, a mathematical model of a process, relevant constraints and an appropriate objective function are needed. The following measurement model is postulated in the absence of gross errors:

$$\tilde{x}=x+\varepsilon \tag{25}$$

where $\tilde{x}$ is the vector of measured variables; ε is a vector of random measurement errors. It is usually assumed that (a) the expected value of ε, $E(\varepsilon)=0$; (b) the successive vectors of measurements are independent, i.e., $E(\varepsilon_i\varepsilon_j^T)=0$, for i i≠j; and the covariance matrix is known and positive definitive, i.e., $\mathrm{cov}(\varepsilon)=E(\varepsilon_i\varepsilon_j^T)=Q$.

The reconciled or adjusted value x' is related to the measured value $\tilde{x}$ by the adjustment, a:

$$x'=\tilde{x}+a \tag{26}$$

The data reconciliation problem may be formulated as the following constrained weighted least squares estimation problem:

$$\min_{x,v}[(\tilde{x}-x)^TQ^{-1}(\tilde{x}-x)=a^TQ^{-1}a] \tag{27}$$

subject to the constraint: Bx=c (28)

The minimization is carried out by using Lagrange Multipliers. The solution is given by

$$x'^k=\tilde{x}-Q^k(B)^T[BQ^k(B)^T]^{-1}[Bx-c] \tag{29}$$

The covariance of measurement errors is updated each iteration.

$$Q^k=[I-2H^k+(H^k)^TH^k]Q^{k-1} \tag{30}$$

$$H^k=Q^{k-1}(B)^T[BQ^{k-1}(B)^T]^{-1}B \tag{31}$$

where

$$x=[F_{5,d};\ F_{10};\ F_{10,d};\ F_{15};\ F_{15,d};\ F_1;\ F_{1,d};\ F_2;\ F_{2,d};\ F_3;\ F_{3,d};\ F_{35};\ F_w]$$

$$B=\begin{bmatrix}-1&1&0&0&0&0&0&0&0&0&0&0&0\\0&-1&-1&1&0&0&0&0&0&0&0&0&0\\0&0&0&-1&-1&1&0&0&0&0&0&0&0\\0&0&0&0&0&-1&-1&1&0&0&0&0&0\\0&0&0&0&0&0&0&-1&-1&1&0&0&0\\0&0&0&0&0&0&0&0&0&-1&-1&0&1\end{bmatrix}\quad c=\begin{bmatrix}0.002\\0\\0\\0\\0\\0\end{bmatrix}$$

In this case, it is assumed that the initial covariance of measurement errors (Q) is a unit diagonal matrix with dimension 13×13. Here, process data are adjusted to satisfy conservation laws based on information of measured variables. Then this reconciled data set is incorporated into model-based controller to control state variables to the desired set point. Fig. 3 shows the flowchart of GMC with data reconciliation.

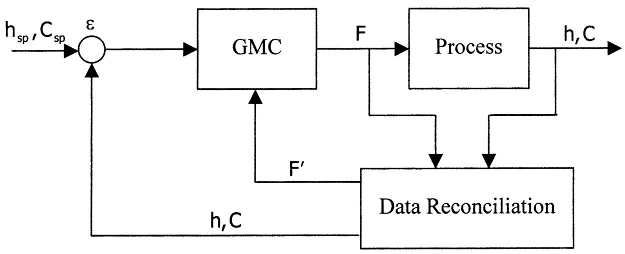

Fig. 3. Flowchart of GMC with data reconciliation.

Table 1. Tuning parameters of GMC

Bath	Height tuning parameters		Concentration tuning parameters	
5% HCl	$K^1_{5,d}$	$K^2_{5,d}$	K^1_{10}	K^2_{10}
	0.1667	0.694	0.891	0.000038
10% HCl	$K^1_{10,d}$	$K^2_{10,d}$	K^1_{15}	K^2_{15}
	0.001667	0.000694	2.55	1.66
15% HCl	$K^1_{15,d}$	$K^2_{15,d}$	K^1_{35}	K^2_{35}
	1.667	0.694	1.333	0.178
Rinsing 1	$K^1_{1,d}$	$K^2_{1,d}$	K^1_2	K^2_2
	16	7.1	1	0.0025
Rinsing 2	$K^1_{2,d}$	$K^2_{2,d}$	K^1_3	K^2_3
	16	7.1	1	0.0025
Rinsing 3	$K^1_{3,d}$	$K^2_{3,d}$	K^1_w	K^2_w
	16	7.1	1	0.0025

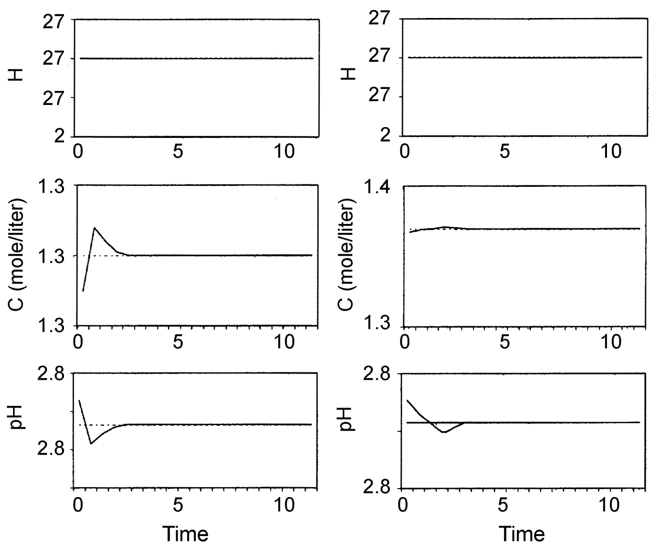

Fig. 4. The control response of GMC without (left) and with (right) data reconciliation in 5% by weight HCl baths.

The measured process flow rates with measurement error ±1% of true values are adjusted via steady state data reconciliation; after that, these reconciled data are incorporated into the Generic Model Control (GMC) algorithm to calculate control actions for control purposes.

SIMULATION RESULTS

The GMC with data reconciliation is applied to control height, acid concentration and pH in the steel pickling process. Each 5%, 10% and 15% by weight HCl bath is controlled to maintain the concentrations at 1.37×10^{-3}, 2.74×10^{-3} and 4.11×10^{-3} mole per liter, respectively. Simultaneously, the pH values of three rinsing baths are controlled within 5.5. The height of each bath is controlled not over 0.274 meters. The performance of a GMC with data reconcil-

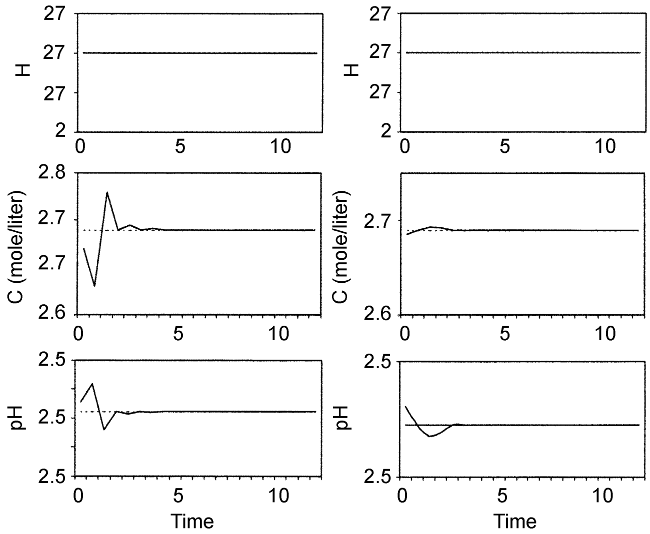

Fig. 5. The control response of GMC without (left) and with (right) data reconciliation in 10% by weight HCl bath.

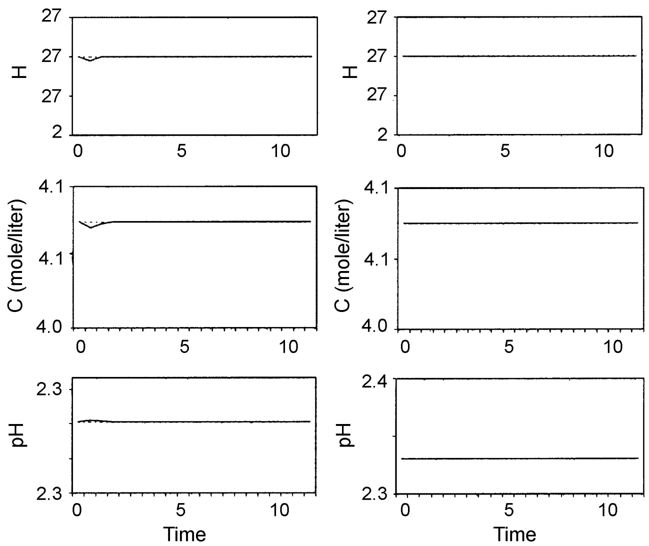

Fig. 6. The control response of GMC without (left) and with (right) data reconciliation in 15% by weight HCl bath.

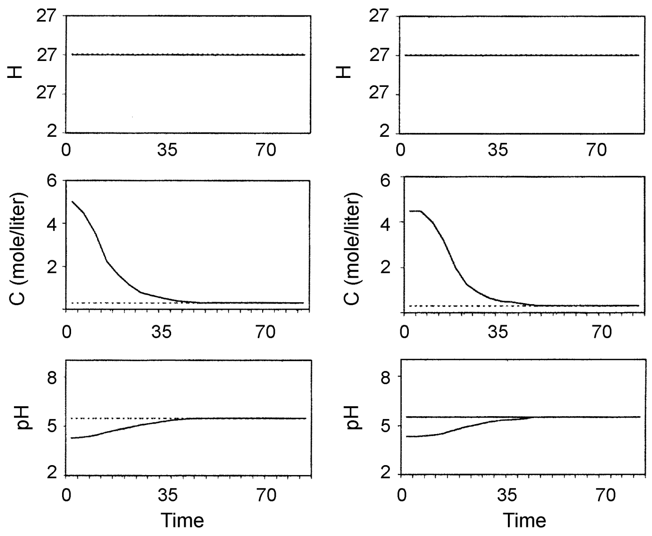

Fig. 7. The control response of GMC without (left) and with (right) data reconciliation in the first rinsing tank.

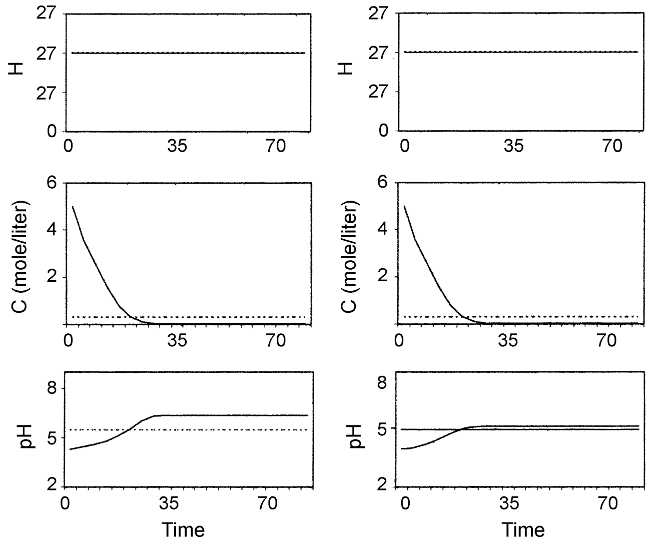

Fig. 8. The control response of GMC without (left) and with (right) data reconciliation in the second rinsing tank.

iation is then compared to that of a GMC controller. The values of GMC tuning parameters are given in Table 1.

Figs. 4-6 show the control response of GMC without and with data reconciliation in the pickling step and Figs. 7-9 show the control response in the rinsing step.

It can be seen from Figs. 4-6 that both conventional GMC without and with data reconciliation can control acid concentrations at the set points with small overshoot. However, the GMC with data reconciliation provides better control performance than that of GMC controller without data reconciliation.

Figs. 7-9 show that the GMC with data reconciliation can control the pH of each bath to the desired set point, whereas the GMC without data reconciliation cannot. Therefore, the inclusion of data reconciliation technique can enhance the control performance of the GMC controller.

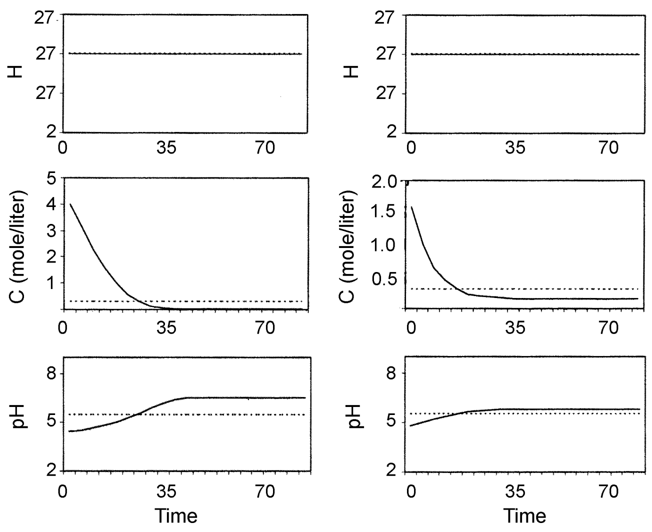

Fig. 9. The control response of GMC without (left) and with (right) data reconciliation in the third rinsing tank.

CONCLUSION

Generic Model Control (GMC), a non-linear model-based controller, requires process models of a plant as well as measurements of process outputs to determine the control action needed to control the plant. Therefore, the performance of the GMC controller relies on the accuracy of not only the mathematical models but also the measurements of process data. In reality, the measurements of process outputs often contain measuring error, signal error and noise. These errors usually lead to poor performance of the GMC controller. In this work, the steady state data reconciliation algorithm is included in the formulation of the GMC control algorithm to reconcile measured process flow rates. For simplification, it is assumed that the available level and concentration are certain. Simulation results have demonstrated that the GMC controller with data reconciliation can provide better control performance than that of the GMC without data reconciliation technique. Therefore, in this case the inclusion of the steady state data reconciliation technique in the GMC control algorithm can deal with errors of flow measurements as well as noise; the GMC controller with data reconciliation technique is applicable to processes with measurement and signal errors.

APPENDIX

A. Tuning Parameters of GMC Controller

Lee and Sullivan [1988] outline a system for tuning the GMC controller based on choosing a target profile of the controlled variable, $y^{sp}(t)$. This profile is characterized by two values, ξ and τ. Lee and Sullivan present a figure that outlines the relative control performances of different combinations of ξ and τ as shown in Fig. A.1. Similar plots to the classical second-order response showing the normalized response of the system y/y^{sp} vs. normalized time t/τ with ξ as a parameter can be produced.

The general form of GMC control algorithm can be written as

$$\tilde{y} = K_1(y^{sp} - y) + K_2\int(y^{sp} - y)dt \tag{A.1}$$

The value of two tuning constants, K_1 and K_2 are obtained by us-

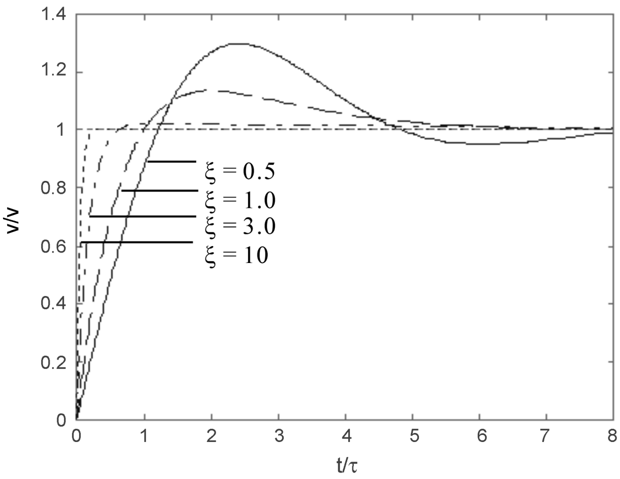

Fig. A.1. Generalized GMC profile specification.

ing the following relationships:

$$K_1=\frac{2\xi}{\tau} \qquad K_2=\frac{1}{\tau^2}$$

In tuning the GMC controller, because overshoot is undesirable, ξ is set to the expected value. After that the value of τ is obtained by examining the tuning charts given by Lee and Sullivan. In this work, twelve controllers are considered here to control the level and concentration of steel pickling process; then each tuning parameter is outlined as follows.

1. 15% acid tank

Level	$\xi=1$,	$t=\tau$	Let t=1.2 min, then τ=1.2
	$K_1=(2\times1\div1.2)=1.667$	and	$K_2=1\div(1.2^2)=0.694$
pH	$\xi=10$,	$t=0.25\tau$	Let t=5.6 min, then τ=22.45
	$K_1=(2\times10\div22.45)=0.891$	and	$K_2=(1\div(22.45^2))\div52=0.000038$

2. 10% acid tank

Level	$\xi=1$,	$t=\tau$	Let t=1.2 min, then τ=1.2
	$K_1=(2\times1\div1.2)\div100=0.001667$	and	$K_2=1\div(1.2^2)\div1000=0.000694$
pH	$\xi=0.5$,	$t=1.29\tau$	Let t=1 min, then τ=0.775
	$K_1=(2\times0.5\div0.775)\times1.98=2.55$	and	$K_2=1\div(0.775^2)=1.66$

3. 5% acid tank

Level	$\xi=1$,	$t=\tau$	Let t=1.2 min, then τ=1.2
	$K_1=(2\times1\div1.2)\div10=0.1667$	and	$K_2=1\div(1.2^2)=0.694$
pH	$\xi=1$,	$t=\tau$	Let t=0.75 min, then τ=0.75
	$K_1=(2\times1\div0.75)\div2=1.3333$	and	$K_2=(1\div(0.75^2))\div10=0.178$

4. The 3rd rinsing tank

Level	$\xi=3$,	$t=0.8\tau$	Let t=0.3 min, then τ=0.375
	$K_1=2\times3\div0.375=16$	and	$K_2=1\div(0.375^2)=7.1$
pH	$\xi=10$,	$t=0.25\tau$	Let t=5 min, then τ=20
	$K_1=2\times10\div20=1$	and	$K_2=1\div(20^2)=0.0025$

5. The 2nd rinsing tank

Level	$\xi=3$,	$t=0.8\tau$	Let t=0.3 min, then τ=0.375
	$K_1=2\times3\div0.375=16$	and	$K_2=1\div(0.375^2)=7.1$
pH	$\xi=10$,	$t=0.25\tau$	Let t=5 min, then τ=20
	$K_1=2\times10\div20=1$	and	$K_2=1\div(20^2)=0.0025$

6. The 1st rinsing tank

Level	$\xi=3$,	$t=0.8\tau$	Let t=0.3 min, then τ=0.375
	$K_1=2\times3\div0.375=16$	and	$K_2=1\div(0.375^2)=7.1$
pH	$\xi=10$,	$t=0.25\tau$	Let t=5 min, then τ=20
	$K_1=2\times10\div20=1$	and	$K_2=1\div(20^2)=0.0025$

From Eq. (A.1), the first expression is to bring the process back to steady state due to change in dy/dt. The last expression is introduced in order to make the process have a zero offset. In this work, the appropriate values of the tuning parameters of each GMC controller to control the concentrations to the desired targets are presented above. With these parameters the control strategy is able to hold the process without offset.

NOMENCLATURE

a : adjustment
A : area of operating tank, meter^2
B : incidence matrix
c : constant matrix
C : HCl concentration, mole per liter
F : volumetric rate, liter per min
h : height of operating tank, meter
k : reaction rate constant, 0.0003267 (min)$^{-1}$·(mole per liter)
K^1, K^2 : tuning parameters of GMC controller
q : amount of acid solution that stuck with samples, 0.002 liter per min
Q : the covariance matrix of measurement errors
Δt : sampling time [min]
x : state variables

Greek Letters

ε : a vector of random measurement errors
~ : measured value
' : estimated value

Subscripts

1 : from the first rinsing tank
2 : from the second rinsing tank
3 : from the third rinsing tank
5 : from 5% by weight HCl tank
10 : from 10% by weight HCl tank
15 : from 15% by weight HCl tank
35 : from 35% by weight HCl tank
d : drain
w : water
sp : setpoint

Superscripts

k : at time k
(k−1): at time (k−1)

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