Control Systems'98, Porvoo, Finland, September 1998
Finnish Society of Automation, Helsinki, Finland

Tuning Feedback Controller of Paper Machine for Optimal Process Disturbance Rejection

M. Zhang[*+], D.M. Gorinevsky[+], and G.A. Dumont[*]

[*]Pulp and Paper Centre, University of British Columbia
2385 East Mall, Vancouver, B.C., Canada V6T 1Z4
Phone: (604) 822-8560 FAX: (604) 822-8563
zhang@ppc.ubc.ca
[+]Honeywell-Measurex

Abstract

This paper presents a method for tuning the feedback controller of paper machine cross-directional control systems. The tuning method is based on identification of the process model, identification of the disturbance model and tuning the feedback controller by minimizing the paper property variations. To obtain a longer disturbance realization sequence and increase data available for identification of the process disturbance, 2-dimensional process identification residuals are used for identifying an integrated moving average disturbance model. The identification method is based on the Recursive Extended Least Squares. Based on the identified process and disturbance models, the Dahlin controller and control filter are tuned to minimize a quadratic performance index which includes the process output variance and the incremental control move variance. A penalty for excessive actuator move can be used to minimize the process variation while keeping the control action within acceptable bounds.

The proposed method has been implemented in an industrial tuning tool. It has been validated using many sets of paper mill data. Extensive tests have shown that the identification algorithms are capable of

identifying the process model as well as the disturbance model with satisfactory precision. The tool predicts the closed-loop process variance and control variance with a satisfactory degree of accuracy.

1. Problem statement

This paper considers the tuning problem of the feedback controller of a commercial paper machine cross-directional control system. Paper machines produce 2-dimensional paper sheet from the pulp suspension. On a paper machine, the paper properties, such as basis weight, moisture content and caliper, are measured and controlled in two directions, the machine direction (MD), i.e. the direction in which the paper sheet moves, and the cross-direction (CD), i.e., across the paper web. The goal of paper machine control systems is to compensate process variability and maintain the paper properties on target in both MD and CD.

CD profiles of paper sheet properties are controlled by various CD actuators. Each type of CD actuator includes a set of the identical actuators located usually at evenly spaced points along the cross-direction. Depending on the application and the actuator type, there can be 20 to 300 individual actuator units in one CD actuator. An example of important CD actuator is the weight actuator, which adjusts the stock distribution across the machine by changing the opening of different sections of the slice lip in the headbox. Sensor measurements are located at a distance down the machine-direction from the actuation. Due to the high cost of sensors, limited number of sensors (1 - 2) measures only a zigzag portion of the paper sheet. From this limited number of measurements, the entire sheet profile must be estimated at each sampling time for feedback control. This estimation can be performed in a straightforward manner using Kalman filtering and averaging techniques [1]. The control problem is to calculate the actuator moves based on the estimated profile at each sampling instance.

For better control of papermaking processes, various advanced control strategies have been proposed and have achieved a certain degree of success [2 - 5]. However, most paper machine control systems still use some kinds of well established simple controllers, such as PI, PID, Dahlin and so on. Tuning of those controllers plays an important role in reducing impact of the process variability on the product uniformity and in ensuring that the process is operated at the chosen target.

Controller auto-tuning has been an important research topic for a long time and various tuning strategies have been proposed in the literature. The Ziegler-Nichols method for tuning PID regulators [6] is a popular and widely accepted scheme. It is based on detection of the critical gain and critical period and a quarter decay criterion for controller parameter design. The Dahlin controller is a well known dead-time compensator and is widely used in industries. Its tuning requires the process model being identified and the closed-loop time constant being chosen. E.B. Dahlin [7] gave some guideline for tuning the closed-loop time constant. G.A. Dumont presented a thorough sensitivity analysis of Dahlin controller when subject to modelling errors [8]. He also proved optimality of Dahlin controller for a first order plus delay process perturbed by a first-order integrated-moving-average disturbance. Cluett and Wang [9] proposed a PID controller tuning method based on a specification of the desired control signal trajectory. In this scheme the users are provided with a tuning parameter that specifies the closed-loop response speed. It does give the users one more degree of freedom to chose the closed-loop performance, but it also increases the tuning burden.

1.1 Paper machine Cross-Directional process model

CD process model

Paper machine CD control involves measuring a few hundreds of data boxes across the sheet and adjusting dozens of control elements (actuators). Adjustment of each actuator affects not only its corresponding measurement zone on the paper sheet but also that of its neighbor actuators. Therefore paper machine is inherently a multi-input-multi-output (MIMO) system with different number of inputs and outputs.

For a conventional CD control system, the high resolution measurement profile is usually transformed into a low resolution profile through a mapping algorithm [15], producing a profile with the same number of measurement output as the actuators (see Figure 1). Such a mapped process can be described as a square MIMO system where number of inputs and outputs is the same:

$$\bar{y}(t) = g(z^{-1})\, G\, \bar{u}(t) + \bar{\xi}(t)\,, \tag{1}$$

where z^{-1} is a backward shift operator; t is discrete time; the output vector $\bar{y}(t)$ has elements $\{y_i(t),\ i = 1,\dots,n\}$ such that each element is an averaged paper property measurement associated with the corresponding actuator zone; $u(t)$ is n by 1 actuator input vector; $\xi(t)$ is n by 1 process disturbance vector, each of its elements representing the lumped amount of process disturbance at a corresponding actuator zone; G, known as the interaction matrix, is a n by n square matrix and each column of G can be formed with the CD response shape of its corresponding actuator; $g(z^{-1})$ is a scalar-valued process time-response model and can usually be described as a first order, delayed process transfer function.

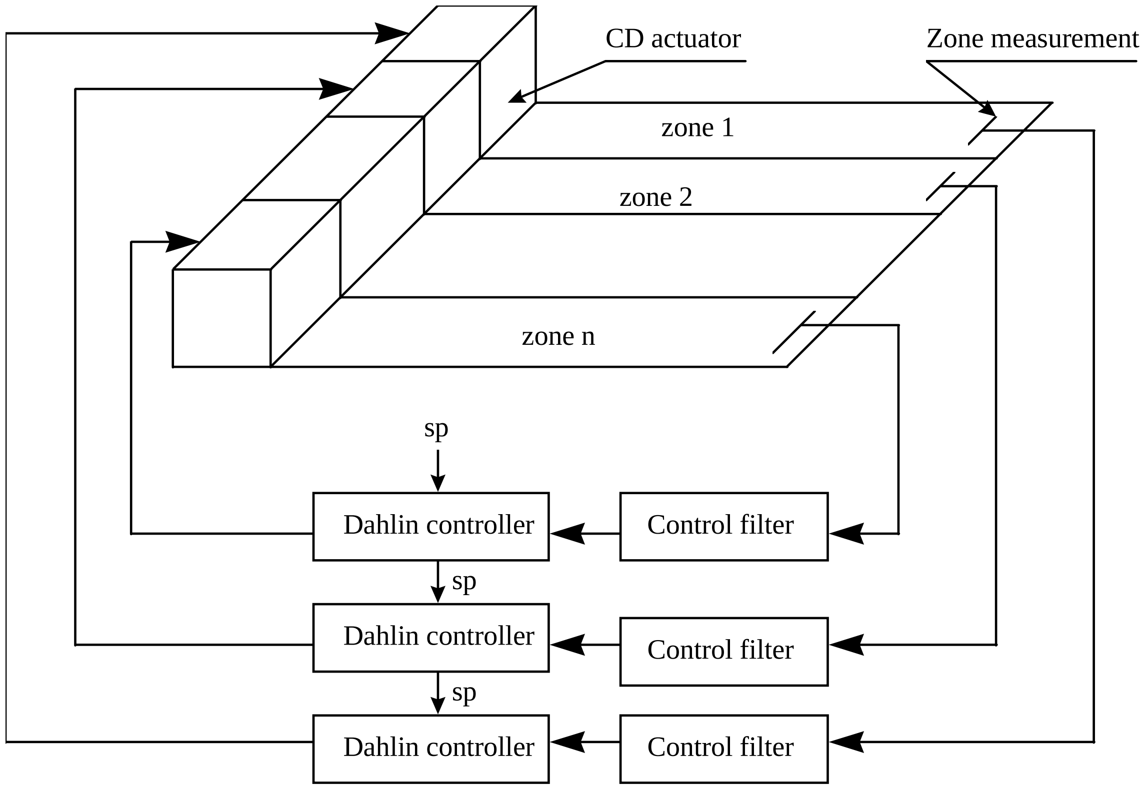

Figure 1: Simplified paper machine process and CD control system

For the considered CD control system, control moves are determined by treating each actuator as an independent element, and then the subsequent control moves are adjusted taking into account spatial interactions using some decoupling techniques. For tractability of the tuning algorithm, it is assumed that the actuator responses do not overlap (in (2.1) G is an identity matrix) and that each of actuators has the same dynamic response which can be described with a first order plus delay model. It is further assumed that the disturbance dynamics for each of actuator control zones are identical and there is no disturbance correlation between adjacent control zones.

1.2 Feedback loop in a typical CD control system

Under the above CD control assumption, the system is simplified as n independent feedback loops, which are identical. One of such loops is shown in Figure 2. It consists of a first order plus delay process model, a Dahlin controller, a control filter (first order), a display filter (first order) and a noise shaping filter. The tuning of the Dahlin controller time constant α and the control filter factor β depends on the dynamics of both the process and the disturbances. The following gives a brief description for each component in the feedback control loop.

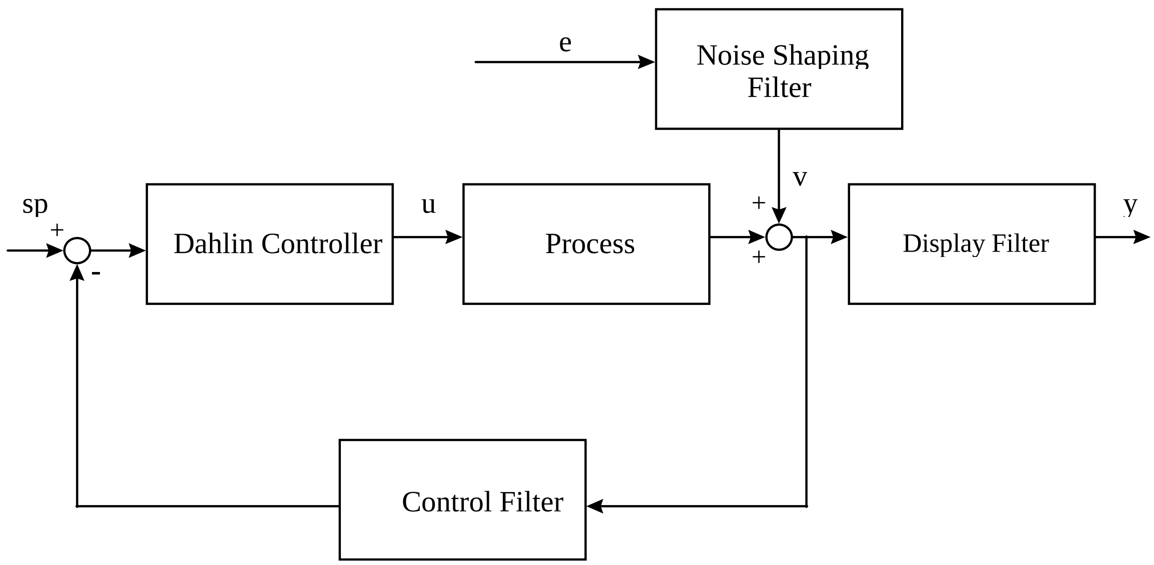

Figure 2: Feedback loop of the considered CD control system

Process time-response model

The process model relating actuator position to the scanned measurement is described by a first order plus time delay transfer function of the form

$$g(z^{-1}) = \frac{k_p(1-a)z^{-d-1}}{1-az^{-1}}, \qquad (2)$$

where z^{-1} is a backward shift operator; k_p is the process gain, d is the discrete process time delay and a defines the process time constant; d and a can be determined through continuous to discrete parameter conversion:

$$\begin{aligned} d &= \mathrm{int}(T_d \ / \ T_s), \\ a &= e^{-T_s/T_r}, \end{aligned} \qquad (2^*)$$

where Ts is the scan time, T_d is continuous process time delay and T_r is continuous process time constant. The process parameters k_p, d and a can be identified using an available method [10] from an identification experiment, such as a bump test. In the remaining context of this paper, it is assumed that the process model is available for tuning of the Dahlin controller and control filter.

Dahlin feedback controller

The feedback controller used in considered CD control system is a Dahlin controller. Its tuning requires a process model being identified and a desired closed-loop time constant α being chosen. From Figure 2, it can be seen that the 'process model' used in design of the Dahlin controller should be a first order model whose dynamics is equivalent to that of the process model plus the first order filter. Thus the discrete-time transfer function of the Dahlin controller can be written as:

$$D(z^{-1}) = \frac{k_c(1-\tau z^{-1})}{(1-z^{-1})[1+(1-\alpha)z^{-1}+\ldots+(1-\alpha)z^{-d}]}, \tag{3}$$

where α defines the desired discrete closed loop time constant; d is estimate of the discrete process time delay; τ is the equivalent time constant of the filtered process (by control filter). The controller gain, k_c is defined as:

$$k_c = \frac{1-\alpha}{k_p(1-\tau)} \tag{4}$$

where k_p is estimate of the process gain. α and τ can be obtained through the conversion:

$$\begin{aligned} \alpha &= e^{-T_s/T_\alpha} \\ \tau &= e^{-T_s/T_\tau} \\ T_\tau &= T_r - \frac{T_s}{\ln(1-\beta)} \end{aligned} \tag{4*}$$

where T_α is desired closed-loop time constant (in seconds), T_τ is the filtered process time constant (in seconds), also called the control time constant, T_s is the scan time and β is the control filter factor.

<u>Control filter</u>

For the considered CD control system, the scanned measurement profile is filtered by a control filter to remove high frequency noise from the profile. The control filter is of the form of an exponential filter. The filter transfer function can be written as follows:

$$F(z^{-1}) = \frac{\beta}{1-(1-\beta)z^{-1}} \tag{5}$$

where β is control filter factor and is one of the tuning parameters.

Display filter

The display filter affects only the displayed process profiles and has no effects on the actuator moves (see Figure 2). Unless the display filter is disabled, it would filter the logged high resolution process profiles used by the identification algorithms, so its effect on the identification of the process and disturbance should be taken into account. The display filter has the form of an exponential filter. The filter transfer function can be written as follows:

$$M(z^{-1}) = \frac{\varphi}{1-(1-\varphi)z^{-1}} \tag{6}$$

where φ is display filter factor.

1.3 Tuning problem

Given the process model parameters (2) and display filter factor (6). The tuning problem is to find a suitable dynamical model of the process disturbance and determine the two tuning parameters: desired closed-loop time constant α of the Dahlin controller and the control filter factor β.

In order to tune the controller and filter optimally, a disturbance model should be established. It is highly desirable to determine this model from the same set bump test data as used for the process model identification, without resorting to additional data collection. The problem of identifying the disturbance model from bump test data can be formulated as follows. The data available for identification of the process disturbance model is residual of the CD process model identification, this residual is obtained by subtracting the process model response to the actuator bump from the measured bump response

$$\bar{\xi}(t) = \bar{y}(t) - g(z^{-1})\, G\, \bar{u}_{bump}(t) \quad , \tag{7}$$

where the process time response model $g(z^{-1})$ and spatial response model G are identified with an available method [11] from the same set of bump test data. In (7) time $t =$ 1, 2, …, m (scan number), where m defines the duration of the bump test, $\bar{u}_{bump}(t)$ is the actuator setpoint vector, and $\bar{y}(t)$ is the measured bump response.

Based on equations (2), (3), (5) and (6) and a noise model to be developed in next section, the Dahlin controller and the control filter are tuned to minimize the following performance index:

$$J = E\{\ Y^2 + \rho\Delta u^2\ \} \quad \rightarrow \text{min}, \tag{8}$$

where *E(.)* denotes mathematical expectation of a random variable; $E(y^2)$ is the process output variance and $E(\Delta u^2)$ is the incremental control move variance; ρ is the control weighting factor that penalizes excessive actuator moves. The tuning objective is to minimize the process variation while keeping control moves within acceptable bounds.

The paper is organized as follows. Section 2 discusses identification of the disturbance model and explains how to use the entire 2 dimensional process identification residuals for the disturbance model identification. Section 3 presents the strategy for tuning the Dahlin controller and control filter used in the considered CD control system. The model based prediction of the process and actuator variation is also discussed. The validation results of the developed tuning algorithms are presented in Section 4. Some conclusions are drawn in Section 5.

2. Identification of the process disturbance model

The disturbances associated with the papermaking process have complicated dynamics and various forms. Besides step-wise load disturbances, such as grade change, stock volume and consistency change, there are substantial periodic disturbances caused by mechanical vibration, hydraulic pulsation and periodic variations in raw material. In order to tune the feedback controller for optimal disturbance rejection, a fairly accurate disturbance model needs to be built for prediction of the process variation and actuator variation.

A suitable disturbance model should reflect generic characteristics of paper machine disturbances and should also be tractable for the automatic controller tuning. For a sheet forming process, such as a paper machine or a plastic film line, modelling the process disturbance in the form of an Integrated Moving Average (IMA) model [12 - 13] proved to be successful. According to our assumption that the disturbance dynamics is the same for all actuator zones and there is no disturbance correlation between adjacent control zones, the IMA model for the disturbance $\xi(t)$ in (7) is assumed to have the form

$$\bar{\xi}(t) = N(z^{-1})\bar{e}(t)\ , \tag{9}$$

$$N(z^{-1}) = \frac{C(z^{-1})}{1 - z^{-1}}\ , \tag{9a}$$

$$C(z^{-1}) = 1 + c_1 z^{-1} + \ldots + c_l z^{-l}\ , \tag{9b}$$

where $\vec{e}(t)$ is a vector containing independent white noise elements with zero mean and variance σ^2 and $C(z^{-1})$ is a monic polynomial of order l. In what follows, $C(z^{-1})$ will be identified from the measured data.

Note that in [8] it is proved analytically that a Dahlin controller is a minimum variance controller for the processes of the form (2) if the disturbance structure has the form (9a), where l = 1. Furthermore the optimal tuning in this case is $\alpha = c_l$ and no filtering (β = 1). This allows for a verification of the tuning methods to be developed further.

2.1 Identification using CD residuals

The CD identification residuals (7) $\vec{\xi}(t) = [\xi_1(t), \ldots, \xi_n(t)]^T$ will be used for the disturbance model identification. Experience with mill data processing shows that due to limited duration (around 20 to 60 scans) of a common industrial bump test the residual sequences for individual zones $\xi_i(t)$ can be too short to give a consistent estimate of disturbance dynamics. If for all zones, the disturbance sequences can be described by the same dynamics and are uncorrelated, as assumed in (9), then each sequence can be regarded as a different realization of the same random process. In our disturbance identification scheme, the zone disturbance sequences are cascaded to form a single vector

$$\vec{v} = [\xi_1(1), \ldots \xi_1(m), \xi_2(1), \ldots, \xi_2(m), \ldots, \xi_n(1), \ldots, \xi_n(m)]^T \tag{10}$$

and used to fit the following model:

$$\vec{v} = \frac{C(z^{-1})}{1 - z^{-1}} \; \vec{e}\,, \tag{11}$$

where $C(z^{-1})$ is a monic polynomial of the form (9b); $\vec{e}$ = [$e(1), \ldots, e(mn)$]^T, is a scalar sequence of white noise with zero mean and standard deviation of σ; The model parameters to be identified include the coefficients of polynomial $C(z^{-1})$ and σ. By using the extended sequence (10), it is possible to obtain much better disturbance identification results and more accurate process variation prediction than by identifying process disturbance dynamics for each zone separately. The discontinuities in the prolonged disturbance sequence (10) due to cascading different zone sequences would affect accuracy of the disturbance identification. This negative impact could be reduced by applying some averaging and windowing techniques at neighborhood of the discontinuities.

Notice that the polynomial $C(z^{-1})$ and the sequence $\vec{e}$ appear in a bi-linear way in equation (11), so a suitable identification method solving the nonlinear parameter estimation problem should be used. In this case a Recursive Extended Least Squares (RELS) identification method [10] is used to estimate simultaneously the white noise sequence $\vec{e}$ and the coefficients of the polynomial $C(z^{-1})$ in (9b). In the following subsection, the basic RELS algorithm is outlined to apply to this case.

2.3 Identification algorithm

In accordance with (9b), the stochastic process in equation (11) can be represented by the following difference equation

$$v(t)-v(t-1) = e(t)+c_1e(t-1)+\ldots+c_le(t-l)\,, \qquad (12)$$

where $v(t)$, $t = 1, 2, \ldots, mn$, is the disturbance sequence given in (10), $e(t)$ is the white noise sequence to be estimated as in (11) and $c_1, c_2, \ldots, c_l$, are the coefficients of the polynomial $C(z^{-1})$ in the disturbance model (9b). The equation (12) can be represented in the regression form as

$$\Delta v(t)=x^T(t)\theta+e(t)\,, \qquad (13)$$

where the differentiated disturbance sequence is given by

$$\Delta v(t) = v(t) - v(t-1), \qquad (14)$$

the parameter vector to be estimated is

$$\theta=[\,c_1, c_2, \ldots, c_l\,]^T\,, \qquad (15)$$

and the regressor vector is

$$x(t)=[\,e(t-1), e(t-2), \ldots, e(t-l)]^T \qquad (16)$$

The difficulty of the identification problem (13)-(16) is related to the fact that the variables *e(t-1), ... , e(t-l)* in the regressor vector *x(t)* (16) are unknown and have to be estimated jointly with the vector θ (15). In this work, such estimation is performed by the Recursive Extended Least Squares (RELS) algorithm. The RELS algorithm can be derived as follows. Assume that for a particular *t*, the regressor vector *x(t)* (16) is known. Define the one-step ahead prediction error as

$$\varepsilon(t) = \Delta v(t) - x^T(t)\hat{\theta}(t-1)\,, \tag{17}$$

where $\hat{\theta}(t)$ is an estimate of the vector θ (15) at the time *t*.

By replacing *e(t-1), …,e(t-l)* in (16) with the prediction error, we can obtain the estimate of *x(t)* at any time:

$$x(t) = [\varepsilon(t-1),\, \varepsilon(t-2),\, ...,\, \varepsilon(t-l)]^T \tag{18}$$

Using (18) as the regressor vector in a recursive Least Squares estimation scheme instead of (16) and propagating the estimate of the residuals $\varepsilon(t)$ (17) and a least squares estimate of parameter vector θ (15) forward in time yields RELS algorithm, which has the form

$$\begin{aligned} &\hat{\theta}(t) = \hat{\theta}(t-1) + K(t)[\Delta v(t) - x^T(t)\hat{\theta}(t-1)], \\ &K(t) = P(t)x(t)\,/\,[1 + x^T(t)P(t-1)x^T(t)], \\ &P(t) = P(t-1) - \frac{P(t-1)x(t)x^T(t)P(t-1)}{[1 + x^T(t)P(t-1)x(t)]}\,, \end{aligned} \tag{19}$$

where *P(t)* is the covariance matrix of the recursive least squares estimator of θ and *K(t)* is the prediction error gain vector at step *t*.

This method, also known as Pseudolinear Regressions (PLR), combine the estimation of the parameter vector and unobserved components in the regressor. The initial conditions of the RELS algorithm are set as follows: the parameter vector $\theta = 0$; the covariance matrix $P = cI$, where *c* is a large positive constant and *I* is identity matrix. The correct selection of the order of the polynomial $C(z^{-1})$ (9b) depends on the characteristics of the disturbances present on the process. Normally assuming the order of $C(z^{-1})$ to be between 1 and 5 is adequate to capture the frequency contents of interest in the disturbance signal.

3 Tuning strategy

In the developed tuning tool, the Dahlin controller and the first order filter are tuned to minimize the following performance index:

$$J = E\{ y^2 + \rho \Delta u^2 \} \ \rightarrow \ \min , \tag{20}$$

where *E(.)* denotes mathematical expectation of a random variable; $E(y^2)$ is the process output variance and $E(\Delta u^2)$ is the increment control variance; ρ is the control weighting factor that penalizes excessive actuator moves. The tuning objective is to minimize the process variation while keeping the control action within acceptable bounds. The performance index (20) can be evaluated in a straightforward way once the process model (2), the controller (3) - (5) parameters, and the stochastic disturbance model (9) are available.

3.1 **Evaluation of the performance index**

Evaluation of the performance index (20) can be divided into two steps

1) Evaluation of $E(y^2)$

2) Evaluation of $E(\Delta u^2)$

The procedures for computing 1) and 2) are similar. We will explain 1) in detail and computations for 2) can be performed in completely similar manner.

From the closed-loop system block diagram shown in Figure 2, we can derive the transfer function relating the process output *y(t)* to the white noise input *e(t)*:

$$H_y(z^{-1}) = \frac{B(z^{-1})}{A(z^{-1})} = \frac{N(z^{-1})M(z^{-1})}{1+g(z^{-1})D(z^{-1})F(z^{-1})}, \tag{21}$$

where $g(z^{-1})$ is the process model given by (2), $D(z^{-1})$ is the Dahlin controller transfer function given by (3), $F(z^{-1})$ is the control filter transfer function in (5), $M(z^{-1})$ is the display filter transfer function in (6), and $N(z^{-1})$ is the disturbance model in (9a); $A(z^{-1})$ and $B(z^{-1})$ are polynomials with real coefficients dependent on the coefficients in *g(z)*, *D(z)*, *F(z)* and *N(z)*.

$$B(z^{-1}) = b_0 + b_1 z^{-1} + \ldots + b_n z^{-n}$$
$$A(z^{-1}) = a_0 + a_1 z^{-1} + \ldots + a_n z^{-n} \qquad (22)$$

Since *e(t)* is the unit variance white noise, the evaluation of $E(y^2)$ can be done according to [16] as

$$E(y^2) = \frac{1}{j} \oint H_y(z) H_y(z^{-1}) z^{-1} dz\ , \qquad (23)$$

where $\oint$ denotes the integral along the unit circle in the complex plane, computed in the counterclockwise direction. Details of computation of (23) can be found in [16].

Evaluation of $E(\Delta u^2)$ can be performed in a similar way. Based on the closed-loop block diagram in Figure 2, the transfer function $H_u(z)$ relating Δu to the white noise input *e(t)* in (11) can be found as

$$H_u(z) = \frac{B_u(z)}{A_u(z)} = \frac{\Delta D(z) F(z) N(z)}{1 + g(z) D(z) F(z)}, \qquad (24)$$

where $\Delta = 1\text{-}z^{-1}$ and $A_u(z)$ and $B_u(z)$ are polynomials with real coefficients computed from (24), (2), (3), (5) and (9a).

The evaluation of $E(\Delta u^2)$ can be performed according to [16] as

$$E(\Delta u^2) = \frac{1}{j} \oint H_u(z) H_u(z^{-1}) z^{-1} dz \qquad (25)$$

The numerical procedure for computing the above integral can be found in [16].

3.2 Minimization of the performance index

Having obtained the formulae for evaluation of $E(y^2)$ and $E(\Delta u^2)$ it is straightforward to compute a value of the performance index (20) against a chosen pair of the tuning parameters α and β. The optimal values of α and β can be obtained by minimization of the performance index (20). A direct global search method is used in our minimization scheme. It includes computing the values of the performance index (20) for different combinations of the tuning parameters α and β, locating the minimum value of the performance index, and finding the corresponding optimal values for α and β.

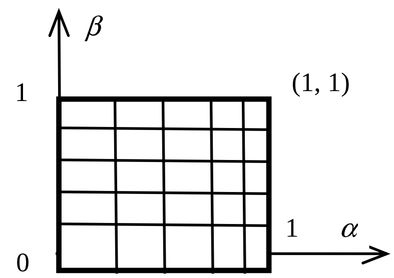

Figure 3: A global search domain for finding optimal tuning parameters α and β

The above method requires determination of a two dimension search domain projected by α and β. Notice that the desired closed-loop time constant $\alpha \in [0, 1]$ and admissible values for the control filter factor β in (5) are also within [0, 1]. Therefore we chose a unit square with vertex coordinates (0, 0), (0, 1), (1, 1), (1, 0) as the search domain (Figure 3). A grid node in the search domain in Figure (3) represents a combination of α and β tested in the search. Increasing the number of tested combinations of α and β improves the accuracy and increases computational load of the global search. Usually 10 to 20 values of the parameters for each of α and β have to be tested to reach a reasonable vicinity of the minimum of the performance index (20). Only approximate optimal values for α and β can be obtained in the described scheme. In our numerical experiments using both mill data and simulated model data, it is found that the performance index surface with respect to α and β is very flat close to the minimum. This suggests that from practical control performance viewpoint the approximate optimal tuning parameters may work as well as the more accurate ones, so it is not necessary to sacrifice computational speed of the tuning algorithms in order to pursue absolutely accurate values of the optimal tuning parameters.

Based on the above described tuning methods, a feedback controller tuning tool has been designed for tuning the Dahlin controller and control filter in Honeywell-Measurex CD control system. The tool is coded in MATLAB and some of its key algorithms have been implemented as ‘C’ modules embedded into a LabVIEW application currently on the market.

4. Validation of the tuning algorithms

As the key parts of this tool, the performance of the identification of disturbance model, as well as prediction of the process variation $E(y^2)$ and incremental control variation $E(\Delta u^2)$ critically influence practical applicability of the tool, therefore these parts need careful testing and validation on real-life data.

4.1 Optimality of the Dahlin controller

Dumont [8] proved that if the process is a first order with dead time and the process noise is described by a first-order integrated moving-average (IMA) process, then the Dahlin controller is a minimum variance controller provided that the closed-loop time constant α is set to c_1 (the only coefficient of the polynomial $C(z^{-1})$ (9b) in the noise model). In the following example, this analytical result is used to verify the developed tuning algorithm.

<table>
<tr><td>Trans. function</td><td colspan="4">$g(z^{-1})$ - process model</td><td colspan="4">$D(z^{-1})$ - Dahlin controller</td></tr>
<tr><td>Parameter</td><td>k_p</td><td colspan="2">T_d</td><td>T_r</td><td>T_α</td><td>k_p</td><td>T_d</td><td>T_τ</td></tr>
<tr><td>Value</td><td>1</td><td colspan="2">60 sec.</td><td>120 sec.</td><td>*</td><td>1</td><td>60 sec.</td><td>120 sec.</td></tr>
<tr><td>Trans. function</td><td colspan="2">$F(z^{-1})$ - control filter</td><td colspan="2">$M(z^{-1})$ - display filter</td><td colspan="4">$N(z^{-1})$ - noise model</td></tr>
<tr><td>Parameter</td><td colspan="2">β</td><td colspan="2">φ</td><td colspan="2">c_1</td><td colspan="2">σ</td></tr>
<tr><td>Value</td><td colspan="2">1</td><td colspan="2">1</td><td colspan="2">0.75</td><td colspan="2">1</td></tr>
</table>

Table 1: Parameter values of each component transfer function

A feedback control loop shown in Figure 2 was simulated The parameters of the transfer function for each component in the feedback control loop are given in Table 1. The scan time is set to 30 seconds. For verification of the Dahlin tuning constant α using the above results, the control filter and the display filter in the feedback loop are disabled (their filter factors are set to 1). The process model is assumed to match the real plant exactly. By continuous to discrete parameter conversion in (2*) and (4*), the considered process is described by

$$y = \frac{0.22z^{-3}}{1-0.78z^{-1}}u + \frac{1-0.75z^{-1}}{1-z^{-1}}e \tag{26}$$

The Dahlin controller for the process (26) is given by

$$D(z^{-1}) = \frac{0.55(1-\alpha)(1-0.78z^{-1})}{1-\alpha z^{-1}-(1-\alpha)z^{-3}}, \tag{27}$$

where α defines the closed-loop time constant T_α in (4*).

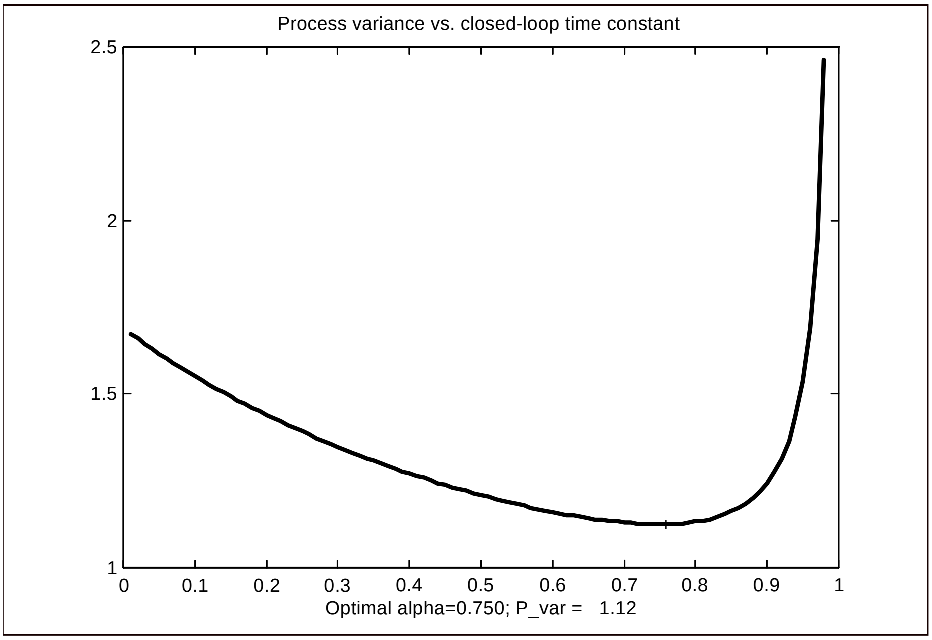

Figure 4: Optimality of the Dahlin controller

The tuning performance index (20), where the control weighting factor ρ was set to 0 for purpose of verification of the tuning algorithms, was computed in accordance with (23) for different values of the tuning parameter α. Figure 4 shows the performance index versus the tuning parameter α. It can be seen in Figure 4 that the optimal α is 0.75 that is the same as the noise model parameter c_1. This confirms the result of [12] and also verifies the consistency of the tuning algorithm and software.

4.2 Validation using paper mill data

In order to validate the developed disturbance identification and process variation prediction algorithm, a mill trial was conducted in a Canada paper mill on July 17, 1997. The paper machine produces 40.5 g. newsprint. The basis weight is controlled by motorized slice lip actuators and moisture by water spray actuators. The average scan time is 26 seconds.

Model identification

During the mill trial, a weight bump test was performed and 38 scan data were collected. The developed software was used to process the bump test data and identified the process time response model. The identified process parameters together with the model fitting curve are shown in Figure 5.

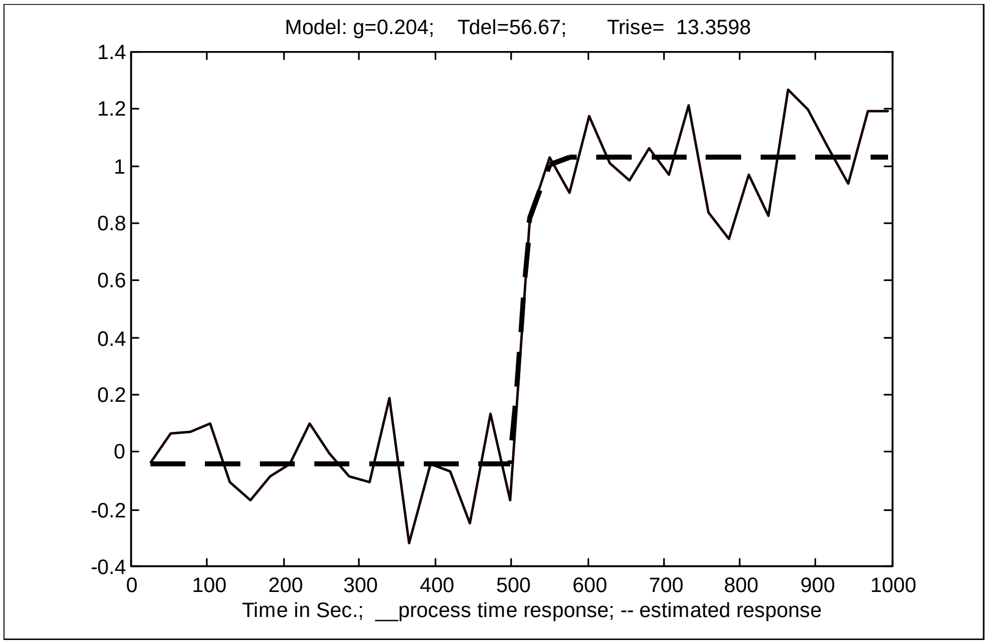

Figure 5: Identification of the process time-response model

An integrated-moving-average model in the form of (11) was used for the process disturbance identification. The degree of the noise shaping filter $C(z^{-1})$ in (9b) is chosen as 1 and the number of the valid control zones is 68. Figure 6 shows the identified parameters and the autocorrelation functions of the process variation and the residual. γ illustrates how close the autocorrelation of the residual (dashed line) is to that of an white noise. A small obtained γ (0.098) indicates that the identification result is credible. Since the original disturbance is close to an white noise (see Figure 6), it is adequate to choose the degree of $C(z^{-1})$ as 1. The identified disturbance model is as follows:

$$N(z^{-1}) = \frac{1-0.81z^{-1}}{1-z^{-1}}, \quad \sigma = 0.1709, \ \gamma = 0.098 \tag{28}$$

where σ is standard deviation of the residual and represents the process variation intensity.

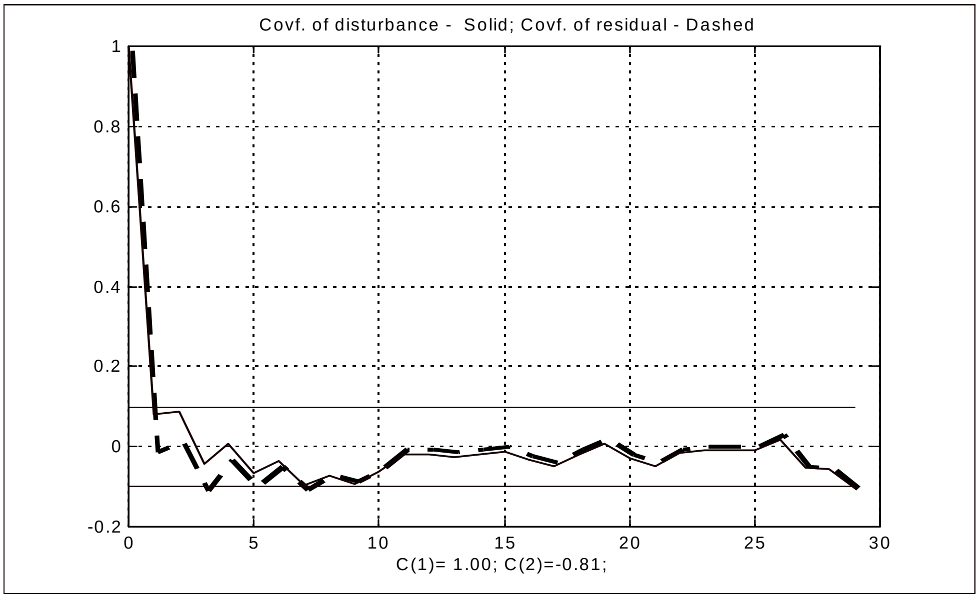

Figure 6: Identification of the process disturbance model

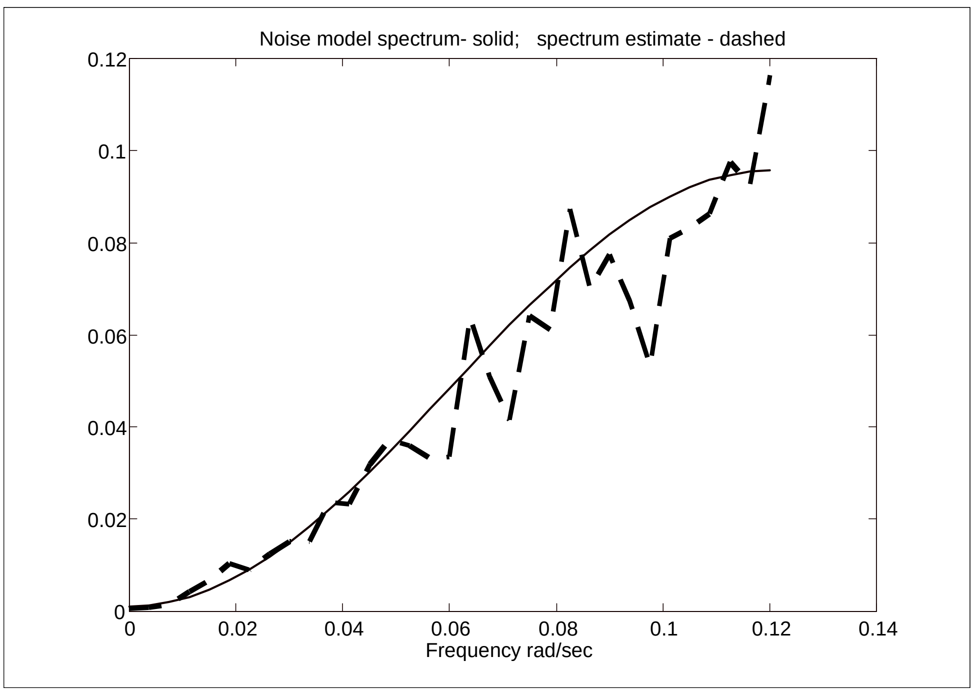

Figure 6a: Spectrum of the open-loop process variation: predicted for the identified variation model (solid) and directly estimated from the data (dashed)

Check of predicted process and actuator variation

In order to validate the above identified models, two different controllers with parameters shown in Table 2 were implemented and 55 scans of steady state closed-loop data for each of them were logged. Controller #1 is used at the mill, the controller #2 was implemented during the trial with the purpose of the prediction verification. In Table 2, T_α represents the continuous desired closed-loop time constant of the Dahlin controller and β stands for the control filter factor ($0 < \beta < 1$, 1 - no filtering). The filtering of the control filter for the controller #2 was smaller than that for the controller #1 by more than 100%, so more aggressive actuator moves for the controller #2 could be expected (see Table 4).

The prediction of the process and actuator variations based on the identified models and the used two controllers was evaluated through (23) and (25). The actual process and actuator variations were computed using TAPPI recommended formula [14], based on the logged process closed-loop steady state data. The predicted variation was compared with the actual variation in Table 3 and 4.

	Controller one	Controller two
Process gain k_p	0.2174	0.1952
Process time delay T_d	85.09	74.77
Control time constant T_τ	129.35	119.27
Closed-loop time constant T_α	258.70	268.4
Control filter factor β	0.2	0.49
Display filter factor φ	1	1

Table 2: Parameters of two tested controllers

Table 3 shows the measured and predicted 2 sigma of process variation for the two tested controllers. The prediction is very accurate and the error is less than 5%. Table 4 shows the predicted 2-sigma and measured 2-sigma for incremental actuator move. Although there were some prediction errors, the change direction of the actuator variation when tuning the controller was predicted correctly. When the controller parameters was changed from the setting one to setting two, the predicted actuator 2σ increased from 0.1601 to 0.4072, which was in satisfactory correspondence with the change in real actuator variation (increased from 0.1657 to 0.4448).

	Controller one	Controller two
Predicted profile 2-sigma (23)	0.3471	0.3439
Measured profile 2-sigma [13]	0.3421*	0.3323*
* consists of MD and residual component		

Table 3: Comparison of predicted 2-sigma and measured 2-sigma for the process variation

	Controller one	Controller two
Predicted incremental control move 2-sigma (25)	0.1601	0.4072
Measured incremental control move 2-sigma [13]	0.1657	0.4448

Table 4: Comparison of predicted 2-sigma and measured 2-sigma for incremental actuator move

Validation of predicted process and actuator spectrum

The above process model and disturbance model identified from the open-loop data were verified by checking accuracy of the power spectrum prediction for the closed-loop operation. The predicted closed-loop process and actuator spectrum based on the identified models and used controller were obtained with (A3) and (A4), while the measured power spectrums were computed from the process steady state measurement data using MATLAB function SPECTRUM.M. The predicted spectrum was compared with the measurement spectrum so that the identified models can be validated.

Open-loop process spectrum check

For the identified disturbance model (28), the predicted incremental process spectrum was obtained using formula (A2)

$$\frac{0.1709^2}{2\pi}|(1-0.81e^{-j\omega})|^2 \tag{31}$$

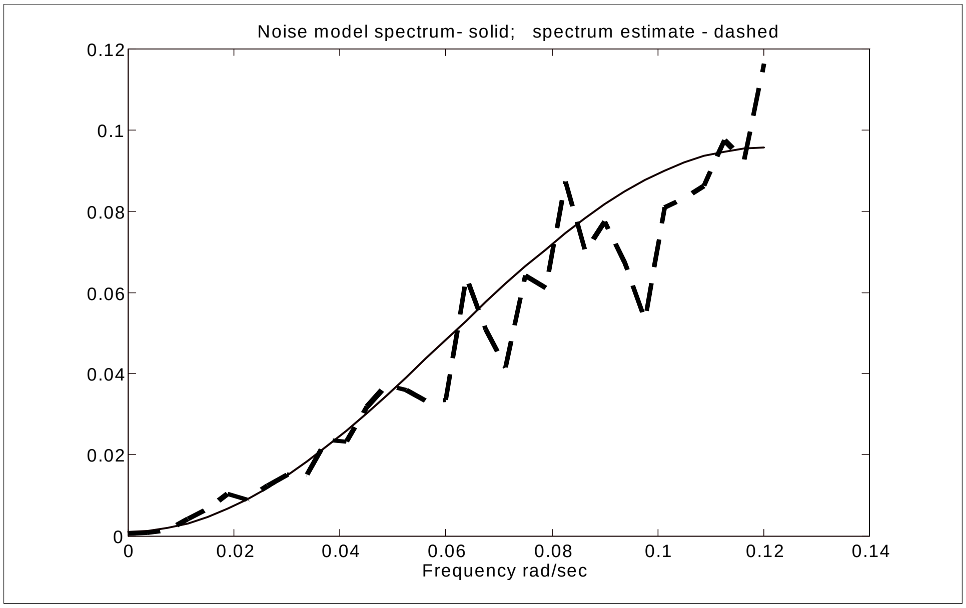

Figure 7: Comparison between predicted spectrum and measurement spectrum of the open-loop process variation

This predicted spectrum was checked with the measurement spectrum computed from the open-loop disturbance sequences using MATLAB function SPECTRUM.M. Here again the zone disturbance sequences were cascaded in order to increase amount of data used for the spectrum estimation.

Figure 7 showed that the predicted spectrum matched the measurement spectrum fairly well. This illustrated a good applicability of the identified disturbance model. Since the same data set (the weight bump test data) was used for the disturbance model identification and for the measurement spectrum estimation, this check could only prove that the disturbance model was adequate and accurate for this data set. It would be shown in the following section that the identified process and disturbance models could be used for predicting the process and actuator spectra while the process was in closed-loop operation.

Closed-loop process spectrum check

The closed-loop transfer function relating the process output *y(t)* to the white noise input *e(t)* was given by (21), where the parameter values in each component were listed in Table 5. These values were obtained from Figure 4, Table 3 and (28), based on the above mentioned process and disturbance identification results. Controller #1 was used for the closed-loop process spectrum validation.

Trans. function	$g(z^{-1})$ - process model			$D(z^{-1})$ - Dahlin controller			
Parameter	k_p	T_d	T_r	T_α	k_p	T_d	T_τ
Value	0.204	56.67	13.36	258.7	0.217	85.09	129.4
Trans. function	$F(z^{-1})$ - control filter	$M(z^{-1})$ - display filter		$N(z^{-1})$ - noise model			
Parameter	β	φ		c_1		σ	
Value	0.2	1		-0.81		0.1709	

Table 5: Paramer value of each component transfer function used in the spectrum check

The closed-loop predicted process power spectrum was obtained by substituting the parameter values in Table 5 into (A3) and was plotted in Figure 8 (solid line). MATLAB function SPECTRUM.M was used to compute the measurement spectrum using the steady state operational data. For comparison, the measurement spectrum was also plotted against the predicted spectrum in Figure 8 (dashed line). Good match between these two spectra shows not only the process model but also the disturbance model were applicable to the real process variation prediction. In Figure 8 the mismatch over very low frequency range was likely caused by the way in which the disturbance sequences were handled. Putting the zone disturbance sequences into one series would generally add some false low frequency component into the signal, so the information over very low frequency range (period > the bump test duration or duration of steady state data collection) should be disregarded.

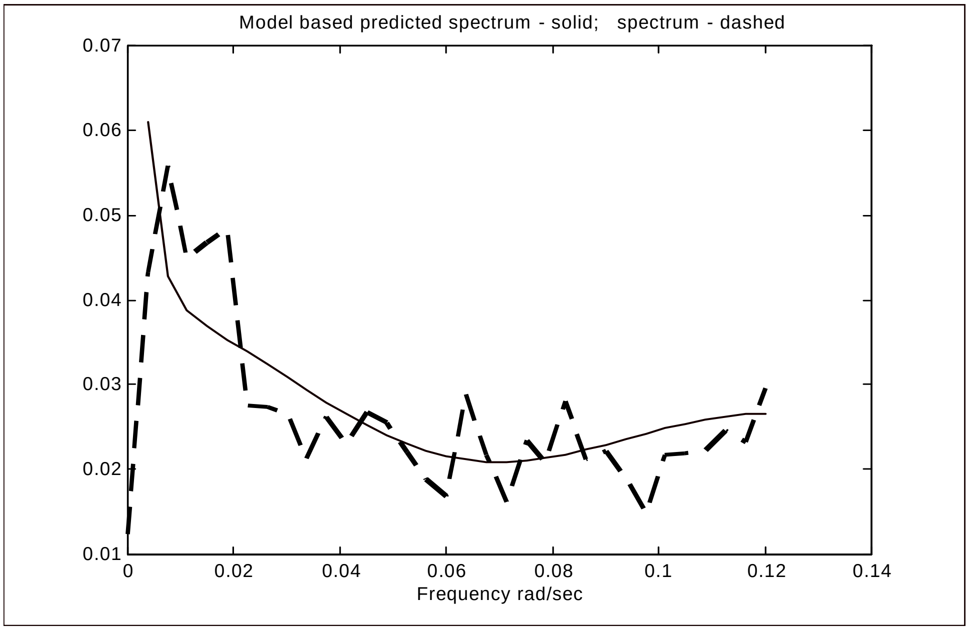

Figure 8: Comparison between predicted process spectrum and measurement spectrum

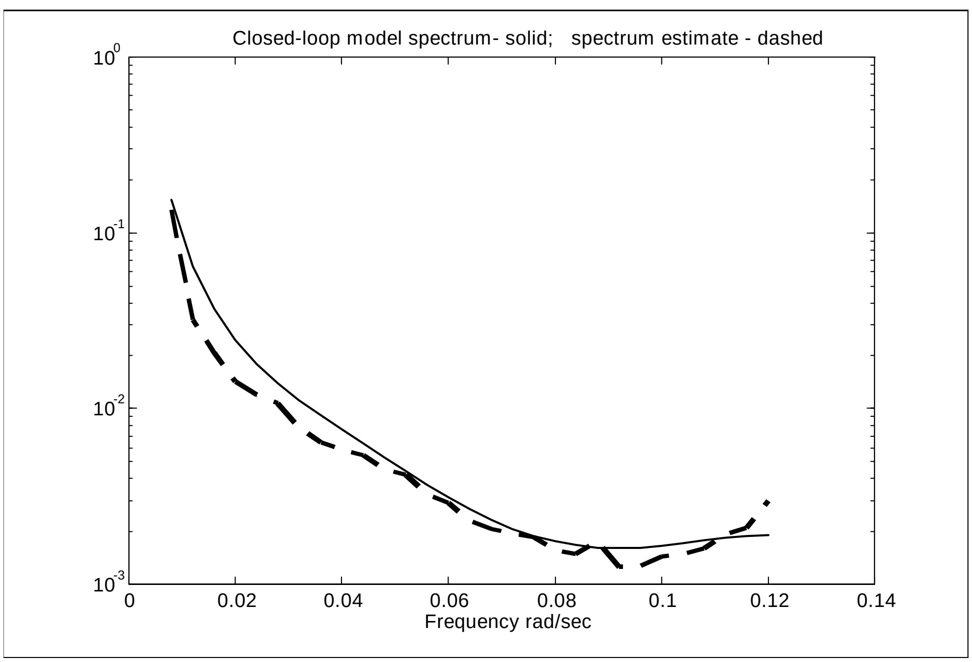

Figure 9: Comparison between predicted spectrum and measurement spectrum for actuator variation

Closed-loop actuator spectrum check

The predicted actuator spectrum was obtained by substituting the parameter values in Table 5 into formula (A4). The measurement spectrum was calculated using MATLAB function SPECTRUM.M based on the steady state data. The predicted actuator spectrum and the measurement spectrum were plotted in Figure 9. Good match between these two curves suggested that the identified process and disturbance models could be used for predicting the process variation and for tuning the feedback controller.

5. Conclusions

Controller automatic tuning is a highly desirable and useful feature for an industrial control system. The feedback controller tuning method presented in this paper is designed to work with industrial Honeywell-Measurex CD control systems and aims at assisting the field personnel in tuning and maintaining the feedback controller of the CD control systems. This would reduce the production loss due to intervention of the controller manual adjustment and improving paper product quality.

In order to tune the Dahlin controller and control filter for optimal disturbance rejection, it is necessary to establish a fairly accurate model of the paper machine process disturbance. To increase data available for identification of the disturbance model, all zone disturbance sequences from the bump test CD residual are cascaded to form a longer disturbance sequence. By doing so, overall accuracy of the disturbance identification is improved due to the significant increase of the data available for the disturbance identification. Since optimality of Dahlin controller for a first order process and first order Integrated Moving Average disturbance has been proved analytically, the used Integrated Moving Average disturbance model allows to verify the developed tuning algorithms by comparing the tuning results to the analytical solution in the literature. It is shown by simulation and mill data tests that the used Recursive Extended Least Squares method has good convergence properties and applicability. For a few cases, when the disturbance data were not sufficiently rich, the RELS failed to give a correct estimate. It is possible to correct it by extending collection of the bump test data.

The tuning of the closed-loop time constant α in the Dahlin controller and control filter factor β is based on minimization of the given quadratic performance index. Although the obtained α and β are approximate optimal values, the accuracy satisfies the most applications of paper machine CD control.

The developed feedback controller tuning tool has successfully tested through simulation model, a hardware-in-the-loop paper machine simulator and many sets of mill data. Simulation has shown that the implemented identification algorithms are capable of identifying the process model as well as the disturbance model with satisfactory accuracy. For mill data tests it is shown that the identified disturbance model captures basic characteristics of the process variation and overall the process variation is predicted with a satisfactory degree of accuracy. Fairly good match between the predicted spectra and the true spectra indicates that the identified models are applicable to prediction of the real process and actuator variation.

The observed process variation prediction errors can be attributed to insufficient and/or inaccurate models, changing disturbance dynamics, actuation nonlinearity, short data sequence for the identification of the process and disturbance models and so on. For better tractability of the problem, in the developed algorithm it is assumed that the disturbances in adjacent zones are independent and the actuator CD response is narrow (about 1 or 2 zones wide). In most cases, the developed algorithms give reasonable tuning parameters as long as these assumptions hold.

Appendix Some formulae for spectral prediction

Consider the feedback loop in Figure 2, the disturbance model (11) can be written as

$$\frac{\Delta\tilde{\xi}(z)}{\tilde{e}(z)} = C(z^{-1})\sigma, \tag{A1}$$

where $\Delta\tilde{\xi}(z)$ is Z transformation of the incremental process variation sequence, $\tilde{e}(z)$ is Z transformation of the white noise sequence with zero mean and unit variance, $C(z^{-1})$ is a monic polynomial of the form (9b), and σ is standard deviation of the disturbance identification residuals. The power spectrum of the predicted incremental process variation is

$$\frac{\sigma^2}{2\pi}|C(e^{-j\omega})|^2 \tag{A2}$$

The closed-loop predicted process power spectrum can be obtained directly from (21)

$$\frac{\sigma^2}{2\pi}|H_y(e^{-j\omega})|^2 \tag{A3}$$

The predicted incremental actuator power spectrum can be obtained from (22)

$$\frac{\sigma^2}{2\pi}|H_u(e^{-j\omega})|^2 \tag{A4}$$

References

[1] Wang, X. G., Dumont, G. A. and Davies, M. S. (1993a), “Estimation in paper machine control”, IEEE Control Systems 13(8): 34-43

[2] Chen, S.-C., and Wilhelm, Jr., R. G., “Optimal control of cross-machine direction web profile with constraints on the control effort, Proceedings of the American Control Conference, pp. 1409 - 1415, 1986.

[3] Braatz, R. D., Ogunnaike, B. A. and Featherstone, A. P., “Identification, Estimation, and Control of Sheet and Film Processes”, 13^{th} Triennial World Congress, IFAC, San Francisco, USA, 1996.

[4] Dumont, G. A., “Application of Advanced Control Methods in the Pulp Paper Industry - A Survey” *Automatica* 22: 143 - 153, 1986.

[5] Heath, W. P. and Wellstead, P. E., “Self-tuning Prediction and Control for Two-dimensional Processes Part 1: Fixed Parameter Algorithms”, *Int. J. of Control* 62: 65 - 107, 1995.

[6] Ziegler, J.G. and Nichols, N. B., “Optimal settings for automatic controller”, Trans. ASME, 64, 759, 1942.

[7] Dahlin, E.B., “Designing and tuning digital controllers”, Instruments and Control Systems, Vol. 41, pp 77-83, 1968.

[8] Dumont, G. A. “Analysis of the design and sensitivity of the Dahlin regulator”. Internal report, Pulp and Paper Research Institute of Canada , 1982.

[9] Cluett, W.R., Wang, L. “New Tuning Rules for PID Control”, Control System ’96, 75 - 80.

[10] Ljung, L. *System Identification: Theory for the User*. Prentice-Hall, 1987.

[11] Gorinevsky, D., Heaven, M., Hagart-Alexander, C., Kean, M and Morgan, S., “New Algorithms for Intelligent Identification of Paper Alignment and Nonlinear Shrinkage”, Control Systems ’96, Halifax, Nova Scotia.

[12] A.P Kjaer, W.P. Heath, and P.E. Wellstead. Identification of cross-directioin behavior in web production: techniques and experience. Control Engineering Practice; 3(1): 21-30, 1995

[13] Duncan, S.R. & Corrscadden, K.W., “Minimising the Range of Cross-directional Variations in Basis Weight on a Paper Machine”, Proceedings of the IEEE international Conference on Control Applications, 1996.

[14] TAPPI , TIP 1101-01, 1996

[15] Heaven, E. M., et al. “Recent advances in cross-machine profile control,” IEEE Control System Magazine, pp. 36 - 46, Oct. 1994.

[16] Åström, K. J. " Introduction to Stochastic Control Theory", Academic Press, Inc., New York, 1970.