Wood Chip Refiner Control

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Abstract

On a chip refiner the gain of the transfer function between the refiner motor load and the plate gap is both nonlinear and time-varying, with reversal in the sign of the gain indicating the onset of pulp pad collapse towards lower values of the plate gap. The control objective is to regulate the motor load while avoiding pad collapse. The problem is principally stochastic in nature, since the gap at which gain reversal occurs can wander unpredictably. An active suboptimal dual controller is designed to control the motor load by manipulating the plate gap. It uses an adaptive Kalman filter to track both slow drifts and sudden sign changes in the gain. The controller minimizes a myopic nonlinear performance index designed especially to reflect the peculiarities of the process. Thus, no heuristic logic is needed. Simulations show the superior performance offered by this strategy.

1 Introduction

Wood chip refiners are now used extensively to produce wood pulp in thermomechanical pulping (TMP) plants and in high-yield or chemical thermomechanical pulping plants. Although there has been a fair amount of activity in the development of control systems for TMP plants, today only a small fraction of TMP plants in operation in the world are under closed-loop control. Among the reasons for this situation, are the problems associated with on-line sensing of the pulp quality and the fact that a chip refiner is a difficult process to control. At the heart of any TMP control system is the refiner motor load control loop. It is a difficult loop to control because its gain is subject to slow drifts as well as to sudden changes in sign.

In the past, there have been a number of different approaches to that problem. Horner and Korhonen (1980) proposed to use gain scheduling to compensate for plate wear, assuming exponential decay of the gain and relying on operator judgment for the severity of plate clashes. Plate gap sensors and plate clash detectors using vibration monitors have been used in conjunction with heuristic logic to try to detect pad collapses. Although very useful as last resort safety devices, they are not used much in practice. A first attempt at applying adaptive control (Åström and Wittenmark, 1995) to the chip refiner was made by Dumont (1982), using a self-tuning regulator consisting of a recursive least-squares parameter estimator with a variable forgetting factor (Fortescue *et al.*, 1981) and a Dahlin controller. A set of rules was used to back out the plates and restore the pulp pad in the case of pad collapse. Although some success on an industrial refiner was reported, the strategy was deemed unreliable for continuous, unsupervised operation. The main problem was in adjusting the variable forgetting factor scheme to track both slow drits and abrupt changes (Dumont, 1986).

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The notion of dual control was first introduced by Feldbaum (1960-61) in the early sixties. A few years later, Åström and Wittenmark (1971) pointed out that adaptive control strategies based on the certainty equivalence principle (Åström and Wittenmark, 1995) can be significantly inferior to the case where dual control is used. The intractability of the optimal dual controller, due to the excessive numerical computations required, has motivated the development of suboptimal approaches (Wittenmark, 1995) that attempt to retain the dual property of the optimal controller. Meanwhile, progress in numerical methods has made possible the computations of the optimal dual control law for a simple process with unknown gain (Åström and Helmersson, 1982). Simulations show that the dual controller behaves well on such a process even when the gain changes sign. Because the model describing the motor load can be reduced to a simple process with unknown gain, it seems reasonable to study the applicability of dual control to that problem. Dumont and Åström (1988) investigated several alternatives including active suboptimal dual control with a nonlinear performance index tailored to fulfill the demands of the process nonlinear nature. Their technique proved reliable and performed well in simulations. Their work, however, was limited to simulation studies of simple, first-order, delay-free systems with white noise disturbances. Allison *et al.* (1995) developed what is probably the first application of dual control to process control. The controller is an active adaptive controller, which consists of a constrained certainty equivalence approach coupled with an extended output horizon, a cost function to get probing and some heuristic logic to deal with the nonlinearity. More recently, Ismail and Dumont (1999) extended the approach in (Dumont and Åström, 1988) to handle time delays and employed adaptive Kalman filtering to accurately track the gain variations. This article further extends that control strategy by considering coloured noise disturbances.

The rest of this article is organized as follows. In the next section, process dynamics are described in some detail. Next to that, process modelling and adaptive Kalman filtering are discussed. Finally, the controller is introduced and the design is supplemented with appropriate simulation.

2 Process Description

A chip refiner consists of either one fixed and one rotating or two rotating grooved plates, with pressure exerted on one of them by a hydraulic cylinder (see figure 1). Wood chips and dilution water are fed near the axis and forced to move outward between the plates by centrifugal and friction forces. Steam produced by evaporation and chips broken down into fibers by mechanical action create a few hundred micrometers thick pad between the plates. Steam and pulp are discharged at the periphery. The specific energy, or energy per mass unit of wood fibres, is a major factor controlling the pulp quality, thus, both wood feed rate and motor load need to be controlled. The chip feed rate must be held constant to meet production requirements. To control the motor load, the plate gap is adjusted by manipulating the hydraulic pressure. Although plate gap sensors are available, the common practice is to simply measure the shaft displacement to indicate plate movement. However, because of plate wear and thermal expansion, this does not provide an absolute measurement of the gap. The hydraulic pressure is generally manipulated by sending a pulse to a microdial commanding a servo valve directing oil to the cylinder (Stebel and Aeby, 1980).

The process dynamics are both nonstationary and nonlinear. The nonstationarity is due to the variability in the feed characteristics, such as wood species, chip size and density as well as to plate wear. As the plates wear, the noise level increases and the process gain drops dramatically (Rogers *et al.*, 1980). Wear generally occurs gradually over a period of several

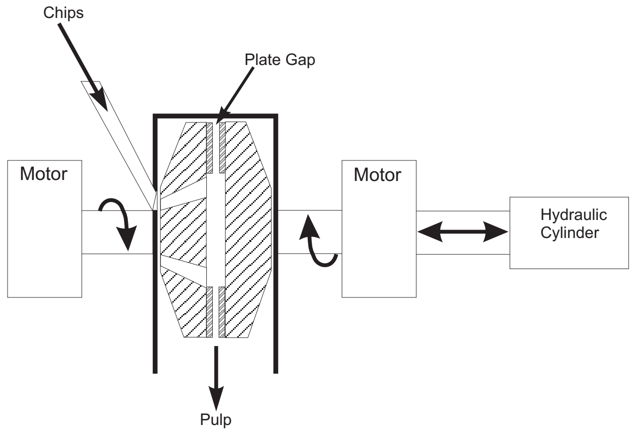

Figure 1: Schematic diagram of a chip refiner.

hundred hours but can also occur quickly in case of plate clash, i.e., metal to metal contact between the plates. In manual operation, plate clashing is a very fast phenomenon primarily related to feeding problems. It is highly undesirable as it disrupts production and damages the plates. An idealized steady-state operating curve for a chip refiner is shown in figure 2. As the gap decreases, a maximum load is reached. If the gap is reduced further, the load drops sharply as the pad -no longer able to sustain the pressure- collapses. This causes the incremental gain between load and gap to change sign. This also corresponds to the point where the refiner starts cutting fibers. Then, for the pad to rebuild and the gain to become negative again, the gap has to be opened past the point where the collapse occured. This corresponds to the hysteresis pattern in figure 2. To avoid plate clashing, the refiner must be operated in the safe region where closing the gap increases the load. Productivity and pulp quality considerations often dictate operating the refiner close to the maximum load where pad collapse is always a possibility. A further complication comes from the fact that the curve in figure 2 depends on feed characteristics, refining zone consistency, plate wear, etc. and thus, the maximum load and the collapse point vary and are unpredictable.

The chip refiner dynamics are essentially due to the hydraulic system. Thus, the chip refiner can be modeled by a discrete linear system with an output nonlinearity as described by the following equations.

$$\Delta x(t) = \frac{k(1-a)}{1-aq^{-1}}\Delta u(t-d) \tag{1}$$

where Δ is the increment operator, Δu the duration of the pulse sent to the hydraulic cylinder, x the plate gap, a the process pole, and d the dead time. The load y is given by

$$y(t) = g(x(t)) \tag{2}$$

where $g(x)$ represents the load-gap nonlinearity. Then,

$$\Delta y(t) = \frac{dg(x)}{dx}\Delta x(t) \tag{3}$$

This linear model is a reasonable approximation of the actual system for small variations around the operating point. Using equation 1, we can write

$$\Delta y(t) = a\Delta y(t-1) + b(x)\Delta u(t-d) \tag{4}$$

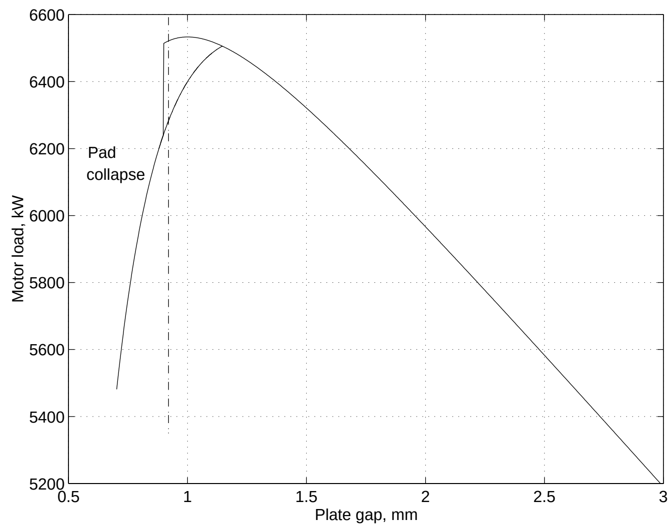

Figure 2: Motor load versus plate gap.

where

$$b(x) = k(1-a)\frac{dg(x)}{dx} \tag{5}$$

Typical values of the dead time and the time constant were found to be respectively 4 sec and 7 sec on a double disc refiner (Rogers *et al.*, 1980). For a sampling interval $T_s = 2$ sec, this gives

$$\Delta y(t) = 0.75\Delta y(t-1) + b(x)\Delta u(t-3) \tag{6}$$

With exact knowledge of k, x and $g(x)$, the control of the system (equation 6) is trivial. Unfortunately, as mentioned earlier, not only is the exact nonlinearity unknown, but it is also time-varying.

A simplistic approach to this control problem is to ignore the nonlinearity and use a fixed-parameter linear controller. As long as a reasonable gain is used for the particular operating point, the performance is satisfactory. However, if, for some reason, the refiner enters the zone where the gain is positive, the closed-loop system becomes unstable. This situation is inevitable if the setpoint were made greater than the maximum load, in which case the controller would actually accelerate pad collapse and induce plate clashing as a result of the gain sign change associated with traversing the critical gap. A solution to prevent plate clashing in case of pad collapse could consist in opening the gap when it is below a given value. However, the collapse point is not constant and is rather unpredictable. Moreover, this can induce a cyclic behaviour, creating oscillations between the open position and the lower gap limit. What is really needed is a control scheme that can recover on its own from a pad collapse without plate clash and that also tracks the slow drift in gain due to plate wear.

3 Process Modelling and Adaptive Kalman Filtering

The linearized stochastic model of a chip refiner is

$$\Delta y(t) = a\Delta y(t-1) + b(t)\Delta u(t-3) + e(t) - ce(t-1) \tag{7}$$

where $e(t)$ is a white noise sequence $N(0,\sigma)$ and c is the noise filter zero. By defining the filtered output $v(t)$ as

$$v(t) = \frac{\Delta y(t) - a\Delta y(t-1)}{1 - cq^{-1}} \tag{8}$$

and $s(t)$ as

$$s(t) = \frac{b(t)\Delta u(t-3)}{1 - cq^{-1}} \tag{9}$$

Then, equation 7 can be rewritten as

$$v(t) = s(t) + e(t) \tag{10}$$

Assuming that the gain b is described by

$$b(t+1) = b(t) + w(t) \tag{11}$$

where $w(t)$ is additional white noise $N(0,\rho)$, then $s(t+1)$ can be expressed as

$$s(t+1) = cs(t) + \Delta u(t-2)b(t) + \Delta u(t-2)w(t) \tag{12}$$

Using equations 10-12, the chip refiner is represented by the following nonlinear state-space model

$$x(t+1) = F(t)x(t) + \gamma(t) \tag{13}$$

$$v(t) = Hx(t) + e(t) \tag{14}$$

where $x(t)$ is the state vector

$$x(t) = \begin{bmatrix} b(t) \\ s(t) \end{bmatrix} \tag{15}$$

$F(t)$ is the state transition matrix

$$F(t) = \begin{bmatrix} 1 & 0 \\ \Delta u(t-2) & c \end{bmatrix} \tag{16}$$

$\gamma(t)$ is the state noise vector

$$\gamma(t) = \begin{bmatrix} w(t) \\ \Delta u(t-2)w(t) \end{bmatrix} \tag{17}$$

and H is the output matrix

$$H = \begin{bmatrix} 0 & 1 \end{bmatrix} \tag{18}$$

The gain b can then be estimated using a standard Kalman filter.

$$\varepsilon(t) = v(t) - H\hat{x}(t|t-1) \tag{19}$$

$$K(t) = P(t|t-1)H^T \left(\sigma^2 + HP(t|t-1)H^T\right)^{-1} \tag{20}$$

$$\hat{x}(t|t) = \hat{x}(t|t-1) + K(t)\varepsilon(t) \tag{21}$$

$$\hat{x}(t+1|t) = F(t)\hat{x}(t|t) \tag{22}$$

$$P(t|t) = (I - K(t)H)\,P(t|t-1) \tag{23}$$

$$P(t+1|t) = F(t)P(t|t)F(t)^T + G(t)\rho^2 \tag{24}$$

where

$$G(t)\rho^2 = \mathrm{E}\left\{\gamma(t)\gamma^T(t)\right\} = \begin{bmatrix} 1 & \Delta u(t-2) \\ \Delta u(t-2) & \Delta u^2(t-2) \end{bmatrix} \rho^2 \tag{25}$$

Dumont and Åström (1988) pointed out that the performance of the estimator is quite influenced by the choice of ρ. It was suggested that ρ should be time-varying due to the fact that the gain undergoes two types of changes: slow drifts due to plate wear and sudden jump changes due to pad collapse. Since no apriori knowledge is available, direct estimation of the process noise variance ρ^2 will be investigated in this paper. In Kalman filtering, the problem of estimating the noise covariances is known as adaptive filtering. Adaptive filtering was a very active field in the late sixties and early seventies. For a recent survey of different approaches see (Isaksson, 1988). An enhanced version of Isaksson's adaptive Kalman filter (Isaksson, 1988) will be used. Isaksson's algorithm is based on expressing $\varepsilon^2(t)$ as a linear function of ρ^2 and σ^2 and using a least-squares approach to estimate the noise variances. We now derive the adaptive filter algorithm.

If we define the estimation error as

$$\tilde{x}(t) = x(t) - \hat{x}(t|t-1) \tag{26}$$

We obtain, using equations 13, 21 and 22,

$$\tilde{x}(t) = F(t-1)\left(I - K(t-1)H\right)\tilde{x}(t-1) + \gamma(t-1) - F(t-1)K(t-1)e(t-1) \tag{27}$$

Now, define the conditional covariance of $\tilde{x}(t)$ as

$$M(t) = \mathrm{E}\left\{\tilde{x}(t)\tilde{x}^T(t)\,|Y_{t-1}\right\} \tag{28}$$

where Y_{t-1} denotes all data observed up to and including time $t-1$. Note that, since the true values of ρ and σ are unknown, the Kalman filter is not optimal, and so, $P(t|t-1)$ does not represent the actual error covariance $M(t)$. Using equation 27, $M(t)$ is evaluated

$$\begin{aligned} M(t) \quad = \quad & F(t-1)\left(I - K(t-1)H\right)M(t-1)\left(I-K(t-1)H\right)^T F^T(t-1) \\ & + G(t-1)\rho^2 + F(t-1)K(t-1)K^T(t-1)F^T(t-1)\sigma^2 \end{aligned} \tag{29}$$

Starting at time t_o, we may rewrite equation 29 as

$$M(t) = f\left(M\left(t_o\right), t\right) + T(t-1)\rho^2 + Q(t-1)\sigma^2 \tag{30}$$

where $T(t)$ and $Q(t)$ can be computed recursively as

$$T(t) = G(t) + F(t)\left(I - K(t)H\right)T(t-1)\left(I-K(t)H\right)^T F^T(t) \tag{31}$$

$$Q(t) = F(t)K(t)K^T(t)F^T(t) + F(t)\left(I-K(t)H\right)Q(t-1)\left(I-K(t)H\right)^T F^T(t) \tag{32}$$

If we have a stable Kalman filter, the first term in equation 30 will tend to zero as t increases. Hence, we may neglect the influence of the initial values and $M(t)$ is then a known linear function in ρ^2 and σ^2. We can use this fact in the following way.

The prediction error, defined in equation 19, can be expressed as

$$\varepsilon(t) = H\tilde{x}(t) + e(t) \tag{33}$$

We get the conditional variance of $\varepsilon(t)$

$$\mathrm{E}\left\{\varepsilon^2(t)\,|Y_{t-1}\right\} = HM(t)H^T + \sigma^2 \tag{34}$$

Hence, it is possible to approximate $\varepsilon^2(t)$ as

$$\varepsilon^2(t) = \left[HT(t-1)H^T\right]\rho^2 + \left[HQ(t-1)H^T + 1\right]\sigma^2 \tag{35}$$

A simple recursive least-squares (RLS) estimator can then be used to estimate ρ^2 and σ^2 based on equation 35. To improve the accuracy of the adaptive filter, two additional approximate linear regressions are derived in the same way for the correlation functions $\mathrm{E}\{\varepsilon(t)\varepsilon(t-1)\,|Y_{t-2}\}$ and $\mathrm{E}\{\varepsilon(t)\varepsilon(t-2)\,|Y_{t-3}\}$. Then,

$$\begin{aligned}\varepsilon(t)\varepsilon(t-1) \;&=\; \left[HF(t-1)\left(I-K(t-1)H\right)T(t-2)H^T\right]\rho^2 \\ &\quad + HF(t-1)\left[\left(I-K(t-1)H\right)Q(t-2)H^T - K(t-1)\right]\sigma^2\end{aligned} \tag{36}$$

and,

$$\begin{aligned}\varepsilon(t)\varepsilon(t-2) \;&=\; \left[HF(t-1)\left(I-K(t-1)H\right)F(t-2)\left(I-K(t-2)H\right)T(t-3)H^T\right]\rho^2 \\ &\quad + HF(t-1)\left(I-K(t-1)H\right)F(t-2) \\ &\quad \cdot\left[\left(I-K(t-2)H\right)Q(t-3)H^T - K(t-2)\right]\sigma^2\end{aligned} \tag{37}$$

The implemented RLS estimator utilizes the three linear regressions (equations 35-37).

Since ρ is assumed time-varying, the RLS estimator employs an exponential forgetting factor. As suggested by Isaksson, the estimates $\hat{\rho}$ and $\hat{\sigma}$ are not used to improve the Kalman filtering of the gain $b(t)$ until they are likely to have converged. This is carried out in the simulations by waiting 500 sec before using $\hat{\rho}$ and $\hat{\sigma}$ in the Kalman filter.

4 Active Suboptimal Dual Control

Most control laws suggested so far for the refiner motor load control loop are all linear in Δu and, because of that, require the addition of heuristic logic to handle pad collapses. Although the exact nonlinearity is not known, its general shape is known apriori. It is thus natural to use a performance index that yields a nonlinear control law. An important feature of the control criterion is that control in the positive gain zone should be severely penalized if not prohibited. When the gain estimate is negative and is relatively of large amplitude, closing the gap should obviously be allowed. However, as the estimate approaches zero, negative control actions should be increasingly penalized. Furthermore, when the estimate is close to zero and the uncertainty is large, probing should not tend to further close the plates. Given all these considerations, the loss function is chosen as

$$J = \mathrm{E}\left\{\left(y(t+3) - y_r(t+3)\right)^2 + e^{mb(t+3)}e^{-\Delta u(t)} + \eta P_b(t+4|t)\,|Y_t\right\} \tag{38}$$

where y_r is the setpoint, m and η are positive weighting constants and the covariance matrix P is represented by $P = \begin{bmatrix} P_b & P_{bs} \\ P_{bs} & P_s \end{bmatrix}$. The minimization is carried out with respect to $\Delta u(t)$.

The nonlinear function $e^{mb(t+3)}e^{-\Delta u(t)}$, first suggested by Dumont and Åström (1988), satisfies all preceding requirements while being simple.

The future variance $P_b(t+4|t)$ is included in the loss function as an artificial way to introduce probing. This was first suggested by Wittenmark (1975) and later refined by Wittenmark and Elevitch (1985). Using equation 24 and the inversion form of equation 23, we may write

$$P(t+2|t) = F(t+1)\left[\frac{1}{\sigma^2}H^T H + P^{-1}(t+1|t)\right]^{-1} F(t+1)^T + G(t+1)\rho^2 \tag{39}$$

Then,

$$P(t+3|t) = F(t+2)\left[\frac{1}{\sigma^2}H^T H + P^{-1}(t+2|t)\right]^{-1} F(t+2)^T + G(t+2)\rho^2 \tag{40}$$

Knowing $\Delta u(t-1)$, $P(t+2|t)$ is determined. $P(t+3|t)$ is dependent on $\Delta u(t)$, yet, $P_b(t+3|t)$ is not. $P_b(t+4|t)$ is given by

$$P_b(t+4|t) = \left[\begin{array}{cc} 1 & 0 \end{array}\right]\left[\frac{1}{\sigma^2}H^T H + P^{-1}(t+3|t)\right]^{-1}\left[\begin{array}{c} 1 \\ 0 \end{array}\right] \tag{41}$$

$P_b(t+4|t)$ is thus a deterministic function of $\Delta u(t)$. $P_b(t+4|t)$ penalizes inaction in the presence of large uncertainty, so, preventing the turn-off phenomenon (Åström and Wittenmark, 1971). In fact, the effect of $P_b(t+4|t)$ is to increase the magnitude of the optimal control that minimizes the loss function J. This excess in magnitude can be viewed as a probing component to enhance the quality of future estimates.

Using equation 7, $y(t+3)$ can be written as

$$\begin{aligned} y(t+3) \quad = \quad & \left(1+a+a^2+a^3\right) y(t) - \left(a+a^2+a^3\right) y(t-1) + b(t+3)\Delta u(t) \\ & + b(t+2)(1+a)\Delta u(t-1) + b(t+1)\left(1+a+a^2\right)\Delta u(t-2) \\ & + e(t+3) + (1+a-c)e(t+2) + \left(1+a+a^2-c(1+a)\right) e(t+1) \\ & - c\left(1+a+a^2\right) e(t) \end{aligned} \tag{42}$$

Provided that a and c are deterministic, the probability distribution of $y(t+3)$ given Y_t is gaussian. Equations 10 and 11 direclty lead to

$$\mathrm{E}\left\{e(t)\,|Y_t\right\} = v(t) - \hat{s}(t|t) \tag{43}$$

and,

$$\hat{b}(t+3|t) = \hat{b}(t+2|t) = \hat{b}(t+1|t) = \hat{b}(t|t) \tag{44}$$

Using equations 42-44 and the facts: $\mathrm{E}\left\{z^2\right\} = \mu^2 + \xi^2$, and $\mathrm{E}\left\{e^{mz}\right\} = e^{m\mu + \frac{m^2}{2}\xi^2}$, where z is $N(\mu, \xi)$, the expectation in equation 38 is evaluated

$$\begin{aligned} J \quad = \quad & \left[\begin{array}{l} \hat{b}(t+1|t)\Delta u(t) + \hat{b}(t+1|t)(1+a)\Delta u(t-1) + \hat{b}(t+1|t)\left(1+a+a^2\right)\Delta u(t-2) \\ +\left(1+a+a^2+a^3\right) y(t) - \left(a+a^2+a^3\right) y(t-1) - c\left(1+a+a^2\right)\left(v(t)-\hat{s}(t|t)\right) \\ -y_r(t+3) \end{array}\right]^2 \\ & + P_b(t+3|t)\Delta u^2(t) + P_b(t+2|t)(1+a)^2\Delta u^2(t-1) + P_b(t+1|t)\left(1+a+a^2\right)^2 \\ & \cdot\Delta u^2(t-2) + 2P_b(t+2|t)(1+a)\Delta u(t)\Delta u(t-1) + 2P_b(t+1|t)(1+a)\left(1+a+a^2\right) \\ & \cdot\Delta u(t-1)\Delta u(t-2) + 2P_b(t+1|t)\left(1+a+a^2\right)\Delta u(t)\Delta u(t-2) + 2c\left(1+a+a^2\right)^2 \\ & \cdot P_{bs}(t|t)\Delta u(t-2) + 2c(1+a)\left(1+a+a^2\right) P_{bs}(t|t)\Delta u(t-1) + 2c\left(1+a+a^2\right) \end{aligned}$$

$$\cdot P_{bs}(t|t)\Delta u(t) + \sigma^2 \left[1 + (1+a-c)^2 + \left(1+a+a^2 - c(1+a)\right)^2\right]$$
$$+ \left[c\left(1+a+a^2\right)\right]^2 P_s(t|t) + e^{m\hat{b}(t+1|t)+\frac{m^2}{2}P_b(t+3|t)} e^{-\Delta u(t)} + \eta P_b(t+4|t) \tag{45}$$

Typical curves of this performance index for several values of b, P and for both a positive and negative control error are plotted in figures 3 and 4. Some comments on the loss function and the resulting control law are now in order:

1. The influence of the nonlinear function $e^{mb(t+3)}e^{-\Delta u(t)}$ is negligible when the estimator is confident that the refiner is operating well inside the desirable zone. As the confidence decreases and the gain estimate increases, it is seen that the optimal control is pushed towards positive values. So, the resulting control law tends to open the gap when closing it is likely to induce a collapse.

2. The resulting control law will never attempt to control the refiner in the pad collapse region.

3. The use of probing is justified by the fact that the gain estimate is the key to identifying a pad collapse and that probing targets a portion of the input energy at contiuously identifying that parameter.

4. No heuristic logic is needed, which makes the resulting controller more appealing for implementation.

5. The optimal control cannot be computed analytically. For simulation purposes, it is obtained through a Newton-Raphson numerical optimization scheme.

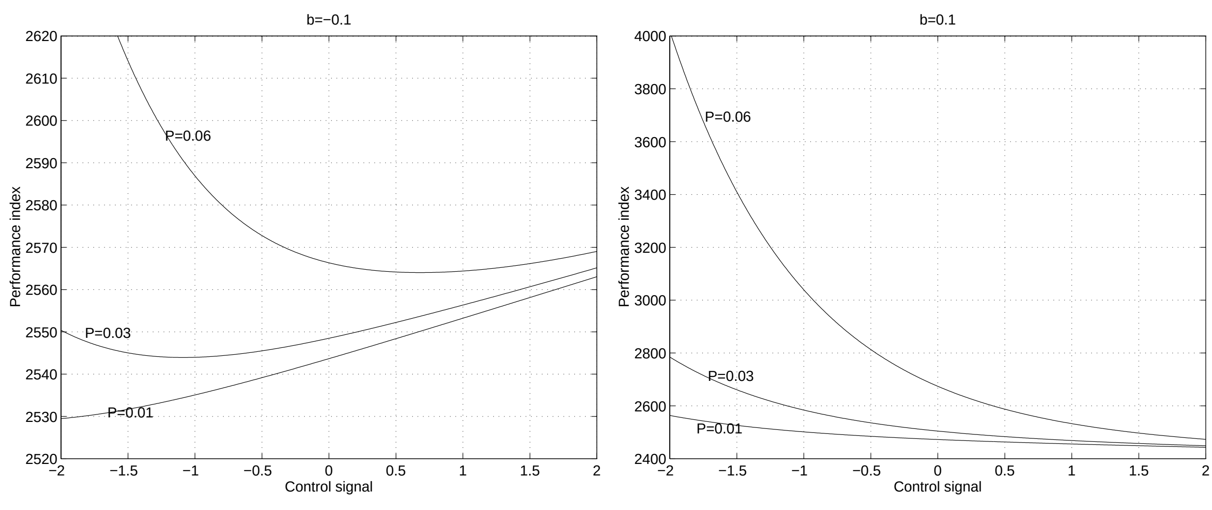

Figure 3: The performance index $J(\Delta u(t))$ (load below setpoint).

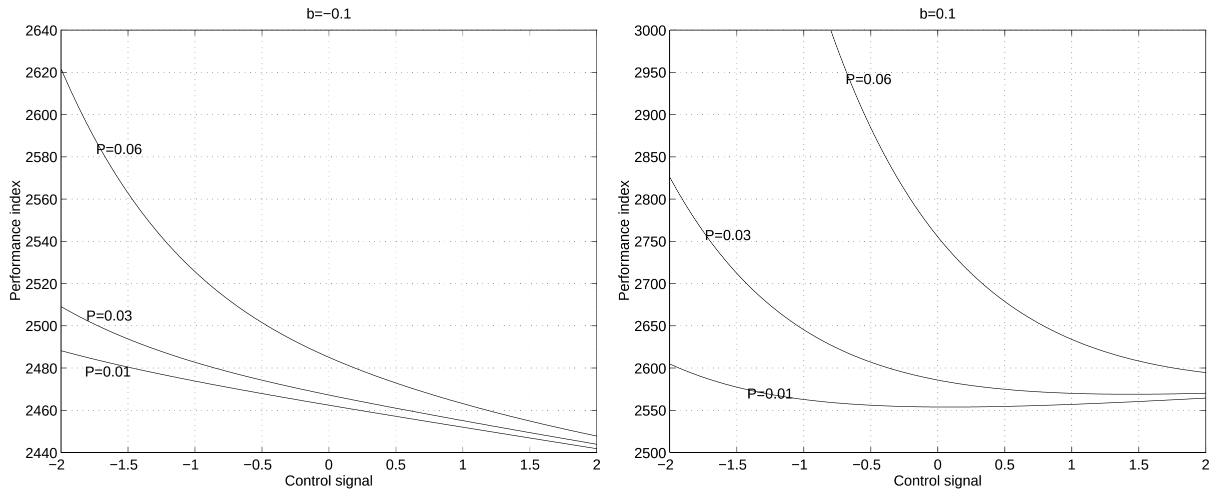

Figure 4: The performance index $J(\Delta u(t))$ (load above setpoint).

5 Simulations

The behavior of the strategy was thoroughly tested by way of computer simulations. The process was simulated by equations 1 and 2 with the output nonlinearity $g(x)$ represented by

$$g(x) = g_1 - g_2 \frac{(\alpha x)^4 + 1/3}{(\alpha x)^3} \tag{46}$$

In normal case $\alpha = 1$. In collapsed state, i.e., when $x < 0.9$ mm, $\alpha = 0.77$. Once in collapsed state, the refiner stays in that state until the plates are opened past the point where the two curves intersect. Maximum load is achieved at $x = 1$ mm. For both curves $g_1 = 7600$ and $g_2 = 800$. Other settings are: process pole $a = 0.75$, noise filter zero $c = -0.95$, sampling interval $T_s = 2$ sec, $m = 12$, $\eta = 100$, $\sigma = 0.5$, initial gap $x_o = 1.6$ mm, process noise standard deviation initial estimate $\hat{\rho}_o = 0.05$ and measurement noise standard deviation initial estimate $\hat{\sigma}_o = 0.4$. In all simulations, it is assumed that the process pole and the noise filter zero are exactly known.

Figure 5 demonstrates the normal operation case, i.e., when the refiner is operating well into the negative gain zone. The control problem is relatively easy in this case as the gain varies little. This is reflected by $\hat{\rho}$ being very small. For $1000 < t < 2000$ sec, the setpoint is raised by 250 kW to an unreachable value. If the controller tries to achieve the new setpoint, it will induce a pad collapse. The controller performs very well as it does not provoke any collapse. It keeps the load as close as possible to the unreachable setpoint while not closing the gap below the collapse point. The adaptive Kalman filter successfully tracks the rapid variations of the gain as the gap alternates around the maximum load point $x = 1$.

In figure 6, the refiner is required to operate near maximum load, a situation preferred in practice in order to maximize production but that carries a high risk of collapse. The controller successfully maintains the motor load close to the setpoint while avoiding any collapse. Again, the controller behaves very well as the setpoint is raised to an unreachable value for $1000 < t < 2000$ sec.

Finally, figure 7 depicts the occurrence of a pad collapse. The adaptive Kalman filter is very fast to react as seen from the process noise variance estimate and the gain estimate. The setpoint is reduced shortly after the gain sign has become positive. This situation (load above setpoint and positive gain) usually poses a challenge to any chip refiner control scheme as the controller will tend to further close the gap if it directly tries to achieve the new setpoint. However, as evident from the gap plot, the implemented controller opens the gap, recovers from the pad collapse and brings the load to the new safe setpoint.

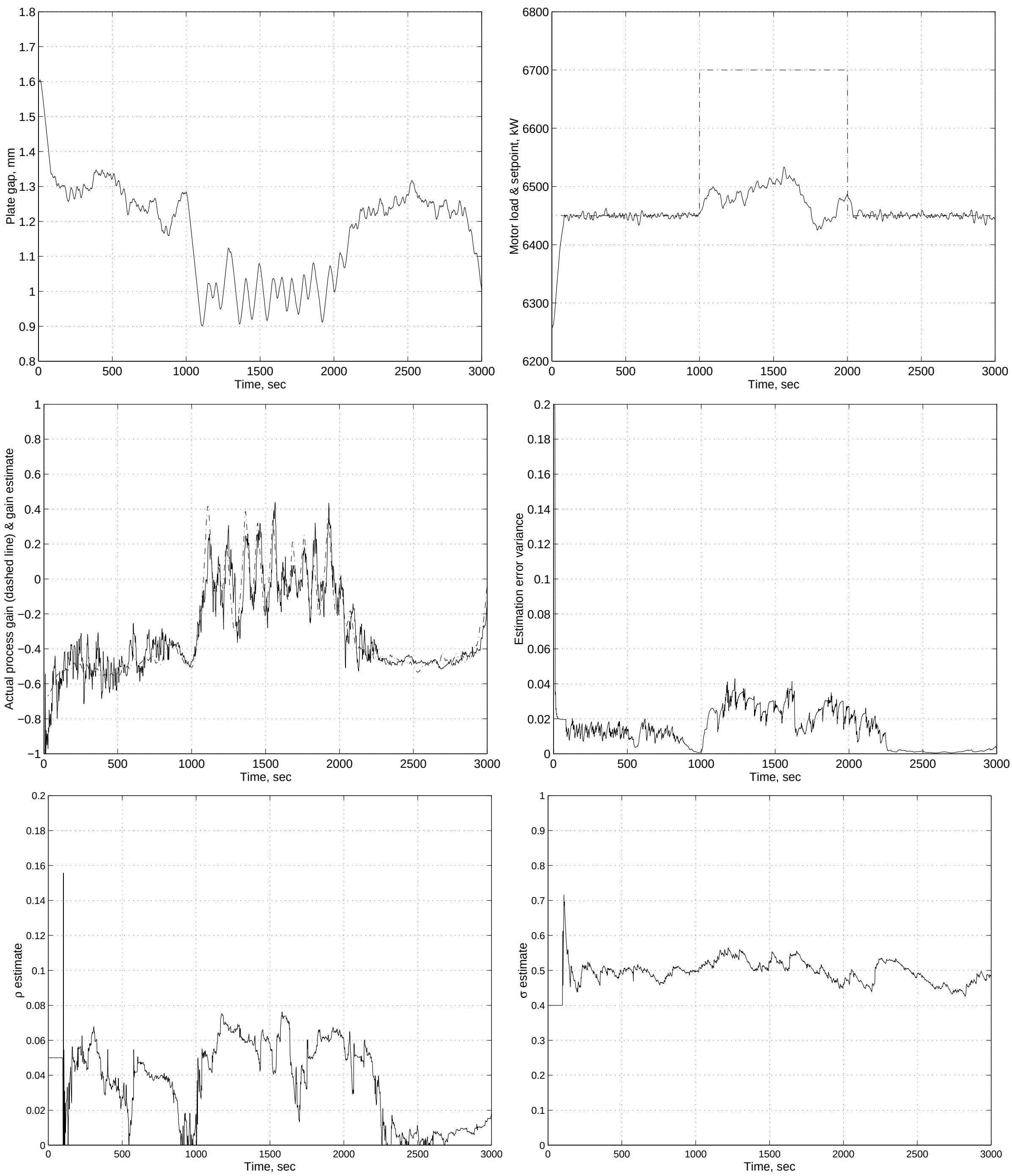

Figure 5: Safe operation, then unreachable setpoint.

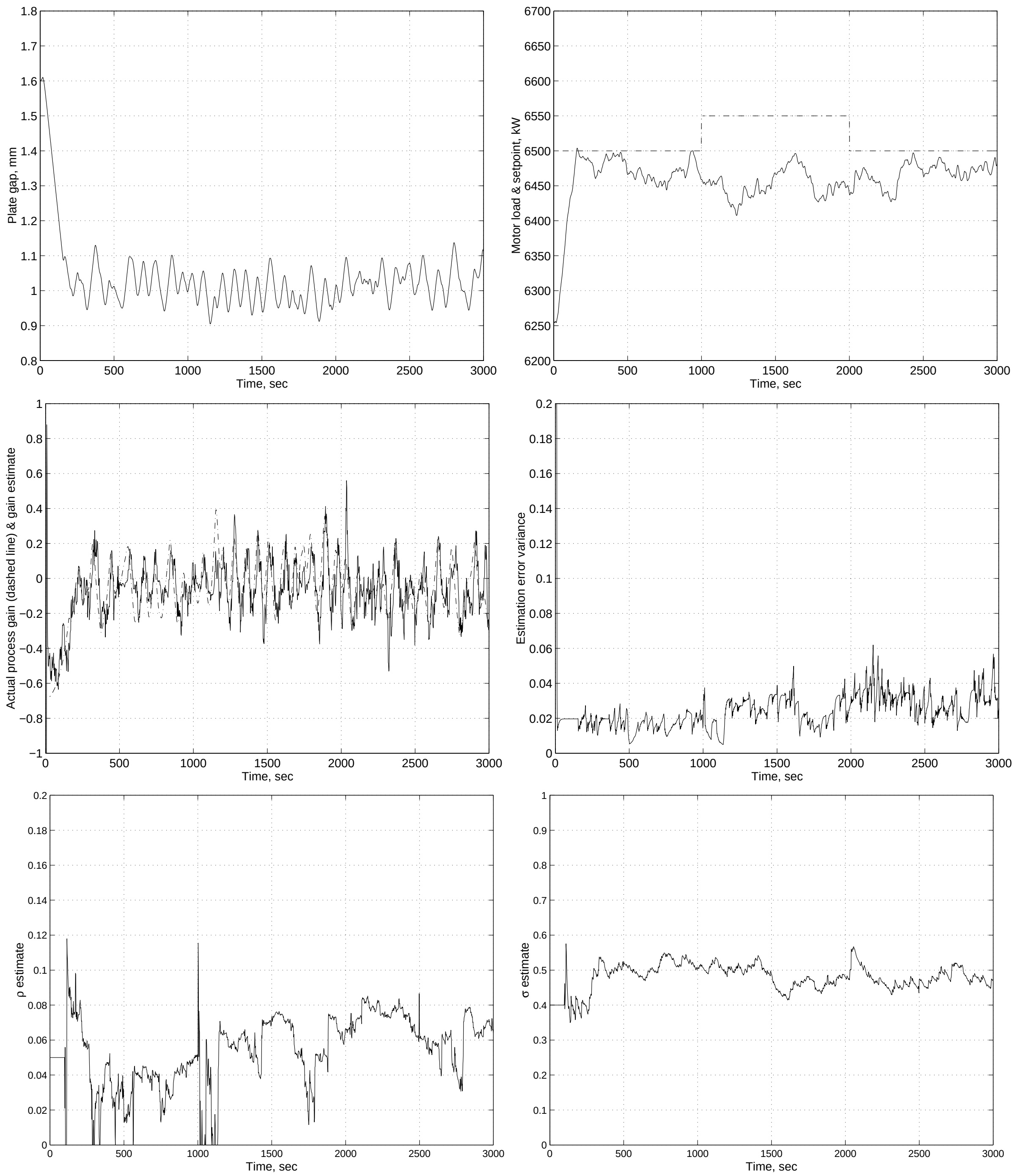

Figure 6: Operation around zero gain.

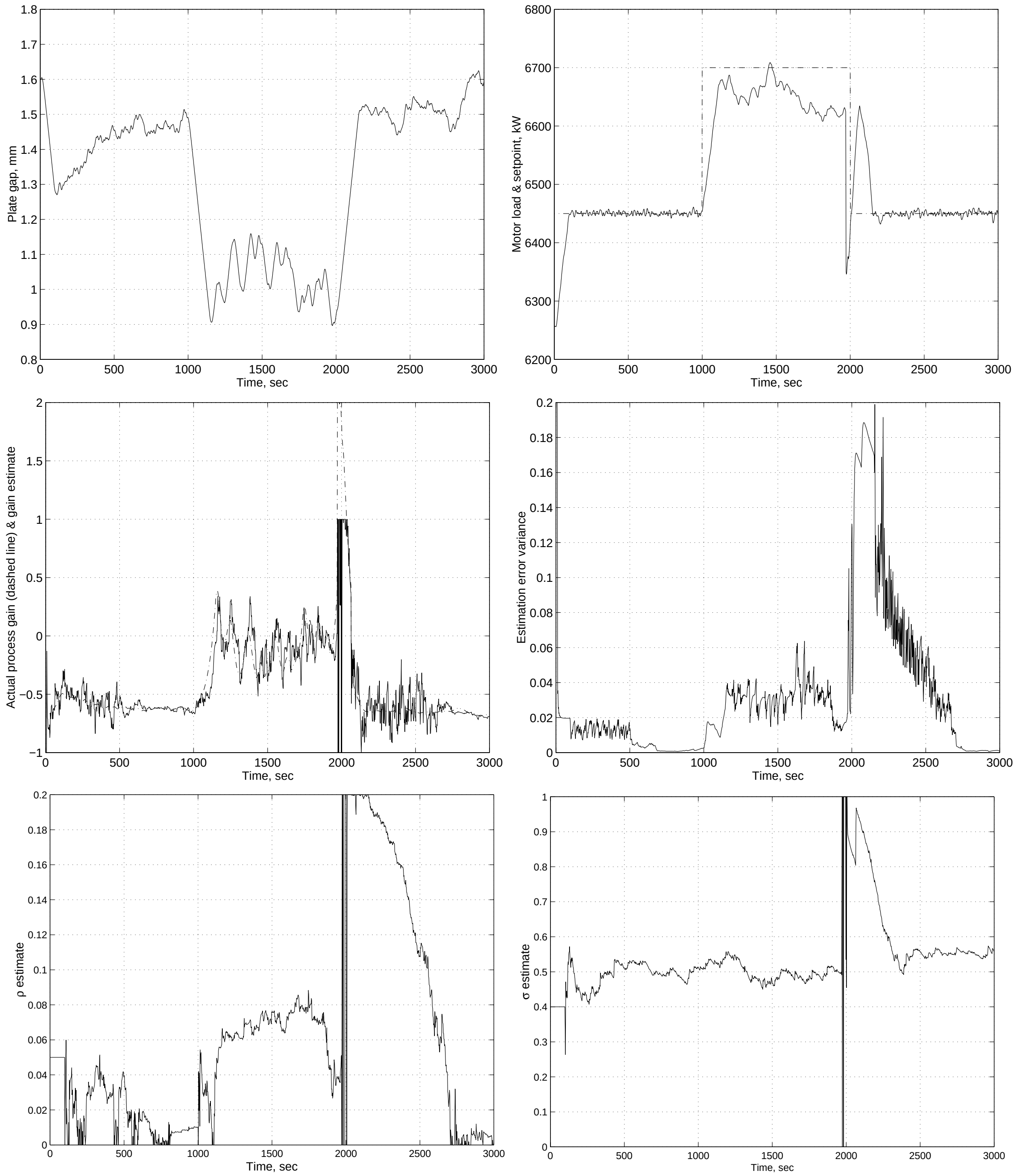

Figure 7: Behavior of the controller when the pad collapses.

6 Conclusions

This paper has demonstrated that it is possible to obtain a reliable controller for the chip refiner motor load. This approach does not require additional heuristic logic or expensive dedicated sensors. The adaptive Kalman filter proved capable of tracking both slow drifts and abrupt sign changes in the gain. Probing seems to be beneficial on various simulations. In the case of pad collapse, the controller rapidly recovers on its own. Future work will focus on applying this strategy to a chip refiner.

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