Proceeding of the 2004 American Control Conference
Boston, Massachusetts June 30 - July 2, 2004

Adaptive Calibration of Surrogate Measurements and Its Application to the Control of Moisture Content in Paper Manufacturing

Zeyu Liu and Perry Y. Li

***Abstract*— Many industrial processes are in cascade configuration in which the material being processed goes through a sequence of processing units. In many cases, direct in-process measurements of the relevant variable are not available at all but at the last processing unit. Surrogate or model based soft measurements in which the relevant in-process variables are inferred from other measurements would be useful in these situations. Models necessary for the surrogate measurements however, are often not accurately known. In this paper, we propose a control method in which the surrogate measurement models are adaptively calibrated and the surrogate measurements are used for in-process feedback. The control law is developed in the context of moisture content control for paper manufacturing via successive vacuum dewatering. A Lyapunov based algorithm is derived and proved. Simulation results show that the proposed control strategy can regulate the exiting moisture content of each box at the desired value.**

Keywords: adaptive calibration, surrogate measurements, soft sensors, paper manufacturing, cascade systems.

I. INTRODUCTION

Many industrial processes are in cascade configuration as shown in Figure 1, where the material being processed goes through a series of processing units. Typically, it is desired that at the end of the process, a process relevant variable x_n (where n denotes the last processing unit) conforms to some desired target $x_n{}^*$. In order to ensure that the process is well behaved, it is often also necessary for each $x_i \to x_i^*$, at each of the $i = 1, \cdots, n$ processing unit. In many cases, the variable we want to control (x_i) is difficult to measure directly during the manufacturing process, although direct measurement of the end product is available at the end of the process (i.e. x_n is measurable). If x_i, the variable which is difficult to be measured, but is related to another variable z_i which can be readily measured, then z_i can be utilized as a surrogate measurement or as a soft sensor to infer what the un-measured variable x_i is ([1], [3], [4] and [6]). The estimate is then used for the pre-emptive feedforward or feedback control. Unfortunately, to infer the unmeasured variable requires the surrogate measurement models, which may not be accurately known.

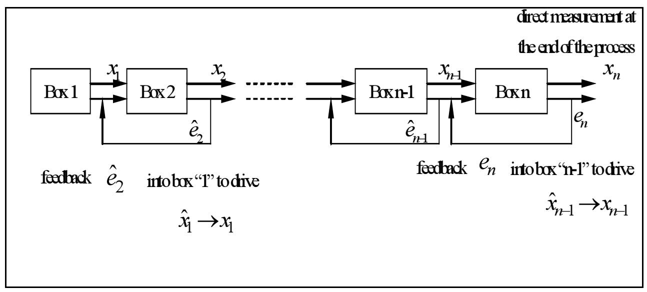

Figure 1. Adaptive calibration scheme

When in-process measurement of x_i is available (via either direct or surrogate measurement), it can be used for process control, and particularly in the compensation of the effect of any upstream disturbances on the downstream processing units. For example, state information from the upstream box *"i-1"* can be used to control of box "*i*" in a feed-forward pre-emptive manner. It can also use information of box *"i"* itself in a feedback term to increase the convergence rate [5].

When x_i cannot be directly measured, it is estimated using the surrogate mesaurement model $\hat{x}_i = F(z_i)$, where $\hat{x}_i$ is the estimate of x_i. However, the surrogate measurement model, which is usually derived empirically from experimental data, may not be accurate and can vary with operating condition. Control performance is directly affected by estimation error by introducing an unknown offset in the target [5]. The estimation error in *"i-1"*th box $\tilde{x}_{i-1} := \hat{x}_{i-1} - x_{i-1}$, also affects the control error $e_i := x_i - x_i^*$ of the downstream box "i*"* since its effect will

This work was supported by the National Science Foundation (NSF/ENG/DMI - 0085230).

Z. Liu is with the Department of Mechanical Engineering, University of Minnesota, Minneapolis, MN 55455 USA (phone: 612-626-7689; fax: 612-626-1854; e-mail: zliu@me.umn.edu)
P. Y. Li [Corresponding author] is with the Department of Mechanical Engineering, University of Minnesota, Minneapolis, MN 55455 USA (e-mail: pli@me.umn.edu)

0-7803-8335-4/04/$17.00 ©2004 AACC

be inadequately compensated for. Therefore, in this paper, we develop an *adaptive calibration* algorithm in which the direct measurement for the last box (which is assumed available) is used to tune the surrogate measurement models of the upstream boxes successively. The idea is that the control error of the last box e_n can be used to tune box *"n-1"* to drive the estimation error to zero ($\hat{x}_{n-1} \to x_{n-1}$). Similarly, the control error of "*i+1*"th box can be used to drive the estimation error of "*i*"th box to 0 for each of the *i=1* to *n-1* boxes.

Although the algorithm can be generalized, we focus on the control of moisture content using the vacuum dewatering in paper manufacture. In paper manufacturing, pulp slurry is dewatered through a series of gravity dewatering, vacuum dewatering, mechanical pressing, and thermal drying (Figure 2). Current closed-loop process control strategy uses a moisture sensor at the end of the process to control the dryer section. This topology has several drawbacks such as product waste, long dead-time resulting in stability issue and control performance limitation, and energy inefficiency. To overcome these drawbacks, we propose to more fully utilize the energy efficient vacuum dewatering and to apply closed-loop control to this section using in-process moisture feedback [5]. Vacuum dewatering takes place at successively vacuum dewatering boxes in which water is sucked out of the wet sheet. However, moisture content cannot be measured directly by the moisture sensor during the vacuum dewatering process because the sheet is too wet to be unsupported. The airflow passing through the wet sheet has been proposed as a viable surrogate measurement for the moisture content since airflow increases as moisture decreases [5]. A preemptive control algorithm using the surrogate measurement was proposed in [5] and an adaptive version of the controller which does not require a precise knowledge of dewatering coefficient was proposed in [2]. In both cases, however, the surrogate measurement model is assumed to be accurate. In reality, the airflow / moisture content relationships are obtained experimentally and can vary. In this paper, an adaptive calibration algorithm that uses a direct moisture sensor at the end of the vacuum dewatering process is proposed to overcome this difficulty. An added complexity of the problem is due to the transport delay between the times when the sheet leaves one dewatering box and enters the next.

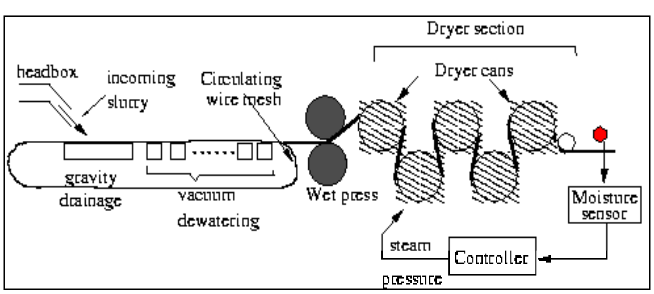

Figure 2. Water removal process in paper manufacturing and current control strategy for the dryer section

The rest of the paper is organized as follows. Vacuum dewatering model, surrogate measurement model, and a generalized model are presented in section II. Preemptive control design with adaptive calibration of the surrogate measurement is presented in section III. Section IV presents the simulation results and the discussion. Section VI contains the summary and conclusions.

II. SYSTEM MODEL

A. Vacuum Dewatering Model of the Paper Manufacturing Process

In [5], a one-segment vacuum dewatering model is proposed,

$$\frac{dw_i}{dt} = -\Omega_i(t)w_i(t) + v \cdot c_{i-1}(t-\tau) \tag{1}$$

$$c_i(t) = \frac{K_i\sqrt{P_i(t)}}{v}\frac{f_i(t)}{1-f_i(t)}w_i(t) = \alpha_i(t)w_i(t) \tag{2}$$

where the state $w_i(t)$ is the total moisture content of the *"i"th* box, output $c_i(t)$ is the exit moisture content of the *"i"th* box, $\Omega_i(t) = \dfrac{K_i\sqrt{P_i(t)}}{1-f_i(t)}$ is a function of control pressure input $P_i(t)$ with $f_i(t) = e^{-\frac{K_i B\sqrt{P_i(t)}}{v}}$, τ_i is the transport time delay for the paper sheet exiting the *"i-1"*th box reaching the *"i"*th box, v is the wire speed, K_i is the transport coefficient which is assumed to be a constant, B is the length of the slot of the dewatering box. The dewatering model has three features, which add much complexity to the problem: (1) the input $P_i(t)$ is coupled with the state, (2) the input appears in the output equation (relative degree is zero), and (3) there is a time delay.

B. Surrogate Measurement Model

As described in section 1, airflow can be used as a viable surrogate measurement for moisture content. Based on the experiment data collected from a series of tests for wet sheets, we found an approximately linear relation for the moisture content, the airflow passing through sheet and the small deviation of the vacuum pressure from the nominal pressure, which is $\hat{w}_i = J(\Delta P, q_i) \approx Q_i^T\hat{\theta}_i$, where $\hat{w}_i(t)$ is the estimation of the total moisture content, $Q_i^T = [1 \; q_i \; \Delta P_i]$ and $\hat{\theta}_i = \begin{bmatrix} a_i \\ b_i \\ c_i \end{bmatrix}$, where q_i is the airflow passing through the sheet, $\Delta P_i = P_i - P_i^*$ is the deviation of the vacuum pressure applied on the sheet from the nominal value, and a_i, b_i, and c_i are the unknown parameters that need to be adaptively calibrated. We assume that dJ/dq_i is bounded and not equal to zero and d^2J/dq_i^2 is bounded, which is not a strict assumption.

C. Generalized System Model

A more generalized system model can be derived as

$$\frac{dx_i}{dt} = -g_1(u_i)x_i + b_i f(y_{i-1}) \quad (3)$$

$$y_i = g_2(u_i)h(x_i) \quad (4)$$

where x_{i-1}, and x_i are the state at the *"i-1"th* box, and the *"i"th* box, respectively, y_i is the output at the *"i"th* box, and u_i is the control applied at the *"i"th* box. The state variable x_i cannot be measured directly except for the last box (x_n is measurable), but it is related to another variable z_i which can be measured readily ($x_i = F(z_i) \approx Z_i^T \zeta_i$, where Z_i^T is the surrogate measurement and ζ_i is the parameter to be adaptive calibrated). In the next section, we will design the preemptive control algorithm with adaptive calibration based on the vacuum dewatering model. As a matter of fact, the proposed adaptive calibration algorithm can be applied to any plant (in cascade connection) with the dynamics described by equations (3) and (4), where *f* and *h* are linear functions of y_{i-1} and x_i respectively, g_1 and g_2 can be nonlinear functions of u_i, and $dg_2 / du_i \neq 0$, dF / dz_i is bounded and not equal to zero and d^2F / dz_i^2 is bounded.

III. Preemptive Control with Adaptive Calibration of the Surrogate Measurement

A. Control Problem Statement

The ultimate control objective is to maintain the exit moisture content at the last dewatering box at target value. We also need to pay attention to the control efforts in the upstream boxes, since we want to remove the water gradually without saturating control or causing catastrophic result like sealing. So a desired moisture content profile is designed along the length of the vacuum dewatering process [5]. That is, for each vacuum dewatering box, a desired total moisture content w_i^* and a desired exit moisture content c_i^* are designed with a feasible nominal operating pressure P_i^*. At the nominal point, the plant model equation (1) satisfies

$$0 = \dot{w}_i^* = -\Omega_i^* w_i^* + v c_{i-1}^* \quad (5)$$

where $\Omega_i^* = \frac{K_i\sqrt{P_i^*}}{1-f_i^*}$, $f_i^* = e^{-\frac{K_i B\sqrt{P_i^*})}{v}}$, and $c_{i-1}^* = \left\{ \frac{K_{i-1}\sqrt{P_{i-1}^*}}{v} \frac{f_{i-1}^*}{1-f_{i-1}^*} \right\} w_{i-1}^* = \alpha_{i-1}^* w_{i-1}^*$. The process is subject to variation in the moisture content of the slurry entering the first dewatering box. The control objective is to control the vacuum pressure $P_i(t)$ so that $\lim_{t\to\infty} c_i(t) = c_i^*$, for *i>1.* Since the incoming slurry is subject to disturbance, the exit moisture content of the first box cannot be controlled exactly at the desired value.

B. Preemptive Control with Adaptive Calibration

Defining the total moisture content error and the exit moisture content error as $e_{wi} = w_i - w_i^*$ and $e_{ci} = c_i - c_i^*$, the open-loop error dynamics can be obtained by subtracting equation (5) from equation (1).

$$\dot{e}_{wi} = -\Omega_i(t)e_{wi}(t) + (\Omega_i^* - \Omega_i(t))w_i^* + v e_{c,i-1}(t-\tau) \quad (6)$$

Since our objective is to control the output of box *"i"* at the desired value, we need to express the output in state equation using dynamic extension technique. Expressing e_{ci} as a function of e_{wi}, we get

$$\begin{aligned} e_{ci} &= \alpha_i(t)w_i(t) - \alpha_i^* w_i^* \\ &= \alpha_i(t)e_{wi}(t) + (\alpha_i(t) - \alpha_i^*)w_i^* \end{aligned} \quad (7)$$

Equation (7) can be transformed to

$$e_{wi} = \frac{1}{\alpha_i(t)}\left[e_{ci} - (\alpha_i(t) - \alpha_i^*)w_i^*\right] \quad (8)$$

The derivative of

$$e_{ci} = \alpha_i(t)w_i(t) - \alpha_i^* w_i^* = \alpha_i(t)e_{wi}(t) + (\alpha_i(t) - \alpha_i^*)w_i^*$$

can be written as

$$\dot{e}_{ci} = \dot{c}_{i,out} - \dot{c}_{i,out}^* = \dot{c}_{i,out} = \dot{\alpha}_i(t)w_i(t) + \alpha_i(t)\dot{e}_{wi} \quad (9)$$

Equation (9) can be rewritten as

$$\dot{e}_{wi} = \frac{1}{\alpha_i(t)}\left[\dot{e}_{ci} - \dot{\alpha}_i(t)w_i(t)\right] \quad (10)$$

Substituting equation (10) and (8) into (6), we get the open-loop output error dynamics of box *"i"* as

$$\begin{aligned} \dot{e}_{ci} &= \dot{\alpha}_i(t)w_i(t) - \Omega_i(t)e_{ci} - \Omega_i(t)\alpha_i^* w_i^* \\ &\quad + \alpha_i(t)\Omega_i^* w_i^* + \alpha_i(t) v e_{c,i-1}(t) \end{aligned} \quad (11)$$

For the last box, the open-loop error dynamics for the exit moisture content is

$$\begin{aligned} \dot{e}_{cn} &= \dot{\alpha}_n(t)w_n(t) - \Omega_n(t)e_{cn} - \Omega_n(t)\alpha_n^* w_n^* \\ &\quad + \alpha_n(t)\Omega_n^* w_n^* + \alpha_n(t) v e_{c,n-1}(t-\tau) \end{aligned} \quad (12)$$

Designing the preemptive control law as

$$\dot{P}_n(t) = \frac{\begin{bmatrix} \Omega_n(t)\alpha_n^* w_n^* - \alpha_n(t)\Omega_n^* w_n^* - k_{cn}e_{cn} \\ -\alpha_n(t) v\hat{e}_{c,n-1}(t-\tau) - \gamma_n(t) - \varepsilon_n(t) \end{bmatrix}}{\{(\partial\alpha_n / \partial P_n) w_n(t)\}} \quad (13)$$

where $\partial\alpha_n / \partial P_n$ is always negative, $w_n(t)$ is the direct measurement at the last box, $\hat{e}_{c,n-1}(t) = \hat{c}_{n-1}(t) - c_{n-1}^*$ is the estimation of the control error of box *"n-1"*, $\Omega_n(t)\alpha_n^* w_n^* - \alpha_n(t)\Omega_n^* w_n^*$ is to cancel the same term in equation (12), $k_{cn}e_{cn}$ is the feedback term to increase the converging rate, and $\alpha_n(t) v\hat{e}_{c,n-1}(t-\tau)$ is the feedforward term (since the moisture content in the *"n-1"th* box is not directly measured, the estimation is used), $\gamma_n(t)$ and $\varepsilon_n(t)$ are to be designed later to deal with the time delay approximation, we get the closed-loop error dynamics as

$$\begin{aligned}\dot{e}_{cn} &= -(k_{cn}+\Omega_n(t))e_{cn} - \gamma_n(t) - \varepsilon_n(t) \\ &\quad + \alpha_n(t)v\alpha_{n-1}(t-\tau)\tilde{\theta}_{n-1}(t-\tau)Q_{n-1}(t-\tau)\end{aligned} \tag{14}$$

where $\tilde{\theta}_{n-1}(t) = \theta_{n-1} - \hat{\theta}_{n-1}(t)$ is the parameter estimation error of the box *"n-1"*. The control pressure of the last box is determined by a differential equation (Eq. (13)), because the relative degree of the system model is zero (Eqs. (1) and (3)). In Eq.(14), $\tilde{\theta}_{n-1}^T(t-\tau)$ is the parameter estimation error of box "n-1 delayed by time " τ ". The time delay will bring difficulty to the parameter adaptation design later, so it is desirable to get rid of the time delay. To do this, $\tilde{\theta}_{n-1}^T(t-\tau)$ can be written as [2],

$$\tilde{\theta}_{n-1}^T(t-\tau) = \tilde{\theta}_{n-1,old}^T(t) + \Delta_{n-1}^T(t) \tag{15}$$

where $\tilde{\theta}_{n-1,old}^T = \dfrac{\lambda}{s+\lambda}\tilde{\theta}_{n-1}^T$ is a first-order approximation of $\tilde{\theta}_{n-1}^T(t-\tau)$ with ($\lambda = 1/\tau$), and $\Delta_{n-1}^T(t)$ is the error of the approximation, which is determined by

$$\begin{aligned}\Delta_{n-1}^T(t) &= \tilde{\theta}_{n-1}^T(t-\tau) - \tilde{\theta}_{n-1,old}^T(t) \\ &= \hat{\theta}_{n-1,old}^T(t) - \hat{\theta}_{n-1}^T(t-\tau)\end{aligned} \tag{16}$$

From the first-order relation between $\tilde{\theta}_{n-1,old}^T$ and $\tilde{\theta}_{n-1}^T$, we get

$$\tilde{\theta}_{n-1,old}^T(t) = \tilde{\theta}_{n-1}^T(t) + \frac{1}{\lambda}\dot{\tilde{\theta}}_{n-1,old}^T(t) \tag{17}$$

Substituting equations (15) and (17) into (14), and designing

$$\gamma_n(t) = \alpha_n(t)v\alpha_{n-1}(t-\tau)\Delta_{n-1}^T(t)Q_{n-1}(t-\tau) \tag{18a}$$

$$\varepsilon_n(t) = \frac{1}{\lambda}\alpha_n(t)v\alpha_{n-1}(t-\tau)\dot{\hat{\theta}}_{n-1,old}^T(t)Q_{n-1}(t-\tau) \tag{18b}$$

where $\dot{\hat{\theta}}_{n-1,old}^T(t) = \lambda(\hat{\theta}_{n-1}^T(t) - \hat{\theta}_{n-1,old}^T(t))$, we get

$$\begin{aligned}\dot{e}_{cn} &= -(k_{cn}+\Omega_n(t))e_{cn} \\ &\quad + \alpha_n(t)v\alpha_{n-1}(t-\tau)\tilde{\theta}_{n-1}(t)Q_{n-1}(t-\tau)\end{aligned} \tag{19}$$

For upstream boxes ($n-1 \ge i \ge 2$), equation (11) can be rewritten as

$$\begin{aligned}\dot{\hat{e}}_{ci} &= -\dot{\alpha}_i(t)\tilde{\theta}_i^T Q_i - \alpha_i(t)\tilde{\theta}_i^T\dot{Q}_i + \alpha_i(t)Q_i^T\dot{\hat{\theta}}_i \\ &\quad + \dot{\alpha}_i(t)(\hat{w}_i(t) + \tilde{w}_i(t)) - \Omega_i(t)(\hat{e}_{ci} + \tilde{c}_i) \\ &\quad - \Omega_i(t)\alpha_i^* w_i^* + \alpha_i(t)\Omega_i^* w_i^* \\ &\quad + \alpha_i(t)v(\hat{e}_{c,i-1}(t-\tau) + \tilde{c}_{i-1}(t-\tau))\end{aligned} \tag{20}$$

where $\tilde{w}_i(t) = w_i(t) - \hat{w}_i(t)$ is the estimation error of the total moisture content, and $\tilde{c}_i(t) = c_i(t) - \hat{c}_i(t)$ is the estimation error of the exit moisture content. For the upstream box *"i"*, we use the same preemptive control structure as that for the last box. However, since the moisture contents of the upstream boxes cannot be measured directly, we need to use the estimated moisture content (inferred from surrogate measurement) in both feedback and feedforward terms. Similar to the last box, designing the preemptive control law as

$$\dot{P}_i(t) = \frac{\begin{bmatrix}\Omega_i(t)\alpha_i^* w_i^* - \alpha_i(t)\Omega_i^* w_i^* - \gamma_i(t) \\ -\varepsilon_i(t) - k_{ci}\hat{e}_{ci} - \alpha_i(t)v\hat{e}_{c,i-1}(t)\end{bmatrix}}{\{(\partial\alpha_i/\partial P_i)\hat{w}_i(t)\}} \tag{21}$$

where $\gamma_i(t) = \alpha_i(t)v\alpha_{i-1}(t-\tau)\Delta_{i-1}^T(t)Q_{i-1}(t-\tau)$

and $\varepsilon_i(t) = \dfrac{1}{\lambda}\alpha_i(t)v\alpha_{i-1}(t-\tau)\dot{\hat{\theta}}_{i-1,old}^T(t)Q_{i-1}(t-\tau)$,

we get the closed-loop error dynamics of box *"i"* as

$$\begin{aligned}\dot{\hat{e}}_{ci} &= -\dot{\alpha}_i(t)\tilde{\theta}_i^T Q_i - \alpha_i(t)\tilde{\theta}_i^T\dot{Q}_i + \alpha_i(t)Q_i^T\dot{\hat{\theta}}_i \\ &\quad - (k_{ci} + \Omega_i(t))\hat{e}_{ci} + \dot{\alpha}_i(t)\tilde{w}_i(t) - \Omega_i(t)\tilde{c}_i \\ &\quad + \alpha_i(t)v\alpha_{i-1}(t-\tau)\tilde{\theta}_{i-1}^T(t)Q_{i-1}(t-\tau)\end{aligned} \tag{22}$$

For the first box, because the moisture content disturbance in the incoming slurry is unknown, so we just set the control pressure at the nominal value without closed-loop control.

To design the parameter adaptation law, select a Lyapunov function candidate as

$$V = \frac{1}{2}e_{cn}^2 + \sum_{i=2}^{n-1}\frac{1}{2}\hat{e}_{ci}^2 + \sum_{i=1}^{n-1}\frac{1}{2}\tilde{\theta}_i^T\Gamma_i\tilde{\theta}_i + \sum_{i=2}^{n-1}\alpha_i\hat{e}_{ci}Q_i^T\tilde{\theta}_i \tag{23}$$

where $\Gamma_i \in R^{2\times 2}$ is a positive definite matrix, which is selected big enough to make V positive. Taking derivative of equation (23), we get

$$\begin{aligned}\dot{V} &= e_{cn}\dot{e}_{cn} + \sum_{i=2}^{n-1}\hat{e}_{ci}\dot{\hat{e}}_{ci} - \sum_{i=1}^{n-1}\tilde{\theta}_i^T\Gamma_i\dot{\hat{\theta}}_i \\ &\quad + \sum_{i=2}^{n-1}\left(\begin{aligned}&\dot{\alpha}_i\hat{e}_{ci}Q_i^T\tilde{\theta}_i + \alpha_i\dot{\hat{e}}_{ci}Q_i^T\tilde{\theta}_i \\ &+ \alpha_i\hat{e}_{ci}\dot{Q}_i^T\tilde{\theta}_i - \alpha_i\hat{e}_{ci}Q_i^T\dot{\hat{\theta}}_i\end{aligned}\right)\end{aligned} \tag{24}$$

Substituting (18), (22) and

$$\dot{\hat{e}}_{ci} = \dot{\hat{c}}_i = \dot{\alpha}_i(t)Q_i^T\hat{\theta}_i + \alpha_i(t)\dot{Q}_i^T\hat{\theta}_i + \alpha_i(t)Q_i^T\dot{\hat{\theta}}_i$$

into (24), we get

$$\begin{aligned}\dot{V} &= -(k_{cn} + \Omega_n(t))e_{cn}^2 \\ &\quad + \left\{e_{cn}\alpha_n(t)v\alpha_{n-1}(t-\tau)\tilde{\theta}_{n-1}(t)Q_{n-1}(t-\tau)\right\} \\ &\quad + \sum_{i=2}^{n-1} -(k_{ci} + \Omega_i(t))\hat{e}_{ci}^2 - \sum_{i=1}^{n-1}\tilde{\theta}_i^T\Gamma_i\dot{\hat{\theta}}_i \\ &\quad + \sum_{i=2}^{n-1}\hat{e}_{ci}\left\{\begin{aligned}&\dot{\alpha}_i(t)\tilde{w}_i(t) - \Omega_i(t)\tilde{c}_i \\ &+ \alpha_i(t)v\alpha_{i-1}(t-\tau)\tilde{\theta}_{i-1}(t)Q_{i-1}(t-\tau)\end{aligned}\right\} \\ &\quad + \sum_{i=2}^{n-1}\left\{\alpha_i\left(\dot{\alpha}_i(t)Q_i^T\hat{\theta}_i + \alpha_i(t)\dot{Q}_i^T\hat{\theta}_i + \alpha_i(t)Q_i^T\dot{\hat{\theta}}_i\right)Q_i^T\tilde{\theta}_i\right\}\end{aligned} \tag{25}$$

Combining the terms in equation (25) with $\tilde{\theta}_{n-1}^T(t)$, $\tilde{\theta}_i^T(t)$ $(n-1 > i > 1)$ and $\tilde{\theta}_1^T(t)$, and designing the adaptation law as

$$\begin{aligned}\dot{\hat{\theta}}_{n-1} &= \left(\Gamma_{n-1} - \alpha_{n-1}^2(t)Q_{n-1}Q_{n-1}^T\right)^{-1} \\ &\quad \left\{\begin{aligned}&e_{cn}\alpha_n(t)\alpha_{n-1}(t-\tau)vQ_{n-1}(t-\tau) \\ &+ \hat{e}_{c,n-1}\dot{\alpha}_{n-1}(t)Q_{n-1} + \alpha_{n-1}^2(t)Q_{n-1}\dot{Q}_{n-1}^T\hat{\theta}_{n-1} \\ &+ \alpha_{n-1}(t)\dot{\alpha}_{n-1}(t)Q_{n-1}Q_{n-1}^T\hat{\theta}_{n-1} \\ &- \hat{e}_{c,n-1}\alpha_{n-1}(t)\Omega_{n-1}(t)Q_{n-1}\end{aligned}\right\}\end{aligned} \tag{26}$$

$$\dot{\hat{\theta}}_i = \left(\Gamma_i - \alpha_i^2(t) Q_i Q_i^T\right)^{-1} \begin{Bmatrix} \hat{e}_{c,i+1}\alpha_{i+1}(t)\alpha_i(t-\tau)\nu Q_i(t-\tau) \\ + \hat{e}_{ci}\dot{\alpha}_i(t)Q_i - \hat{e}_{ci}\alpha_i(t)\Omega_i(t)Q_i \\ + \alpha_i(t)\dot{\alpha}_i(t)Q_iQ_i^T\hat{\theta}_i + \alpha_i^2(t)Q_i\dot{Q}_i^T\hat{\theta}_i \end{Bmatrix}$$

$$\text{for } n-2 \ge i \ge 2 \qquad (27)$$

$$\dot{\hat{\theta}}_1 = \Gamma_1^{-1}\left\{\hat{e}_{c2}\alpha_2(t)\alpha_1(t-\tau)\nu Q_1(t-\tau)\right\} \qquad (28)$$

the derivative of Lyapunov function becomes

$$\dot{V} = -(k_{cn} + \Omega_n(t))e_{cn}^2 - \sum_{i=2}^{n-1}(k_{ci} + \Omega_i(t))\hat{e}_{ci}^2 \qquad (29)$$

From the adaptation laws (equations (26) - (28)), we can see that for each box (except for the first one) the estimated control error fedback from the downstream box and the estimated control error from its own box are used to calibrate the estimation of the moisture content on-line as shown in Figure 3. We call it a smart dewatering box.

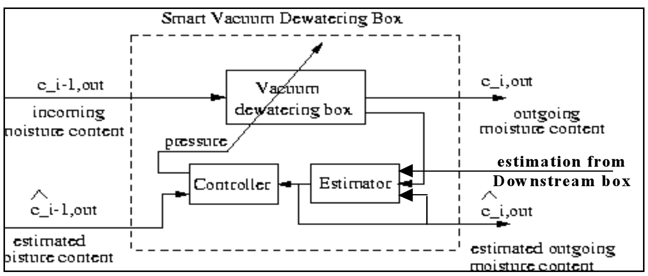

Figure 3. Scheme of the smart dewatering box

From Barbalat's Lemma ($\dot{\Omega}_n, \dot{e}_{cn}$, and $\dot{\hat{e}}_{ci}$ are bounded), we get

$$\lim_{t\to\infty} e_{cn} = 0, \text{ and } \lim_{t\to\infty} \hat{e}_{ci} = 0, \text{ for } n-1 \ge i \ge 2 \quad (30)$$

Since dJ/dq_i is bounded and not equal to zero and d^2J/dq_i^2 is bounded, we can get $\ddot{Q}_i \in L_\infty$ and $\ddot{\hat{c}}_i \in L_\infty$. Then from Barbalat's Lemma, we have $\lim_{t\to\infty} \dot{\hat{e}}_{ci} = 0$, which means that $\lim_{t\to\infty} \dot{\hat{\theta}}_i = 0$. From the Mean Value Theorem, we know that $\lim_{t\to\infty}(\tilde{\theta}_i(t) - \tilde{\theta}_i(t-\tau)) = 0$. From equation (30) and (19) and an extension of Barbalat's Lemma, we can get

$$\lim_{t\to\infty} \tilde{c}_{n-1} = 0 \text{ , then } \lim_{t\to\infty} e_{c,n-1} = 0 \qquad (31)$$

Based on equations (30) and (31), repeatedly applying extension of Barbalat's Lemma to the closed-loop error dynamics of the upstream boxes (equation (22)) until the first box, we get $\lim_{t\to\infty} \tilde{c}_i = 0$, for $n-2 \ge i \ge 1$, then

$$\lim_{t\to\infty} e_{ci} = 0, \text{ for } n-2 \ge i \ge 2 \qquad (32)$$

Finally, we check the signals to make sure that all of them are bounded. The control objective is realized.

The property of the above control design is summarized in the following theorem.

***Theorem** 1: For the system with the dynamics described by equations (1) and (2), if the control law of each box is determined by equations (13) and (21), and parameter adaptation law of each box is determined by equations (26), (27), and (28), then the closed-loop system is stable and the control error of each box (except for the first box) will converge to zero. i.e.,* $\lim_{t\to\infty} e_{ci} = 0$, for $n \ge i \ge 2$

IV. Simulation Results and Discussion

To test the effectiveness of the proposed preemptive control algorithm with adaptive calibration, it is simulated for a paper machine with four vacuum dewatering boxes. The length of the slot *B=0.05 m.* The machine speed is *20 m/s.* The transport coefficients for the four boxes are $K_1 = 0.6$, $K_2 = 0.48$, $K_3 = 0.4$, and $K_4 = 0.33$. The nominal incoming moisture content is $c_0^* = 15\, kg/kg$ and the desired the exit moisture contents for the four boxes are $c_1^* = 13.5641\, kg/kg$, $c_2^* = 12.1837\, kg/kg$, $c_3^* = 10.9706\, kg/kg$, and $c_4^* = 9.7955\, kg/kg$. The nominal vacuum pressures for the four boxes are $P_1^* = 4500\, Pa$, $P_2^* = 8000\, Pa$, $P_3^* = 11000\, Pa$, and $P_4^* = 15000\, Pa$. To simulate the moisture disturbance which exists in the incoming slurry, a 10 *HZ* sinusoidal disturbance with a magnitude of 1.5 *kg/kg* (10% of c_0^*) is added to the incoming moisture content.

The desired and actual exit moisture content with adaptive calibration is shown in Figure 4, from which we can see that except for the first box the actual exit moisture content is regulated exactly at the desired value. The exit moisture content of the first box has 10% percent fluctuation around the desired value. This is because of the 10% moisture content disturbance in the incoming slurry, which is unknown and cannot be cancelled by the feedforward control. Figure 5 shows the estimation error of the exit moisture content of the second box. We can see that the estimation error is driven to zero by the adaptive calibration algorithm design. Notice that the estimated parameters do not converge to the actual parameter value, which is shown in Figure 6. It is typical of direct adaptive control schemes which do not generally guarantee parameter convergence. The estimation errors of the exit moisture contents and parameters for the first and third boxes are similar to the second box. So, they are not shown here because of the space limitation.

To simulate the real case and to test the robustness of the proposed controller to noises, noises are added to the surrogate measurements. The performance of the controller is shown in Figure 7. We can see that although the actual exit moisture content has some oscillation around the desired value, the deviation is within 0.2% of the desired the value, so the controller still provides satisfactory performance.

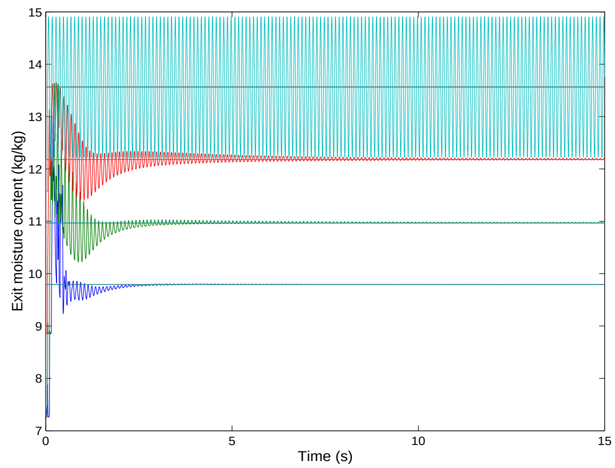

Figure 4. Desired (the straight line) and actual exit moisture content with incoming 10 Hz sinusoidal disturbance

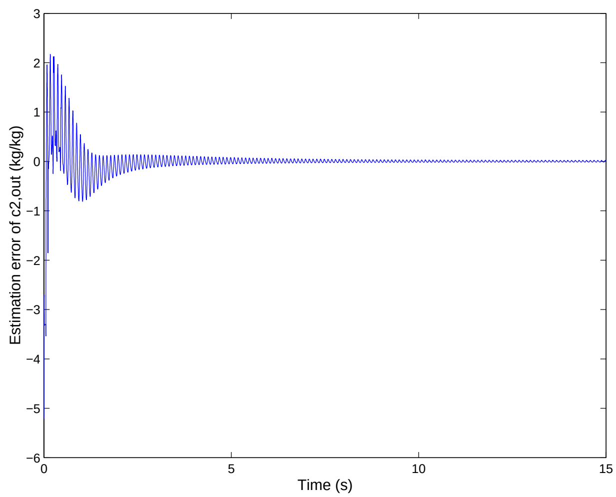

Figure 5. The estimation error of the exit moisture content of the second box

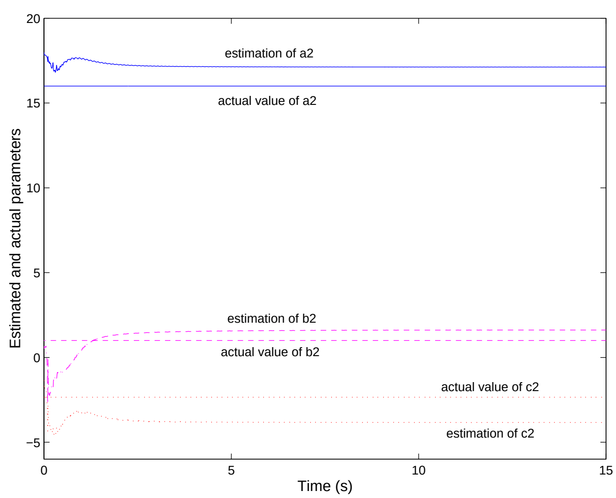

Figure 6. Parameter estimation of the second box (straight – actual value, Curve – estimation; solid – a_2, dashed - b_2, dotted - c_2)

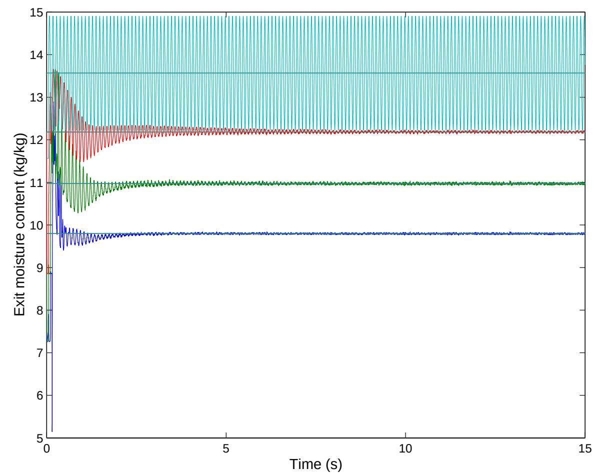

Figure 7. Desired (the straight line) and actual exit moisture content with incoming 10 Hz sinusoidal disturbance and with noises

V. Summary and Conclusions

In this paper, an algorithm to adaptively calibrate the surrogate measurement models, with application to a paper moisture content control problem [5] is proposed. Using the proposed method, each box uses the estimated control error fedback from the downstream box and the estimated control error from its own box to calibrate the estimation of the moisture content on-line (drive the estimation to the actual value). Simulation results show the effectiveness the proposed adaptive calibration algorithm. The proposed method can be generalized to other control cascade processes.

VI. References

[1] Assis, A. J., and Filho, R.M.., "Soft sensors development for on-line bioreactor state estimation", *Computers and Chemical Engineering*, Vol. 24, 1099-1163, 2000.

[2] Bjegovic, P. and Li, P.Y., "Adaptive Control of Nonlinearly Parameterized System with Time Delay", *2002 IFAC Congress*, Barcelona, July 2002.

[3] Dong, D, and McAvoy, T.J., "Emission monitoring using multivariate soft sensors", *Proceedings of American Control Conference*, Seattle, June 1995.

[4] Goodwin, G.C., "Predicting the performance of soft sensors as a route to low cost automation", *Annual Reviews in Control*, Vol.24, 55-66, 2000.

[5] Li, P.Y., Bjegovic, P., and Ramaswamy, S., "Preemptive control of moisture content for paper manufacturing" , *Transactions of the Institute of Measurements and Control*, Special Issue on Paper Manufacturing Industry, 25(1), pp. 36—56, 2003.

[6] Park, S., and Han, C., "A nonlinear soft sensor based on multivariate smoothing procedure for quality estimation in distillation columns", *Computers and Chemical Engineering*, Vol. 24, 871-877, 2000.