Full Papers

Adaptive control of basis weight and moisture content for a paperboard machine

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The development and industrial application of a MIMO adaptive control strategy for a paperboard machine are investigated. The control strategy incorporates a conventional regulatory control technique, multivariable k-incremental predictor and self-tuning control algorithm. The pulp consistency and flow rate, and the steam pressure are simultaneously manipulated to control the reel basis weight and moisture content. The control system demonstrates a satisfactory performance. The variations in reel basis weight and moisture content are greatly reduced.

Keywords: adaptive control; predictive control; paperboard machine

Basis weight and moisture content are the most important quality variables of paper products. Good control of them can significantly improve paper quality, increase production rate and reduce raw material and energy consumption. Previous studies[1,2] have shown that applications of advanced process control produce good economic returns. Typical returns have been in the order of decreasing fibre by 5% and steam consumption by 10%, and increasing annual production by 5–10%.

The basis weight and moisture content in a paperboard machine are difficult to control due to the following reasons: (1) paperboard machines have large parameter drifts, external disturbances and random noises. Some of the external disturbances are measurable and others are not; (2) the dynamics of the machine are nonlinear and time varying; (3) there exist long time delays (dead times) in basis weight and moisture content control loops; (4) there are serious interactions between the two control loops. The first two result in time and operating condition dependent changes in the process dynamics. The last two imply that a multivariable controller which can deal with multiple long time delays is required.

Adaptive control has long been considered as an ideal solution to the control problem of time varying stochastic systems. Its ability to adapt to changing process behaviour, particularly the changes caused by the underlying nonlinearity of process dynamics, makes the adaptive control approach very appealing. Åström initiated the application of a self-tuning regulator to paper machines[3]. Since then, a number of adaptive control techniques have been applied to pulp and paper processes[4–8].

This paper investigates the development of a general multi-input/multi-output (MIMO) adaptive controller for paperboard machines with multiple time delays, and measurable and unmeasurable disturbances. The model of the paperboard machine is identified by a recursive forgetting algorithm. A k-incremental predictor is applied to eliminate the steady state errors in parameter identification and control. As a result, the robustness of the control system against machine rate changes and unmeasurable disturbances as well as stochastic noises is greatly improved. An auxiliary control variable is introduced to deal with the time-delay difference between the two control loops.

Fundamentals of the paperboard machine

The paperboard machine investigated is a cylinder-mould machine in a paper mill in P.R. China, which produces packing board using straw pulp and wood pulp. *Figure 1* presents the flow diagram of the machine.

The straw pulp and wood pulp are pumped into high-level tanks and diluted with water, from where they flow through sand tray and rotary screens to remove impurities. The diluted and cleaned pulp flows pass to the distributor and are distributed into four straw pulp flows and one wood pulp flow. These five pulp flows pass to the five wire-covered cylinders (forming cylinders). The paper web is formed on the surface of wire-covered cylinders in the cylinder forming vats. The vats are partially filled with diluted fibre suspensions. As the forming cylinder rotates through the vat of stock, the water flows

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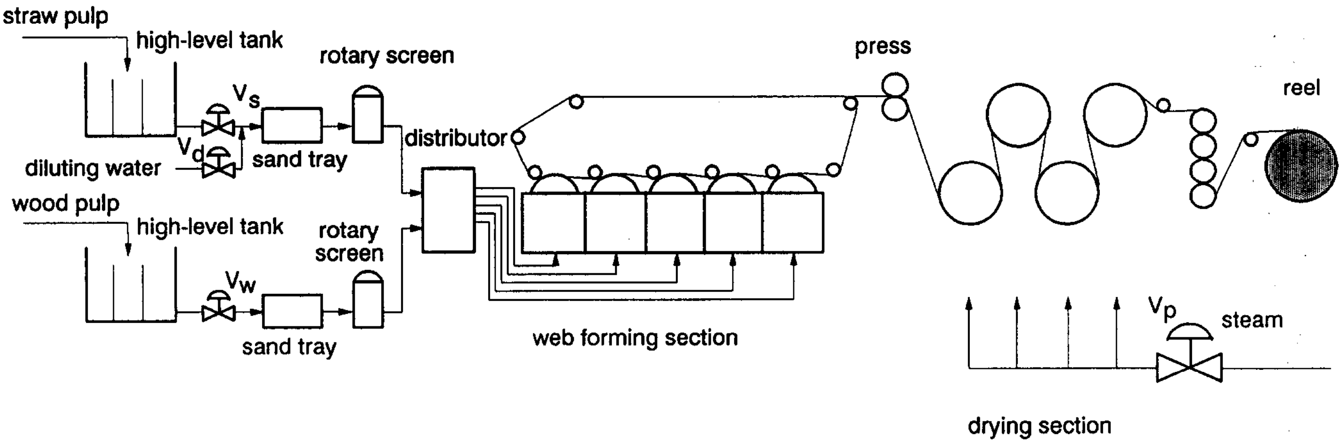

Figure 1 Flow diagram of the paperboard machine

through the surface of the cylinder and the fibres catch on the wire, forming the web of paper.

A moving felt is pressed against the wet web and removes the wet web from the forming cylinder at this point. The felt and web picked up from the first cylinder proceed to the second cylinder, where they are pressed against the web formed there to pick it up. The felt continues through the forming section, picking up webs from all the five vats in succession. After all webs are picked up by the felt and are combined to form a thick composite board web, it goes through the press section. The web which leaves the press section end is passed around a series of steam-filled cylinders where the remaining water is removed by evaporation. The web travels in such a way that it passes over the top and under the bottom cylinders, so that first one side of the web, then the other, is heated.

Since the wood pulp forms a web on the top surface of the paperboard, it is called surface stock, whereas the straw pulp is called inner stock.

The operation of the paperboard machine requires the basis weight and moisture content to meet process specifications while minimizing the energy and pulp consumption per ton of paperboard product. The basis weight is controlled by the straw pulp control valve V_s, while the moisture content is controlled by the steam control valve V_p.

The paperboard machine used to be controlled by two single-loop PID regulators which maintained constant pulp flow rate and steam pressure. Operation experience showed the reel basis weight and moisture content presented large variations under the control of single-loop regulators.

The difficulties in the paperboard machine control arise from:

(1) The machine produces packing paperboard of basis weight as high as 360 g m^{-2}. However, the machine speed is as low as 50 m min^{-1}. Greater thickness of the web requires more drying cylinders. There are 45 drying cylinders in the paperboard machine. This results in a long time delay. The time delay from the straw pulp control valve to reel basis weight is about 6 min. The time delay from the steam control valve to reel moisture content is about 3 min.

(2) There are serious couplings between the control of basis weight and moisture content. If moisture content increases by 1%, the basis weight will increase by 4 g m^{-2}. Similarly, a change in basis weight has a great influence on moisture content. The couplings make the paperboard machine a multivariable system. The system could be triangularized by considering moisture content and dry basis weight. However, since the paper company considered the basis weight rather than the dry basis weight as a quality variable, the operators required the system to control the basis weight directly.

(3) The capability of the forming cylinders to catch fibres varies with the wear of wires and felts. The variation of machine speed also changes the dynamics of the paperboard machines.

Considering the above problems, we propose the following multivariable adaptive controller for basis weight and moisture content control.

Control strategy

The basis weight and moisture content are affected by many variables. Some of them are measurable, such as the consistency of straw pulp and wood pulp, machine speed, steam pressure, etc. Others are unmeasurable, such as the quality of pulps, the capability of forming cylinders to catch fibres, the stock level of vats, the efficiency of the press and coating, etc. Due to the long time delays, some auxiliary feedback and feedforward control loops are required to maintain the basis weight and moisture content within the specifications.

The structure of the basis weight and moisture content control strategy is shown in *Figure 2.* The important features of this strategy are:

(1) The consistency of the straw pulp from the pulp preparation section varies widely and has a large influence on the reel basis weight. To keep it constant, the consistency is controlled by a PID controller through adjusting the flow rate of the diluting water.

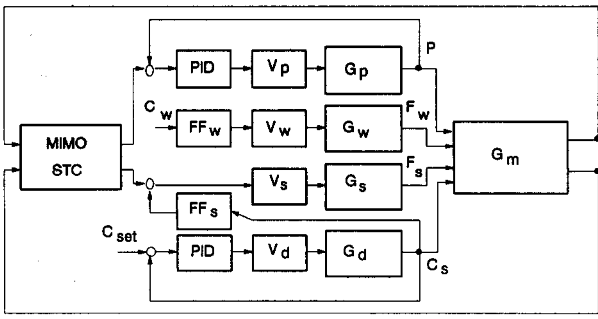

Figure 2 Adaptive control strategy for the paperboard machine

(2) Another PID controller is used to control the steam pressure.

(3) The measurements of the straw pulp and wood pulp consistency serve as feedforward signals to adjust the opening of the control valves V_s and V_p, respectively. In this way, the varying of pulp consistency is compensated for before it finally affects the paperboard quality.

(4) The multivariable self-tuning controller provides the setpoint for the PID steam pressure controllers and the opening of the straw pulp control valve V_s.

The control strategy has the following advantages: despite the long time delay in basis weight and moisture control loops, the effects of the variations of straw pulp and wood pulp consistency and the steam pressure on the final paperboard can be eliminated quickly. The self-tuning controller is used to compensate unmeasurable disturbances.

Self-tuning controller

Self-tuning controllers combine a recursive parameter estimator and a control design mechanism. The parameter estimator obtains a plant model from input/output data. The control design mechanism accepts the parameter estimates as if they were exact and from which the parameters of a feedback control law can be deduced. A self-tuning control sytem provides the capability of automatically compensating for parameter and environmental variations that may occur during operation. In the case of a paperboard machine, such a system has the potential for providing uniform basis weight and moisture content despite the process dynamics variation and external disturbances.

Since the middle of the 1970s, many researchers have been investigating multivariable self-tuning controllers. Borisson proposed a self-tuning controller for a MIMO system[9]. The controller was only applied to systems with equal numbers of inputs and outputs, or square systems. Koivo and Tanttu derived a self-tuning controller for the case where the number of outputs is not necessarily equal to the number of inputs, i.e. non-square systems[10].

Many simulation studies have concentrated on the dynamics and data which have zero mean level so that no offsets are obtained. However, the input/output data supplied to the parameter estimator are very often insufficient to provide an accurate value of the effective additive constant in the plant model. To deal with non-zero mean disturbance and offset problems, Clarke and his coworkers proposed a novel k-incremental predictor, in which the control law and identification use the differences of the inputs and outputs instead of the inputs and outputs themselves. Digital simulation and application studies have shown the advantages of the k-incremental predictor[11].

In the basis weight and moisture content control system of the paperboard machine, we mainly apply the multivariable self-tuning controller developed by Koivo and Tanttu[10], and make a number of modifications:

(1) The k-incremental predictor[11] is generalized into a multivariable case and applied to a self-tuning controller. The purpose is to eliminate the offset terms in the parameter estimation and control algorithm, to improve the regulation against non-zero disturbances such as those induced by load changes.

(2) An auxiliary control variable is introduced to solve the problem arising from the difference in time delay in two control loops.

Multivariable k-incremental predictor and self-tuning controller

The linearized model of the controlled process is assumed to be:

$$A(z^{-1})y(t) = B(z^{-1})z^{-k}u(t) + C(z^{-1})e(t) + d \qquad (1)$$

where $k \geq 1$ is the time delay of the system, $y(t)$ and $u(t)$ are r-dimensional output and input vectors, respectively. The operator matrices $A(z^{-1})$, $B(z^{-1})$ and $C(z^{-1})$ are defined as follows:

$$A(z^{-1}) = I + A_1z^{-1} + A_2z^{-2} + \cdots + A_nz^{-n}$$

$$B(z^{-1}) = B_0 + B_1z^{-1} + B_2z^{-2} + \cdots + B_nz^{-n}, \quad B_0 \neq 0$$

$$C(z^{-1}) = I + C_1z^{-1} + C_2z^{-2} + \cdots + C_nz^{-n}$$

where all zeros of $B(z^{-1})$ and $C(z^{-1})$ lie strictly outside the unit disc, that is, the solutions of $B(z^{-1}) = 0$ and $C(z^{-1}) = 0$ satisfy $|z| < 1$. $e(t)$ is a sequence of independent $(0,\Omega)$ variables representing the stochastic part of the disturbance. d is an unknown constant vector which arises from:

(i) load disturbances, such as changes in the consistency and flow rate of the straw pulp and wood pulp;

(ii) the fact that the steady-state incremental gain $\partial y/\partial u$ of a process does not equal the static gain y/u: a consequence of the large signal nonlinearity of most plant;

(iii) non-zero-mean noise.

Our task is to find a control vector $u^*(t)$ that minimizes the cost function:

$$I_p = E\{\|P(z^{-1})y(t+k) - R(z^{-1})w(t) + Q'(z^{-1})u(t)\|^2\} \quad (2)$$

where $w(t) \in R^r$ is the reference signal sequence, $P(z^{-1})$, $R(z^{-1})$ and $Q'(z^{-1})$ are $(r \times r)$-dimensional polynomial matrices with:

$$P(z^{-1}) = P_0 + P_1 z^{-1} + \cdots + P_p z^{-p}$$
$$R(z^{-1}) = R_0 + R_1 z^{-1} + \cdots + R_l z^{-1}$$
$$Q'(z^{-1}) = Q'_0 + Q'_1 z^{-1} + \cdots + Q'_s z^{-s}$$

We define an auxiliary output $\Phi(t)$ by:

$$\Phi(t+k) := Py(t+k) - Rw(t) + Qu(t) \quad (3)$$

where $Q = ((P_0B)^{-1}(Q'_0))^{\mathrm{T}}Q'$. To derive an optimal predictor, consider the identity:

$$PC = AE + z^{-k}F \quad (4)$$

Given A, P, C and k, the coefficients of $E(z^{-1})$ and $F(z^{-1})$ polynomials:

$$E(z^{-1}) = E_0 + E_1 z^{-1} + \cdots + E_{k-1} z^{-k+1}$$
$$F(z^{-1}) = F_0 + F_1 z^{-1} + \cdots + F_{n_F} z^{-n_F}$$

can be uniquely determined from Equation (4) where $n_F = \max(n-1, p+n-k)$. Denoting $\tilde{E}$ and $\tilde{F}$ as the left and right coprime factorizations of E and F, that is:

$$\tilde{E}F = \tilde{F}E \quad (5)$$

with

$$\det \tilde{E} = \det E, \quad \det \tilde{F} = \det F$$

and defining a polynomial matrix $\tilde{C}(z^{-1})$ such that:

$$\tilde{C}P = \tilde{E}A + z^{-k}\tilde{F} \quad (6)$$

from Equations (4) – (6), we obtain:

$$\tilde{C}E = \tilde{E}C \quad (7)$$

Premultiplying Equation (1) by $\tilde{E}$ and using Equations (6) and (7) gives:

$$\tilde{C}Py(t+k) = \tilde{F}y(t) + \tilde{E}Bu(t) + \tilde{E}d + \tilde{C}Ee(t+k) \quad (8)$$

Hence, the prediction model is:

$$\tilde{C}[Py(t+k|t)]^* = \tilde{F}y(t) + \tilde{E}Bu(t) + \tilde{E}d \quad (9)$$

where $[Py(t+k|t)]^*$ is the prediction of $Py(t+k|t)$ given data up to t. The prediction error is given by:

$$\begin{aligned}\zeta(t+k) &= Py(t+k) - [Py(t+k|t)]^* \\ &= Ee(t+k)\end{aligned} \quad (10)$$

Without the loss of generality, we assume that the noise matrix C equals the identity matrix. It can be shown[10] that $\tilde{C} = I$. Defining $\tilde{E}d = d_1$, Equation (9) can be rewritten as:

$$[Py(t+k|t)]^* = \tilde{F}y(t) + \tilde{E}Bu(t) + d_1 \quad (11)$$

or equivalently:

$$[Py(t+k|t)]^* = [Py(t|t-k)]^* + \tilde{F}\Delta_k y(t) + \tilde{E}B\Delta_k u(t) \quad (12)$$

where:

$$\Delta_k y(t) = y(t) - y(t-k) \quad \Delta_k u(t) = u(t) - u(t-k) \quad (13)$$

From Equation (10), we have:

$$[Py(t|t-k)]^* = Py(t) - \zeta(t) \quad (14)$$

Substituting the above equation into Equation (12) gives the multivariable k-incremental predictor:

$$[Py(t+k|t)]^* = Py(t) - \zeta(t) + \tilde{F}\Delta_k y(t) + \tilde{E}B\Delta_k u(t) \quad (15)$$

The optimal k-incremental prediction of the auxiliary output $\Phi(t+k)$ is then:

$$\begin{aligned}\Phi^*(t+k) = {}& Py(t) - \zeta(t) + \tilde{F}\Delta_k y(t) + \tilde{E}B\Delta_k u(t) \\ & - Rw(t) + Qu(t)\end{aligned} \quad (16)$$

It can be shown[10] that the optimal control $u^*(t)$ which minimizes the cost function I_p can be solved from the identity:

$$\Phi^*(t+k) = 0 \quad (17)$$

The self-tuning control law is given by:

$$(Q + \tilde{G}\Delta_k)u(t) = Rw(t) - Py(t) - \tilde{F}\Delta_k y(t) + \zeta(t) \quad (18)$$

where $\tilde{G} := \tilde{E}B$.

Parameter estimation

Let us briefly discuss the parameter updating for easier reference. From Equations (10) and (15) we have:

$$\begin{aligned}Py(t) = {}& Py(t-k) - \zeta(t-k) + \tilde{F}\Delta_k y(t-k) \\ & + \tilde{G}\Delta_k u(t-k) + \zeta(t)\end{aligned} \quad (19)$$

Let:

$$\begin{aligned}\Psi &:= [\psi_1\psi_2\cdots\psi_r]^{\mathrm{T}} \\ &= [P_0P_1\cdots P_p]\end{aligned}$$

$$\zeta(t)=[\zeta_1(t)\zeta_2(t)\cdots\zeta_r(t)]^T$$

$$\begin{aligned}X(t-k) := \{&[y(t-k)-y(t-2k)]^T\\ &\times[y(t-k-1)-y(t-2k-1)]^T\\ &\cdots[y(t-k-m)-y(t-2k-m)]^T\\ &[u(t-k)-u(t-2k)]^T\\ &\times[u(t-k-1)-u(t-2k-1)]^T\\ &\cdots[u(t-k-q)-u(t-2k-q)]^T\}\end{aligned}$$

$$\begin{aligned}Y(t) := \{&[y(t)-y(t-k)]^T\\ &\times[y(t-1)-y(t-k-1)]^T\\ &\cdots[y(t-p)-y(t-k-p)]^T\}\end{aligned}$$

$$\begin{aligned}\Theta &:= [\theta_1\cdots\theta_r]^T\\ &= [\tilde{F}_0\tilde{F}_1\cdots\tilde{F}_m\tilde{G}_0\tilde{G}_1\cdots\tilde{G}_q]\end{aligned}$$

$$Z_i(t) := \psi_i Y(t)$$

where p, m and q are the order of $P(z^{-1})$, $\tilde{F}(z^{-1})$ and $\tilde{G}(z^{-1})$, respectively.

Equation (19) is rewritten as:

$$Z_i(t) = X(t-k)\theta_i + \zeta_i(t-k) + \zeta_i(t), \quad i = 1,2,\ldots,r \tag{20}$$

The controller parameters can be estimated with the standard recursive least square algorithm:

$$\hat{\theta}_i(t) = \hat{\theta}_i(t-1) + K_i(t)[Z_i(t) - X(t-k)\hat{\theta}_i(t-1)] \tag{21}$$

$$K_i(t) = [\lambda_i + X(t-k)V_i(t-1)X^T(t-k)]^{-1} \times V_i(t-1)X^T(t-k) \tag{22}$$

$$V_i(t) = [V_i(t-1) - K_i(t)X^T(t-k)V_i(t-1)]/\lambda_i \tag{23}$$

where λ_i is the forgetting factor.

The self-tuning control algorithm is obtained directly:

Step 1. Read the new setpoint $w(t)$ and output $y(t)$.
Step 2. Compute the offset, $\zeta_i(t)$

$$\hat{\zeta}_i(t) = Z_i(t) - X(t-k)\hat{\theta}_i(t-1) - \hat{\zeta}_i(t-k)$$

Step 3. Estimate the controller parameters using Equations (21)–(23).
Step 4. Compute the new control from Equation (18).
Step 5. Set $t:=t+1$ and return to step 1.

Implementation issues for the self-tuning controller

Implementing the self-tuning controller on the paperboard machine raises a number of practical issues. Among them is the identification of system dynamics. Although the self-tuning controller is not sensitive to model parameter errors, the model structure or model order has an important impact on system performance. Besides, a relatively accurate initial model can avoid improper control action. Higher order models can offer the advantage of higher modelling accuracy, but increase the computation load of the parameter estimation algorithm. Therefore, a compromise between model accuracy and computation burden is required.

The recursive parameter estimation algorithm provided for scalar controlled ARMA processes[12] is extended to multivariable systems and applied to obtain the initial model of the paperboard machine. The input signal for identification is a pseudo-random binary sequence (PRBS). Since the paperboard machine is a two-input/two-output system, the two input signals should be linearly independent in order to obtain an accurate model. We generate a PRBS of length N_p. The first $(N_p - 1)/2$ numbers serve as first input, and the second $(N_p - 1)/2$ numbers serve as second input. Based on knowledge of the process dynamics, we choose the PRBS of length $N_p = 127$, interval $\Delta = 2.0$ min, amplitude $a_1 = 1.5$ mA and $a_2 = 0.3$ mA, and sampling time $T_s = 1.0$ min.

The models obtained from system identification are:

$$\begin{aligned}(1.0 - 1.15z^{-1} + 0.33z^{-2})y_1(t) &= (6.1 - 3.36z^{-1})z^{-6}u_1(t) - (3.4-2.03z^{-1})\\ &\quad\times z^{-3}u_2(t) + e_1(t)\\ (1.0 - 1.32z^{-1} + 0.43z^{-2})y_2(t) &= (0.4 - 0.25z^{-1})z^{-6}u_1(t) - (1.20 - 0.91z^{-1})\\ &\quad\times z^{-3}u_2(t) + e_2(t)\end{aligned}$$

where y_1 and y_2 are basis weight and moisture content, respectively. u_1 and u_2 are the positions of the straw pulp control valve and the value of the steam pressure.

Since the basis weight and moisture content control loops have different time delays, normal multivariable self-tuning control algorithms fail to provide a feasible solution. To solve the problem, an auxiliary control variable $u_2'(t)$ is introduced:

$$u_2'(t) := u_2(t-3)$$

This means that the control action for the steam control valve will be delayed for three sampling intervals before it is issued. This artificially introduced delay may deteriorate the performance of moisture content control. In a practical implementation it has been found that the two control loops can cooperate quite well by introducing only one samplng interval delay.

The system dynamics of the paperboard machine can be described by:

$$A(z^{-1})y(t) = B(z^{-1})z^{-k}u(t) + C(z^{-1})e(t)$$

where $y(t) = (y_1(t)y_2(t))^T$, $u(t) = (u_1(t)u_2(t))^T$ and:

$$A(z^{-1}) = I + \begin{pmatrix}-1.15 & 0\\ 0 & -1.32\end{pmatrix}z^{-1} + \begin{pmatrix}0.33 & 0.0\\ 0.0 & 0.43\end{pmatrix}z^{-2}$$

$$B(z^{-1}) = \begin{pmatrix} 6.1 & -3.4 \\ 0.4 & -1.2 \end{pmatrix} + \begin{pmatrix} -3.36 & 2.03 \\ -0.25 & 0.91 \end{pmatrix} z^{-1}$$

$$C(z^{-1}) = I, \quad k = 6$$

The weighting polynomials in the cost function are chosen as:

$$P = I, \quad R = I,$$

$$Q' = \begin{pmatrix} 10.0 & 0.0 \\ 0.0 & -1.0 \end{pmatrix} - \begin{pmatrix} 10.0 & 0.0 \\ 0.0 & -1.0 \end{pmatrix} z^{-6}$$

Based on the initial parameters of the process model, the initial parameters of the controller can be calculated from Equations (4)–(7):

$$\tilde{E} = I + \begin{pmatrix} 1.15 & 0 \\ 0 & 1.32 \end{pmatrix} z^{-1} + \begin{pmatrix} 1.0 & 0.0 \\ 0.0 & 1.31 \end{pmatrix} z^{-2} + \begin{pmatrix} 0.76 & 0.0 \\ 0.0 & 1.31 \end{pmatrix} z^{-3} + \begin{pmatrix} 0.54 & 0.0 \\ 0.0 & 0.79 \end{pmatrix} z^{-4} + \begin{pmatrix} 0.37 & 0 \\ 0 & 0.79 \end{pmatrix} z^{-5}$$

$$\tilde{F} = \begin{pmatrix} 0.25 & 0 \\ 0 & 0.61 \end{pmatrix} + \begin{pmatrix} -0.12 & 0.0 \\ 0 & -0.33 \end{pmatrix} z^{-1}$$

$$\tilde{G} = I + \begin{pmatrix} 6.1 & -3.4 \\ 0.4 & -1.2 \end{pmatrix} + \begin{pmatrix} 3.66 & -1.9 \\ 0.28 & -0.67 \end{pmatrix} z^{-1} + \begin{pmatrix} 2.2 & -1.0 \\ 0.19 & -0.37 \end{pmatrix} z^{-2} + \begin{pmatrix} 1.31 & -0.57 \\ 0.13 & -0.2 \end{pmatrix} z^{-3} + \begin{pmatrix} 0.79 & -0.31 \\ 0.1 & -0.1 \end{pmatrix} z^{-4} + \begin{pmatrix} 0.47 & -0.17 \\ 0.07 & -0.15 \end{pmatrix} z^{-5} + \begin{pmatrix} -1.28 & 0.77 \\ -0.20 & 0.71 \end{pmatrix} z^{-6}$$

In the parameter estimation algorithm (21)–(23), the values of the forgetting factors are $\lambda_1 = \lambda_2 = 0.985$. The initial values of the covariance matrices are $P_1 = P_2 = I_{16\times 16}$.

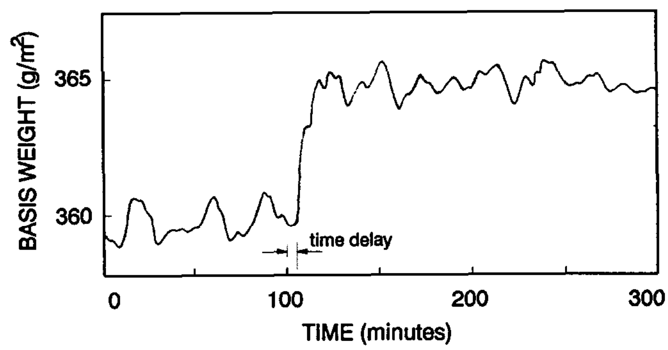

Figure 3 Response of basis weight when setpoint changes

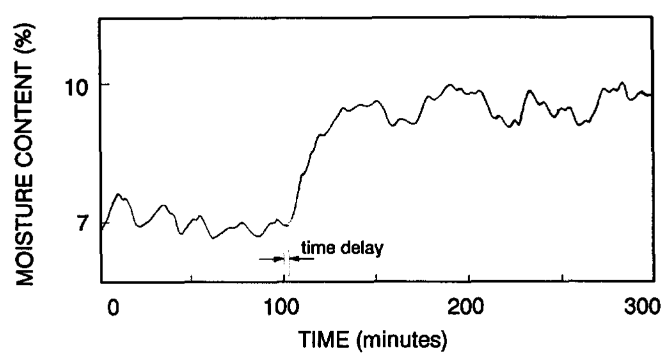

Figure 4 Response of moisture content when setpoint changes

The adaptive control strategy for basis weight and moisture content was implemented on an IBM PC-based process computer using Basic and Assembly language. The real-time computer control system has been in operation for five years. The system demonstrates a satisfactory performance. *Figures 3* and *4* show the responses of the system when the setpoint $w = [w_1, w_2]^T$ is changed, respectively, from $[360, 7]^T$ to [365, 7] and from $[365, 7]^T$ to $[365, 10]^T$ when $t = 100$. The reel basis weight converges to a new setpoint within 20 sampling intervals (including six intervals time-delay). The reel moisture content converges to a new set-point within 40 sampling intervals. *Figure 5* shows the variation of reel basis

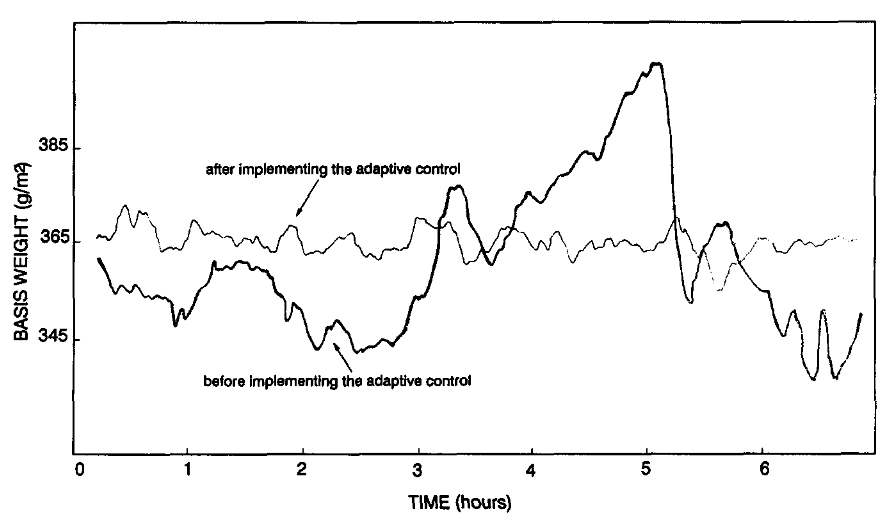

Figure 5 Comparison of basis weight variation before and after implementing the adaptive control

weight under the control of the adaptive control system and the PID regulators. It can be seen that the variation is greatly reduced after implementing the adaptive control system. The standard deviation of basis weight over 20 days is reduced from 14 g m^{-2} to 5 g m^{-2}. Sheet breaks are significantly reduced and the percentage of top quality product is increased.

Since the paperboard machine produces product of several different grades, we have developed a nominal model for each grade. The model presented in this section is for the most important grade. In grade transition, the system selects the nominal model for the new grade, then starts parameter estimation. To reduce the computation burden of the adaptive algorithm, time delays were not included in on-line parameter estimation. They were estimated off-line for each product grade according to machine speed. It is necessary to point out that if the available process model is proven to be accurate enough, on-line estimation of parameters is not necessary. The parameter estimation is initiated either on the request of operators or when the deviations of basis weight and moisture content from their targets in the past one hour exceed some threshold.

Conclusion

This paper has presented the successful application of an adaptive control strategy in a paperboard machine. The combination of conventional controls, a multivariable k-incremental predictor and a multivariable self-tuning controller has been shown to be very effective for the control of basis weight and moisture content on a paperboard machine. A measure of the success and acceptance of the new control system is that the paperboard machine has been controlled by the strategy for five years and is still in operation. The significant reduction in the variation of basis weight and moisture content implies good economic return.

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