Adaptive Profile Control for Sheetmaking Processes

By S. C. Chen, R. M. Snyder and R. G. Wilhelm Jr.

Presented at the:
6th IFAC*/IFIP/IMEKO Conference on Instrumentation and Automation in the Paper, Rubber, Plastics and Polymerization Industries 1986, Akron, Ohio, USA, 27-29 October 1986

Abstract

Successful control of cross-machine direction (CD) or profile variations in sheet properties is difficult to achieve consistently using conventional control methods. Due to coupling in the cross direction and constraints on the actuators used for profile control, a sophisticated multivariable controller is necessary to compute optimal control corrections. Changing machine speeds, environmental conditions, product grades, and raw material quality will change the profile process response making on-line adaptation of the controller necessary. This paper presents an adaptive control algorithm which is being used to control the weight profile on paper machines. The controller minimizes a quadratic cost function based on a process response model and the necessary actuator constraints. The process model is identified on line using a modified generalized least squares algorithm. Results from simulations and many actual paper machine installations have shown this approach to be superior to less sophisticated methods.

*** International Federation of Automatic Control**

ADAPTIVE PROFILE CONTROL FOR SHEETMAKING PROCESSES

S.-C. Chen, R. M. Snyder, and R. G. Wilhelm, Jr.

AccuRay Corporation, 650 Ackerman Road, Columbus, OH 43202, USA

Abstract. Successful control of cross-machine direction (CD) or profile variations in sheet properties is difficult to achieve consistently using conventional control methods. Due to coupling in the cross direction and constraints on the actuators used for profile control, a sophisticated multivariable controller is necessary to compute optimal control corrections. Changing machine speeds, environmental conditions, product grades, and raw material quality will change the profile process response making on-line adaptation of the controller necessary. This paper presents an adaptive control algorithm which is being used to control the weight profile on paper machines. The controller minimizes a quadratic cost function based on a process response model and the necessary actuator constraints. The process model is identified on line using a modified generalized least squares algorithm. Results from simulations and many actual paper machine installations have shown this approach to be superior to less sophisticated methods.

Keywords. Adaptive control; Identification; Industrial control; Optimal control; Paper industry; Parameter estimation; Process control.

INTRODUCTION

Sheet properties such as basis weight and moisture are a function of location on the sheet in two dimensions, usually referred to as the Machine Direction (MD) and the Cross Direction (CD). Their variations can thus be generally characterized as:

$$y = y(\tau, \lambda) \tag{1}$$

where

τ represents the MD coordinate;
λ $(0 < \lambda < L)$ is the CD coordinate;
L is the width of the sheet.

In general such a function is not separable into two functions of one dimension, but the characteristics of sheet forming machines are usually such that significant portions of the variations may be characterized as pure MD or pure CD, thus:

$$y(\tau,\lambda) = y_{MD}(\tau) + y_{CD}(\lambda) + y_R(\tau,\lambda) \tag{2}$$

where

$y_{MD}(\tau)$ is the pure MD variation;
$y_{CD}(\lambda)$ is the pure CD variation;
$y_R(\tau,\lambda)$ is the residual component of the variation.

The implications of this fact have given rise to vast oversimplification of the so-called "cross-direction control" problem. In particular, it is customary to treat the MD and CD control problems as separable, viewing the MD variations as dynamic and the CD part as static. Such control strategies considerably simplify the synthesis of the control algorithms but do not address the important source of variance represented by the residual term $y_R(\tau,\lambda)$ in equation (2). The broader implications of equation (2) have been treated in some detail by Wilhelm (1984), who points out that the pure CD component of variation as defined in equation (2) may be thought of as only the DC (steady-state) component of a whole spectrum of time variations in the profile. The residual component, then, contains the remainder of this spectrum, and the CD control problem may address whatever part of the spectrum can be removed by control. Examples given in the aforementioned reference show how stochastic control theory may be used to predict the percentage of total variance removable by feedback control, as well as to formulate appropriate control algorithms. Bergh and MacGregor (1985) have discussed the use of spatial time series modeling to formulate an LQG control strategy integrating both MD and CD control (in the broad sense).

Any such control approach will require a model of the process response to actuator adjustment. The problem of basis weight profile control on a paper machine is particularly interesting in this regard. Although the MD response reduces to a simple transport delay (plus the response characteristics of the actuators themselves), the spatial (CD) response to a single actuator is often strongly coupled (overlapping) with that of adjacent actuators. This spatial response may assume a rather complex shape due to the fluid mechanics involved, and the shape may change substantially from one grade to another or as machine operating conditions change. The underlying causes of the response are so complex as to defy on-line modelling based upon physical principles. Thus any control strategy sophisticated enough to make use of a response model may need on-line adaptive model identification.

Another very important aspect of the basis weight profile control problem is the role of actuator constraints. When the slice is used to control the profile the bending moment at any point must not exceed the elastic limits of the lip. In addition, the high and low position limits of each actuator must be observed. Even if mechanical devices are employed to assure that no constraints are exceeded, the control algorithm must account for them explicitly since decoupling (compensation for the inherently coupled process response) is very sensitive to each actuator doing its respective part. Actuators which are fixed by the operator or which are temporarily out of service also represent important constraints which must be recognized by the control algorithm.

In the following sections we show how these requirements have been met in a successful commercial cross-direction control system.

CONSTRAINED OPTIMAL CD CONTROL

The CD variation of any sheet property is normally affected by certain control efforts and many disturbances. For CD basis weight control, the profile is a function of slice actuator settings, machine speed, headbox consistency, fluid dynamics on the wire,etc. Generally, we may model this behavior as:

$$\mathbf{y}_t = \mathbf{g}\ (\mathbf{u}_t,\ \mathbf{v}_t,\ t,\ \ldots) \qquad (3)$$

where

$\mathbf{y}_t$ is a vector whose elements are the discretized points of y_{CD} at time t;

$\mathbf{u}_t$ is a vector of the slice actuator setting at time t;

$\mathbf{v}_t$ is a vector of disturbances affecting the profile at time t.

The functional relationship of equation (3) for a real paper-making process may be very complex and time-varying. But, for a relatively stable process, this relationship is usually slowly varying over a reasonable time horizon and can be treated as time-invariant behavior of the process. In this case, we may reduce (3) to a linearized static model as:

$$\Delta \mathbf{y} = \mathbf{G}\ \Delta \mathbf{u} + \mathbf{F}^{-1}\ \mathbf{w}_t \qquad (4a)$$

or

$$\mathbf{y}_t - \mathbf{y}_{t-T} = \mathbf{G}\ (\mathbf{u}_t - \mathbf{u}_{t-T}) + \mathbf{F}^{-1}\ \mathbf{w}_t \qquad (4b)$$

where

$\mathbf{y}_{t-T}$ is the steady profile measured before the new control setting $\mathbf{u}_t$;

$\mathbf{u}_{t-T}$ is the last control setting;

$\mathbf{w}_t$ represents the disturbance that affects the profile $\mathbf{y}_t$;

$\mathbf{G}$ is a matrix of steady-state partial derivatives of the profile with respect to the control changes;

$\mathbf{F}$ is a matrix describing the effect of disturbances;

T (in subscript) is the time interval to make the CD control.

For most paper-making processes, the spatial response due to one actuator adjustment is negligible beyond some finite distance from that actuator. For a normally operating process, we may assume that the response shape to each actuator movement is approximately symmetric and uniform for all actuators, so that $\mathbf{G}$ tends to be a "symmetric banded" toeplitz matrix. This character of the model is very useful in order to introduce both an appropriate identification method and an efficient calculation algorithm for control.

The fundamental objective of the CD control is to force the profile to some desired shape which is generally flat but may be any arbitrary shape. The objective can be interpreted as the minimization of a generalized quadratic index J of the profile deviation from the desired shape.

$$J = \tfrac{1}{2}\ (\mathbf{y}_t - \mathbf{y}_r)^T\ \mathbf{W}\ (\mathbf{y}_t - \mathbf{y}_r) \qquad (5)$$

where

$\mathbf{y}_r$ is a vector representing the desired profile;

$\mathbf{W}$ is a diagonal matrix of weighting factors;

T (in superscript) means "transpose".

The quadratic index defined in (5) is directly proportional to the variance of the profile deviation if the weightings are all equal (i.e., $\mathbf{W}$ = the identity matrix).

Theoretically, the control which minimizes this quadratic index is the best solution to the problem if the process model perfectly describes the process behavior. For any real process, not only is an exact model normally unavailable, but the ideal optimal control may also be unrealizable because of some physical constraints on the control efforts.

The constraints in the weight profile control include the limitation of the available range for actuator movement, the bending deformation limit on a slice lip, and possibly broken and/or manually controlled actuators. All these constraints may prevent control settings from realizing the ideal solution. To make the control feasible, we must formulate the constraints as a set of inequalities and take them into account while solving for the control setting.

The constraints can be formulated as follows:

1) The available range of actuator adjustments may be expressed as:

$$\mathbf{u}_{min} \le \mathbf{u} \le \mathbf{u}_{max} \qquad (6)$$

2) The bending moment of a slice lip is proportional to a vector $\mathbf{b}$ whose elements b(j) are discretized second moments of the actuator setting,

$$b(i) = u(i-1) - 2u(i) + u(i+1) \qquad (7a)$$

$\mathbf{b}$ may also be expressed in matrix form as:

$$\mathbf{b} \equiv \mathbf{Bu} \qquad (7b)$$

with

$$\mathbf{B} \equiv \begin{pmatrix} -1 & 1 & 0 & 0 & & \ldots & 0 \\ 1 & -2 & 1 & 0 & & \ldots & 0 \\ 0 & 1 & -2 & 1 & & & . \\ 0 & 0 & 1 & -2 & 1 & & . \\ . & . & . & . & . & . & . \\ . & & & & 1 & -2 & 1 \\ 0 & \ldots & & & 0 & 1 & -1 \end{pmatrix} \qquad (7c)$$

The limit on the bending deformation of the slice lip is then expressed as:

$$-\mathbf{b}_{max} \le \mathbf{b} \le \mathbf{b}_{max}$$

where $\mathbf{b}_{max}$ is a vector of whose elements are the allowable bending limits.

3) The immobile (broken or manually controlled) actuators may be described as:

$$u_t(j) = u_{t-T}(j) \qquad (8)$$

where $u_{t-T}(j)$ is the setting of the j^{th} actuator before the present control action.

Boyle (1977) and Chen and Wilhelm (1986) have shown that the optimal control subjected to these constraints can be obtained with quadratic programming. The quadratic programming method, however, expands the dimension of the problem considerably and the involved operation - pivoting

- is very sensitive to the condition of the process model **G**.

Wilhelm (1986) has shown that including the quadratic index (5) with penalty factors on bending, the control deviation from the mid-range and the movement of immobile actuators produces a practical solution. The modified quadratic index is

$$J_1 = J + \tfrac{1}{2}p(\mathbf{u}_t-\mathbf{u}_m)^T(\mathbf{u}_t-\mathbf{u}_m) + \tfrac{1}{2}q\mathbf{b}^T\mathbf{b} + \tfrac{1}{2}(\mathbf{u}_t-\mathbf{u}_{t-T})^T\mathbf{V}(\mathbf{u}_t-\mathbf{u}_{t-T}) \quad (9)$$

where p and q are scalar penalties which must be appropriately chosen to assure that the control **u** satisfies the constraints of equations (6) and (7). **V** is a diagonal matrix with large values on the diagonal elements corresponding to fixed actuators of equation (8) and zeros elsewhere. $\mathbf{u}_m$ is a vector representing the mid-range between $\mathbf{u}_{min}$ and $\mathbf{u}_{max}$.

Minimizing the quadratic index J_1 in (9) yields the solution:

$$\mathbf{u} = -(\mathbf{G}^T\mathbf{W}\mathbf{G} + p\mathbf{I} + q\mathbf{B}^T\mathbf{B} + \mathbf{V})^{-1}[\mathbf{G}^T\mathbf{W}(\mathbf{y}_{t-T} - \mathbf{y}_r) - (\mathbf{G}^T\mathbf{W}\mathbf{G} + \mathbf{V})\,\mathbf{u}_{t-T} - p\mathbf{u}_m] = \mathbf{A}^{-1}\mathbf{z} \quad (10a)$$

where

I is the identity matrix

$$\mathbf{A} = \mathbf{G}^T\mathbf{W}\mathbf{G} + p\mathbf{I} + q\mathbf{B}^T\mathbf{B} + \mathbf{V} \quad (10b)$$

$$\mathbf{z} = -\mathbf{G}^T\mathbf{W}(\mathbf{y}_{t-T} - \mathbf{y}_r) + (\mathbf{G}^T\mathbf{W}\mathbf{G} + \mathbf{V}) + p\mathbf{u}_m \quad (10c)$$

The optimal p and q can be found through an iterative searching procedure, checking constraints at each step. The control setting **u** in (10a) needs to be calculated repeatedly with different penalty values of p and q. The calculation of **u** consists of solving a system of simultaneous equations with large dimensions. This is very time-consuming and sensitive to accuracy with general methods such as Gaussian elimination. As we examine equation (10) carefully, we find that the **A** matrix in (10b) is positive-definite, symmetric and mostly banded. According to the factorization theory of matrices, the simultaneous equations defined in (10a) can be solved in a very efficient way by taking advantages of the special structure of the **A** matrix (Chen and Wilhelm, 1986). The significant saving of computation and the storage requirement make the quadratic penalty function approach feasible in practical implementations.

MODEL IDENTIFICATION

As was mentioned previously, the width and shape of the weight profile process response to a slice actuator movement can change significantly due to many factors: machine speed, weight target, headbox consistency, gross slice opening, pulp quality, etc. In order to achieve consistently good profiles, the process response model used by the control algorithm must be adapted to take into account variations in any of these process parameters. Since the effects of these variations on the response are not known exactly, an on-line model identification algorithm is necessary.

Regardless of the asymmetric response near the edge of the sheet, we can rewrite our process model equations using polynomial notation as:

$$\Delta y(k) = g(d)\Delta u(k) + \varepsilon(k), \quad k = m+1, m+2, \ldots, n-m \quad (11a)$$

$$f(d)\varepsilon(k) = w(k) \quad (11b)$$

$$g(d) = g_0 + g_1(d^1 + d^{-1}) + \ldots + g_m(d^m + d^{-m}) \quad (11c)$$

$$f(d) = 1 + f_1(d^1 + d^{-1}) + \ldots + f_p(d^p + d^{-p}) \quad (11d)$$

where

- n is the number of control zones;
- m is the order of process model;
- p is the order of noise model, $p \le m$;
- d is a spatial shift operator defined by $d^i\,u(k) \equiv u(k+i)$;
- w(k) is a spatially independent noise at time t.

This expression is consistent with our three major assumptions about the profile response shape:

1) the response shape is symmetric
2) the response shape is the same for all actuators
3) the total profile response is the sum of the responses to each actuator

The form of the spatial model in (11) is a special case of the general ARMAX model for time-series analysis. In this case, the deterministic part of the model is a two-sided moving-average process and the stochastic part is a two-sided autoregressive noise process.

Since the profile disturbances are correlated with each other, the least squares estimates of the coefficients of g(d) will be biased, thus a different approach is necessary. The intent of the Generalized Least Squares (GLS) algorithm is to take a problem which cannot be solved by ordinary Least Squares (LS) and break it up into two smaller problems, both of which can be solved by LS (Strejc, 1980; Hsia, 1977). This is done by first assuming that the noise model is known and then filtering or "pre-whitening" the input/output data with this filter. This allows one to rewrite (11) as:

$$\Delta y'(k) = g(d)\Delta u'(k) + w(k) \quad (12a)$$

where

$$\Delta y'(k) \equiv f(d)\Delta y(k) \quad (12b)$$
$$\Delta u'(k) \equiv f(d)\Delta u(k) \quad (12c)$$

One can now formulate this as a LS problem to solve for the coefficients of the moving average polynomial g(d).

$$\mathbf{h}(k) = [\Delta u'(k),\ \Delta u'(k+1) + \Delta u'(k-1),\ \ldots,\ \Delta u'(k+m) + \Delta u'(k-m)]^T \quad (13a)$$

$$\mathbf{H} = [\mathbf{h}(m+1),\ \mathbf{h}(m+2), \ldots,\ \mathbf{h}(n-m)]^T \quad (13b)$$

$$\theta = [g_0\ g_1 \ldots g_m]^T \quad (13c)$$

$$\Delta\mathbf{y}' = \mathbf{H}\,\theta + \mathbf{w} \quad (13d)$$

$$\hat{\theta} = (\mathbf{H}^T\mathbf{H})^{-1}\mathbf{H}^T\Delta\mathbf{y}' \quad (13e)$$

Using this estimate of the process model, one can formulate a second LS problem to estimate the noise model parameters.

$$\varepsilon(k) = \Delta y(k) - g(d)\Delta u(k) \quad (14a)$$

$$f(d)\varepsilon(k) = w(k) \quad (14b)$$

$$\varepsilon(k) = f^*(d)\varepsilon(k) + w(k) \quad (14c)$$

$$f^*(d) = 1 - f(d) \quad (14d)$$

$$h_\varepsilon(k) = [\varepsilon(k+1) + \varepsilon(k-1), \dots, \varepsilon(k+p) + \varepsilon(k-p)]^T \quad (14e)$$

$$H_\varepsilon = [h_\varepsilon(p+1), h_\varepsilon(p+2), \dots, h_\varepsilon(n-p)]^T \quad (14f)$$

$$\theta_\varepsilon = [-f_1 \ -f_2 \ \dots \ -f_p]^T \quad (14g)$$

$$\varepsilon = H_\varepsilon \theta_\varepsilon + w \quad (14h)$$

$$\hat{\theta}_\varepsilon = (H_\varepsilon^T H_\varepsilon)^{-1} H_\varepsilon^T \varepsilon \quad (14i)$$

This improved estimate of the noise model can be used to obtain a better estimate of the process model, which is then used to improve the estimate of the noise model, etc. This procedure is repeated until the estimates of both models converge and these final values are used as the parameter estimates.

There are several process factors which affect the performance of the identification algorithm to varying degrees. Firstly -- and most critical -- is the mapping of the profile measurements into appropriate control zones which bear a direct correspondence with the slice actuators. Between the slice and the scanning frame, three things happen which will affect this mapping:

1) The sheet edges may be trimmed from 1 to 4 inches, depending on the desired reel trim of the product being produced

2) The sheet will shrink (due to drying) from 2 to 6 per cent depending on the weight and final moisture content of the sheet

3) The whole sheet may shift (due to unequal dryer loading) up to 6 inches in the cross direction

Recognizing that slice actuators are generally spaced either 4.5 or 6 inches apart, the control and identification algorithms will both yield incorrect results unless these factors are accounted for in the mapping procedures.

Secondly, the long term signal-to-noise ratio for the profile may be very small which will also have a negative impact on the identification algorithm. The reason for this is that the controllable portion of the pure CD component of the profile variance is removed by the first control actions. After that, the majority of the corrections will be very small unless the time varying profile disturbances are very large. The profile response to these small (0 - 1.0 mil) corrections may be in the range of 0 - 0.25 lbs. which is usually smaller than the magnitude of the high frequency temporal profile disturbances. To complicate matters more, the slice displacement sensors are also corrupted by noise (electrical and vibrational) of up to 0.1 mils. Thus, in order to ensure good identification results, a deadband on the magnitude of the control corrections is used so that that estimates are based only on significant actuator movement.

Thirdly, the system must be able to track variations in the profile process response. Step changes to the parameters (as in the case of a grade change) can be tracked by using a gain scheduling approach, where the initial values of the model parameters are the final values which were estimated the last time a particular grade was produced. If several grade changes are made per day, this approach would probably be adequate. However, on machines where a single grade is run for several days or weeks at a time, it is necessary to be able to track slow variations in the parameters due to changes in the operating environment as discussed earlier. The equivalent of the variable forgetting factor used in recursive parameter estimation schemes has been implemented in the batch GLS algorithm to accomplish this. Of course, there is a trade off between the parameter tracking and noise sensitivity of the estimates so the exact tuning of the forgetting factor will be machine and/or grade dependent.

Finally, since we are working with a static process model, we must be sure that, when we calculate the process response (i.e., change in the profile), we use an accurate static profile before and after the control action. This requires filtering information from several profiles before and after the correction is made in order to attenuate the high frequency temporal disturbances in the profile. Large MD process upsets also cause severe upsets to the profiles, so it is essential that the MD controls be very well tuned before attempting to do CD control on weight, moisture, caliper, or any other process variable. It is also important that profiles corrupted in this manner not be used for control or identification purposes since they could cause gross errors. In addition to being able to accurately determine the process response, it is equally important to be able to accurately measure the true slice displacement. If any electrical or mechanical failure prevents an actuator from achieving its setpoint, model identification based on the desired slice displacement will yield incorrect results. Also, without measurement of the absolute position, the control could eventually violate one or more of the actuator constraints and permanently damage the slice lip and/or an actuator. Thus, accurate and reliable slice displacement sensors are critical to the performance of both the identification and the control algorithms.

RESULTS

The following examples may show the effectiveness of the CD control algorithm discussed in this paper. Assume that the curve shown in Fig. 1 illustrates the spatial response of the weight profile to a unit actuator movement. Regardless of all constraints, the error profile and the ideal control settings are shown in Fig. 2. Although theoretically the ideal control can completely correct the error profile, the control setting may exceed some limits as we mentioned before. The control setting which takes into account the bending limit, bmax = 0.5, with the proposed approach is shown in Fig. 2b. The corresponding resultant profile is shown in Fig. 2a. With such a small residual variation in the profile, the smoothness of the slice shape has been significantly improved with the proposed method. Figure 3 shows how other constraints such as the fixed actuators (fixed 3rd and 16th actuators) are taken into account by the algorithm. Results show that the quadratic penalty method gives good control provided that the process model is accurate. If the true process response (Fig. 4) is different from the model used for control, the resulting profile as shown in Fig. 5 will not be as good as it should be. The adaptive adjustment of the model with the on-line identification surely will improve the overall performance.

The best way to demonstrate the benefits of on-line identification versus fixed control is to look at the results of two trials on the same paper machine, producing the same grade on two consecutive days. The paper machine in question was Fourdrinier machine with 31 slice actuators producing 26 lb. liner board. Figure 6a shows the conditioned weight profile while running with a fixed controller based on a process model of θ = [0.080 0.000]. The identification algorithm was activated at the time this printout was made. Figure 6b shows the same profile 35 minutes later when the process model calculated was θ = [0.069 -0.005] . Note the nearly 50% reduction in the profile standard deviation. Figure 7a was printed the following day while still on the same grade. The identification algorithm had been deactivated again and the machine was running with the model calculated the previous day. Obviously, the previous day's model was no longer valid due to changes in the operating conditions. Upon talking to the machine operators, it was discovered that the moisture target had been increased and the machine speed had also increased in order to maximize throughput. The algorithm was reactivated and 54 minutes later the profile standard deviation had been reduced by more than 50% (see Fig. 7b.) and the new model was θ = [0.055 -0.007] . These two examples demonstrate both the advantages of on-line identification and the importance of being able to track variations in the process parameters in order to maintain the best control at all time.

These algorithms have been incorporated into the AccuRay Profile Manager™ Family of Cross Machine Control Modules and have been implemented on more than 70 paper machines world wide, ranging from high speed newsprint machines to the most difficult to control board machines. The installations include both twin-wire and conventional Fourdrinier formers as well as a variety of slice actuators and headboxes. Figures 8 and 9 show the results from two recent installations. Both are Fourdrinier machines producing fine paper grades and both are equipped with AccuRay MICROSET™ Linear Stepper Slice Actuators, the first on a Beloit air padded headbox and the second on a Valley headbox. Both figures show the error profiles before and after control was turned on and both show an initial reduction in the "2sigma" value (twice the standard deviation of the profile error) of more than 50%. These results are comparable to other installations and are repeatable.

CONCLUSIONS

The control of Cross Direction variations in sheet properties is a complex problem with many facets. Some of the problems discussed here may be absent in any given application, but many processes present all of them simultaneously. The solutions discussed here have all been implemented in a successful commercial Cross Direction Control package and have been in use in many installations for over a year. We do not see these solutions as the ultimate cross direction control algorithm; indeed, this area will provide many interesting research and development challenges for many years to come. We do believe, however, that the methods discussed here represent valuable solutions to the most important problems encountered in many cross direction control problems.

REFERENCES

Wilhelm, R. G., Jr. (1984). On the controllability of cross-direction variations of sheet properties Proc. of Tappi Eng. Conf., Boston, MA.

Bergh, L.G., and J.F. MacGregor. (1985). Spatial control of sheet and film forming processes. Canadian Journal of Chemical Engineering. (to be published).

Boyle, T. J. (1977). Control of cross-direction variations in web forming machines. The Canadian Journal of Chemical Eng., 55, 457-461.

Beecher, A. E., and R. A. Bareiss. (1970). Theory and practice of automatic control of basis weight profiles. Tappi, 53, 847- 852.

Chen, S.-C., and R.G. Wilhelm, Jr. (1986). Optimal control of cross-machine direction web profile with constraints on the control effort. Proc. of the 1986 American Control Conference, Seattle, WA.

Wilhelm, R. G., Jr. (1986). Of least squares and engineering judgement: Practical application of quadratic performance criteria in control. Proc. of the 12th Annual Advanced Control Conference, Purdue University.

Strejc, V. (1980). Least squares parameter estimation. Automatica, 16, 535- 550.

Hsia, T. C. (1977). Identification : Least Squares Methods. Lexington Books, Lexington, MA.

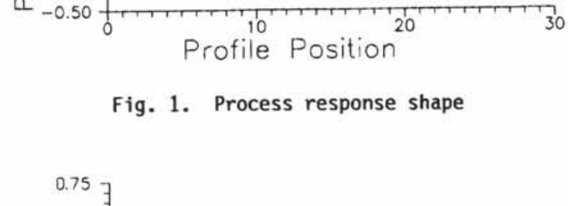

Fig. 1. Process response shape

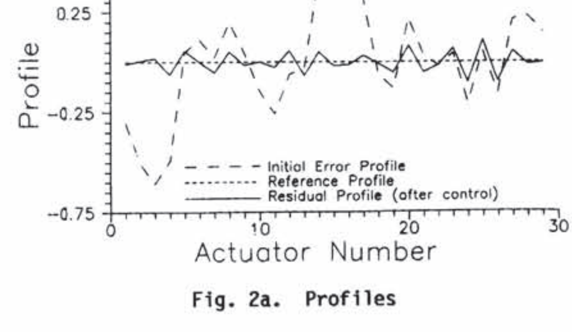

Fig. 2a. Profiles

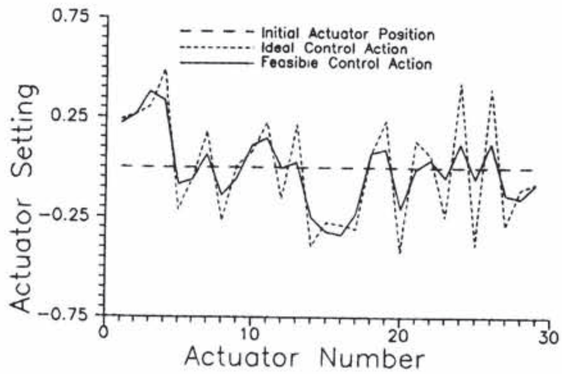

Fig. 2b. Actuator settings

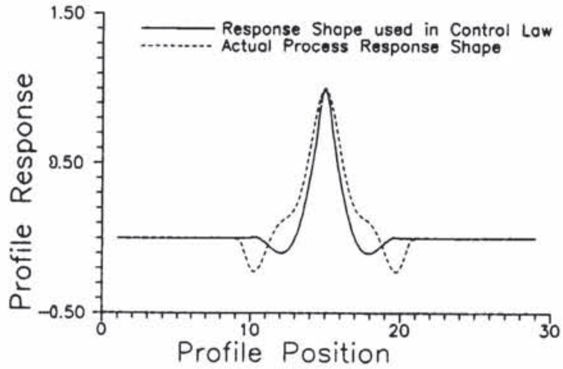

Fig. 4. Modelling error

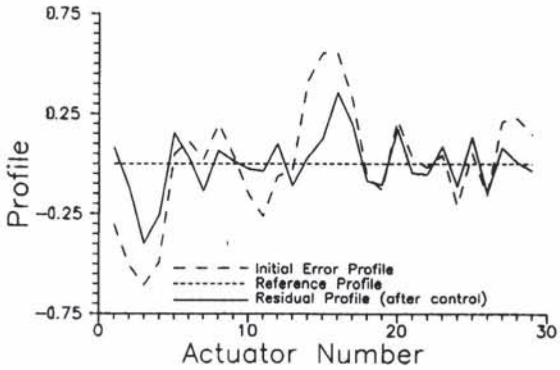

Fig. 3a. Profiles, actuators 3 and 16 fixed

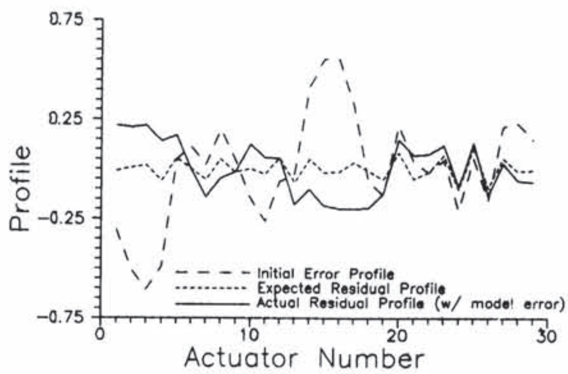

Fig. 5. Profiles with modelling error

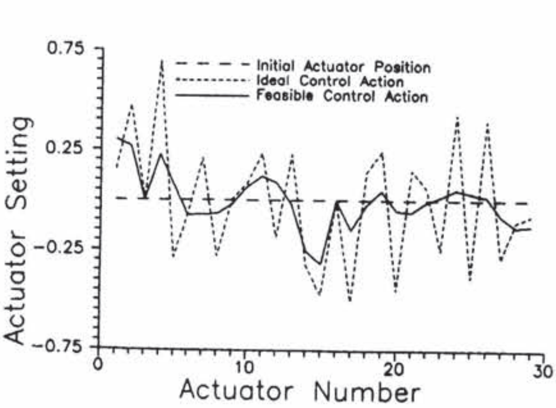

Fig. 3b. Actuator settings, acts. 3 and 16 fixed

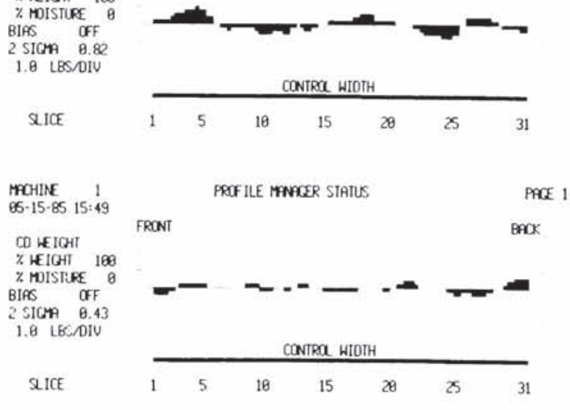

Fig. 6. Identification trial 1

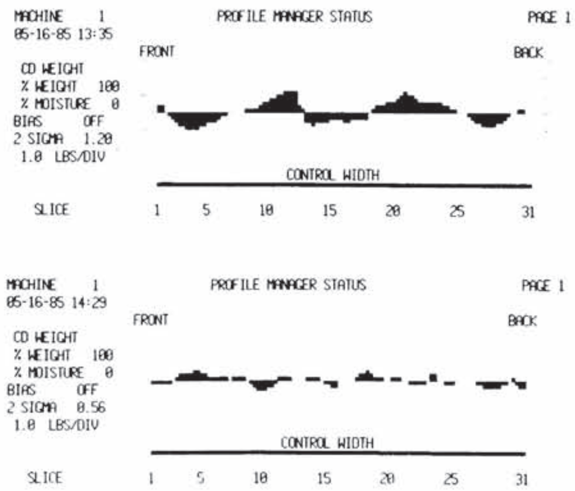

Fig. 7. Identification trial 2

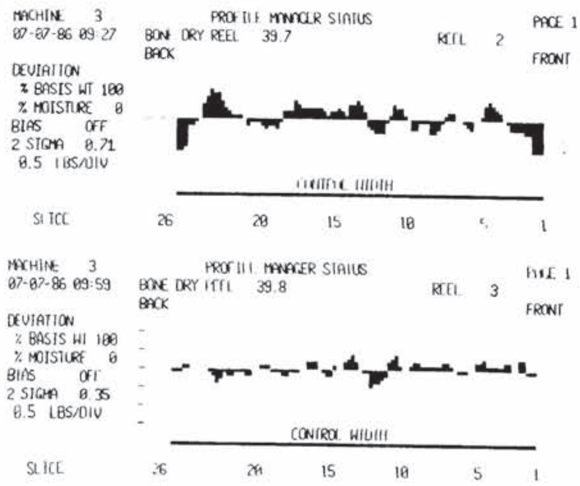

Fig. 8. Product - 40 lb. release backing

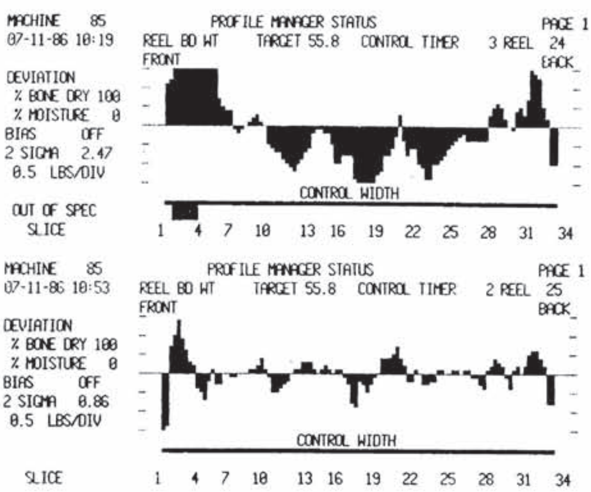

Fig. 9. Product - 59 lb. release base