Dry chip feedrate control using online chip moisture

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ABSTRACT: Normal practice in continuous digester operation is to set the production rate through the chip meter speed. This speed is seldom, if ever, adjusted except to change production, and most of the other digester inputs are ratioed to it. The inherent assumption is that constant chip meter speed equates to constant dry mass flow of chips. This is seldom, if ever, true. As a result, the actual production rate, effective alkali (EA)-to-wood and liquor-to-wood ratios may vary substantially from assumed values. This increases process variability and decreases profits. In this report, a new continuous digester production rate control strategy is developed that addresses this shortcoming. A new noncontacting near infrared–based chip moisture sensor is combined with the existing weightometer signal to estimate the actual dry chip mass feedrate entering the digester. The estimated feedrate is then used to implement a novel feedback control strategy that adjusts the chip meter speed to maintain the dry chip feedrate at the target value. The report details the results of applying the new measurements and control strategy to a dual vessel continuous digester.

Application: A new method of dry chip feedrate control could help mills stabilize and potentially increase production rates and achieve better production quality when combined with existing liquor dosing controls.

In kraft pulping, the primary goals are to manufacture uniform, high quality pulp, maximize production, and minimize costs. This is a substantial challenge given that the raw material (i.e., wood chips) is a heterogeneous material with high inherent variability. Normal practice in continuous digester operation is to set the production rate through the chip meter speed. The chip meter is effectively either a screw feeder of known volume or a rotating wheel with pockets designed to deliver a uniform volume of chips per revolution. The speed is seldom, if ever, adjusted except to change production. The dry wood mass feedrate is estimated by applying factors for the chip dry bulk density and the pocket fill factor. An estimate of the pulp production rate is then obtained by applying a yield factor. Most of the other inputs to the digester are ratioed to the assumed dry wood feedrate. Of particular importance are the white and black liquor flow rates, which are set through the effective alkali (EA)-to-wood and liquor-to-wood ratios. The inherent assumption here is that constant chip meter speed equates to constant dry mass flow of chips. This is seldom true.

Variability in chip shape, size distribution, moisture content, and temperature (thawed or frozen chips) affects the packing of chips (bulk density) in the pockets. Moreover, the pockets are not always full. The degree of pocket filling may be time-varying, or it may vary with chip meter speed. The end result is that the actual production rate, EA-to-wood ratio, and liquor-to-wood ratio may vary substantially from the assumed values. The actual production rate will almost always be less than expected as the production rate calculation typically assumes full pockets. Variability in EA-to-wood and liquor-to-wood ratios causes disturbances in the EA profile and chip residence time in the digester, resulting in pulp quality variability, most notably in the kappa number. For a 1000 tons/day mill, a 1% loss of production reduces revenues by approximately US$1 million/year, assuming a marginal profit of US$300/ton. Simulation results indicate that undetected variability in the dry mass flow of chips to a continuous digester of ±5% causes the EA-to-wood ratio to vary ±1.5% and the kappa number to vary ±8 units when pulping softwood to kappa no. 30 at an EA-to-wood ratio of 15%. Similar observations have been reported elsewhere [1-3].

One way to compensate for variability in the wood chip feed entering a continuous digester is through feedback control via a liquor analyzer [2,4]. Feedback control of the residual effective alkali is, however, limited in its effectiveness by the extremely long process dynamics. Residual effective alkali control also fails to address variability in the liquor-to-wood ratio. A better approach is to measure the wood chip mass flow and moisture content before the chips enter the digester and use this for feedforward control to the other inputs. Various devices have been proposed to achieve this [1,5], but most of these require a chip sampling system and are, therefore, difficult to maintain. Furthermore, the measurements are most often made on the chip belt upstream of the chip bin so proper compensation must be made for variability caused by the chip bin level controller. This aspect of the problem has received little attention in the literature.

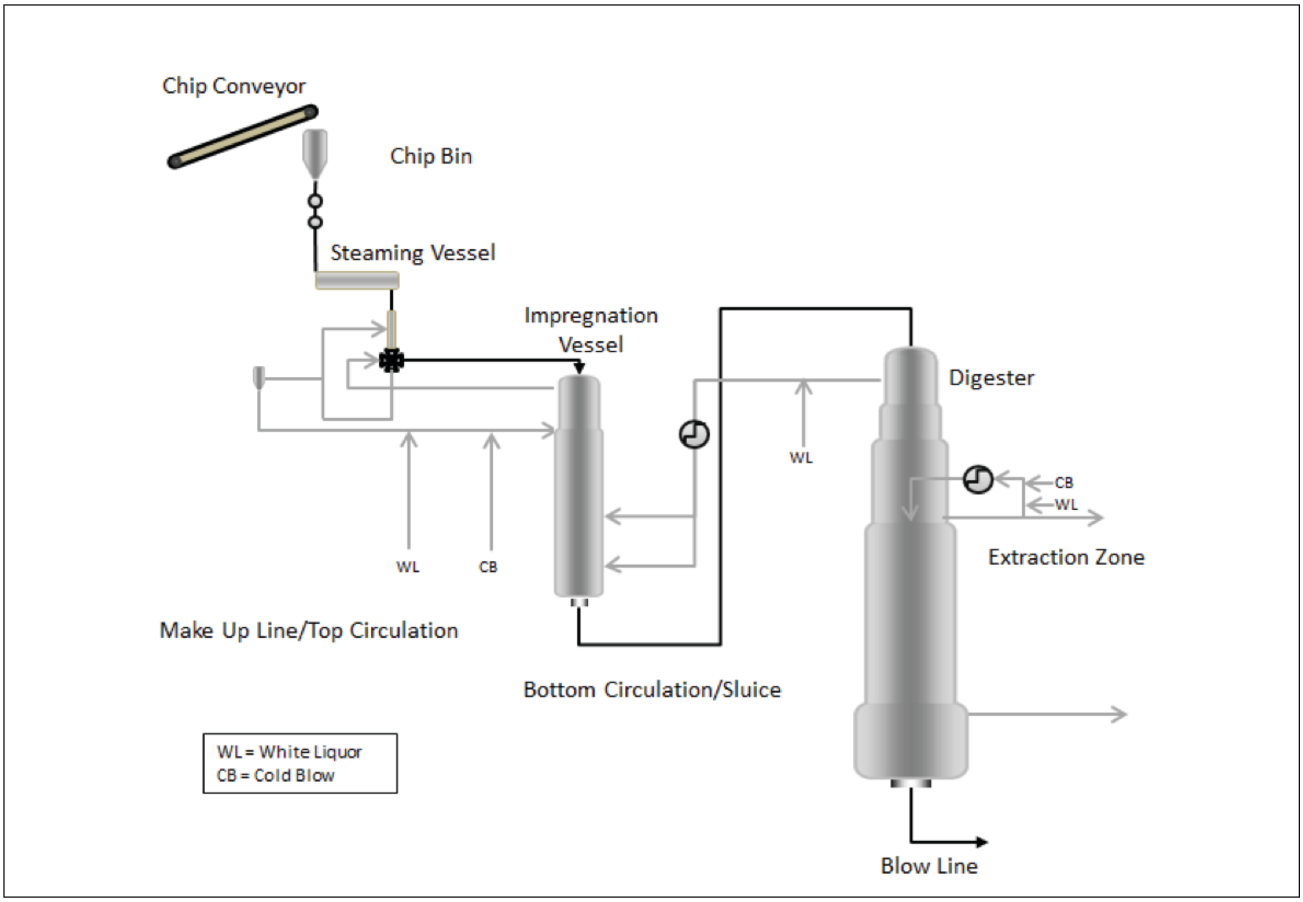
In this report, a new continuous digester production rate control strategy is proposed that addresses these shortcomings. A new noncontacting near infrared (NIR)-based chip moisture sensor [6] is combined with a weightometer to measure the actual dry wood mass feedrate entering the digester. In addition to using the new measurement for feedforward control as has been proposed in the past, a novel feedback control strategy is developed that adjusts the chip meter speed to maintain the feedrate at the target value.

Chircoski et al. [7] trialed a dry chip feedrate control strategy, but their implementation required a chip volume measurement in addition to chip weight and moisture, and no details were given on how compensation for variability caused by the chip bin level controller was achieved. One difficulty faced during development of the feedback control strategy is that the chip weight and moisture sensors are located on the chip belt on the inlet side of the chip bin. The flow of chips is highly variable in this location, and therefore inappropriate as a basis for control, because of the actions taken by the chip bin level controller. What was needed was a measurement of the dry wood flowrate through the chip meter, on the outlet side of the chip bin. Because this quantity is unmeasured, a chip bin mass balance was used to devise a state estimator for this purpose. The chip bin model, state estimator, and feedrate control strategy are described and the results of applying the new measurements and control strategy to a dual vessel continuous digester are discussed.

PROCESS DESCRIPTION

A dual vessel hydraulic digester is depicted in **Fig. 1**. Chips are fed via a conveyor system to the chip bin, where saturated steam at atmospheric pressure is added to heat the chips and remove entrained air. The level in the chip bin is controlled by manipulating the volume of chips feeding the bin. The chips are metered and then enter the steaming vessel where steam at a higher pressure further increases temperature. Chips are then mixed with cooking liquors in the chip chute and fed to a high-pressure feeder. The high-pressure feeder exposes the mixture to the higher operating pressures required for liquor impregnation and to a high-velocity liquor flow to transfer the chips to the impregnation vessel. Most of the white liquor addition occurs at the feed to the impregnation vessel, and the high pressure drives penetration of the liquor into the wood chip. Proper impregnation ensures cooking liquor fills all internal void spaces inside the chip, resulting in a uniformly cooked chip.

The next vessel is the digester, which is divided into different zones. The purpose of the digester is to remove the lignin from the wood chips, leaving behind the hemicellulose and cellulose fibers. The reaction is driven by pressure, temperature, and cooking chemicals. The top of the digester is called the bottom circulation zone, which circulates liquor from the



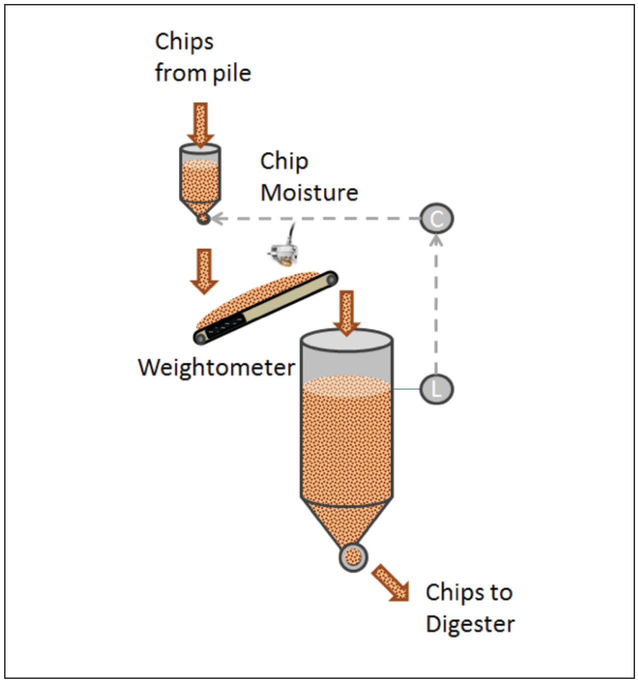
1. Continuous dual vessel hydraulic digester.

top of the digester to the bottom of the impregnation vessel. The circulated liquor is heated to the cooking temperature and is used to help sluice the chips out of the bottom of the impregnation vessel to the top of the digester. A small amount of liquor is added to the bottom circulation zone to ensure the specified amount of effective alkali for the cooking process. The chips and liquor flow concurrently down to the next set of liquor extractions screens, which is called the modified cooking zone. This zone removes a portion of the cooking liquor and replaces it with fresh white liquor and some extracted wash liquor. The fresh liquor and wash liquor are heated before being introduced into the digester to keep the digester temperature at the desired target. The chips then continue down to the digester wash zone, where more liquor is extracted and cooled black liquor filtrate from brownstock washing, called cold blow, is added to cool the bottom of the digester. The chips then pass out the blowline where the chips become pulp fibers as the pressure drops across the blowline valves.

The amount of liquor and temperature in the digester are controlled to ensure a uniform cook of the chips. The cooking reduces the kappa number and hemicellulose content of the chips, while retaining the cellulose. The amount of white liquor at the different zones is added to maintain a desired alkali residual profile in the digester. A too high residual can lead to yield loss as cellulose could also be damaged, while a too low residual can lead to lignin precipitation. A temperature profile is also maintained in the digester for similar reasons. The amount of cooking in the digester is measured by the kappa number.

Figure 2 is a detailed diagram of the chip feed system. Wood chips reclaimed from chip piles are transported to the chip bin via a belt conveyor. The rate of chip removal from the bin is determined by the chip meter, which is a pocket or screw feeder equipped with a variable speed drive. The chip meter ultimately controls the chip feedrate to the digester. The mill is equipped with a Kistler-Morse 1700 weightometer (Kistler-Morse; Spartanburg, SC, USA) and a chip moisture sensor [5]. Both sensors are located on the chip belt upstream of the chip bin.

As mentioned previously, the mass flow of chips on the belt is highly variable due to the chip bin level controller, which manipulates the rate at which chips are reclaimed and placed on the belt. This is illustrated in **Fig. 3**, which shows the chip bin level and its setpoint in the upper plot, the chip bin level controller output in the middle plot, and the mass flow rate of bone dry chips on the belt (moisture corrected weightometer signal) in the lower plot over an 8-h period. The output of the level controller is inversely correlated with the level, as expected, and positively correlated with the dry chip mass flow rate. This short-term variability in dry chip mass flow, which is 60 tons/hour peak to peak or roughly 40% of the nominal value, is only present to correct the level. More to the point, it is not indicative of the dry chip feedrate to the digester through the chip meter and, therefore, is an inappropriate signal for control.



2. Chip feed handling system.

DEVELOPMENT OF CONTROL STRATEGY

What is needed to properly control the digester production rate is a measurement of the dry wood flowrate through the chip meter, on the outlet side of the chip bin. Because this quantity is unmeasured, a chip bin mass balance was used, together with the available measurements, to devise a state estimator (extended Kalman filter or EKF [8]) for this purpose. This section begins with the development of a nonlinear process model for the chip bin level, required for state estimation.

Nonlinear dynamic model for chip bin level

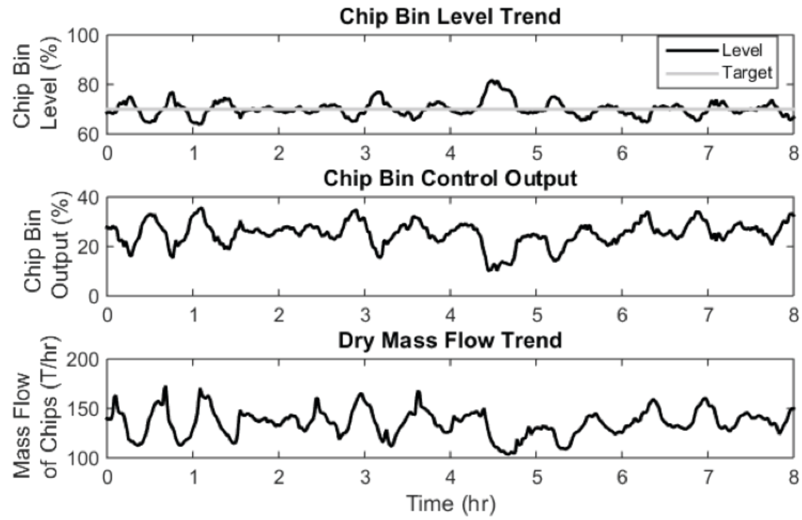
A level model for the chip bin is derived from the material balance of a vessel with fixed cross-sectional area and constant material density (Eq.1):

$$\frac{dL}{dt} = \frac{1}{\rho A}(\dot{m}_{in} - \dot{m}_{out}) \tag{1}$$

where ρ is the density of the material, A is the fixed cross-sectional area, and $\dot{m}_{in}$ and $\dot{m}_{out}$ are the mass flows in and out, respectively. The dry mass flow of chips into the bin is a combination of the chip mass flow measurement (weightometer) and chip moisture (chip sensor), as in Eq. 2:

$$\dot{m}_{in} = (1 - x_w)\dot{m}_c \tag{2}$$

where x_w is the mass fraction of water in the chips and $\dot{m}_c$ is the mass flow of wet chips. As mentioned previously, both variables are measured on the belt leading to the chip bin.



3. Response of weightometer to chip bin level controller.

Here it is assumed that the small transport delay between the locations of the weightometer and the chip sensor is small compared with the dynamics of the chip bin level controller. At the exit of the vessel, only the chip meter speed is known. An additional unknown parameter is required for the conversion to mass flow (Eq. 3):

$$\dot{m}_{out} = \theta S \tag{3}$$

Here S represents the chip meter speed in revolutions per time. The unknown parameter θ represents the amount of dry chip mass per revolution; it is the product of the chip meter volume per revolution, its fill factor, and the chip dry bulk density. Finally, combining Eqs. 1–3 gives the chip bin level model (Eq. 4):

$$\frac{dL}{dt} = \frac{1}{\rho_{bd}A}\left((1 - x_w)\dot{m}_c - \theta S\right) \tag{4}$$

The constants of Eq. 4 include the dry bulk density of the chips ρ_{bd} and the chip bin cross-sectional area A. While the area of the bin is accurately known, the dry bulk density is known to vary as stated earlier. A steady-state analysis of Eq. 4 implies that errors in the bulk density only affect the dynamic component of the model (i.e., unsteady-state level deviations). Therefore, no persistent biasing of the unknown parameter θ is to be expected when using Eq. 4 for estimation.

Extended Kalman filter

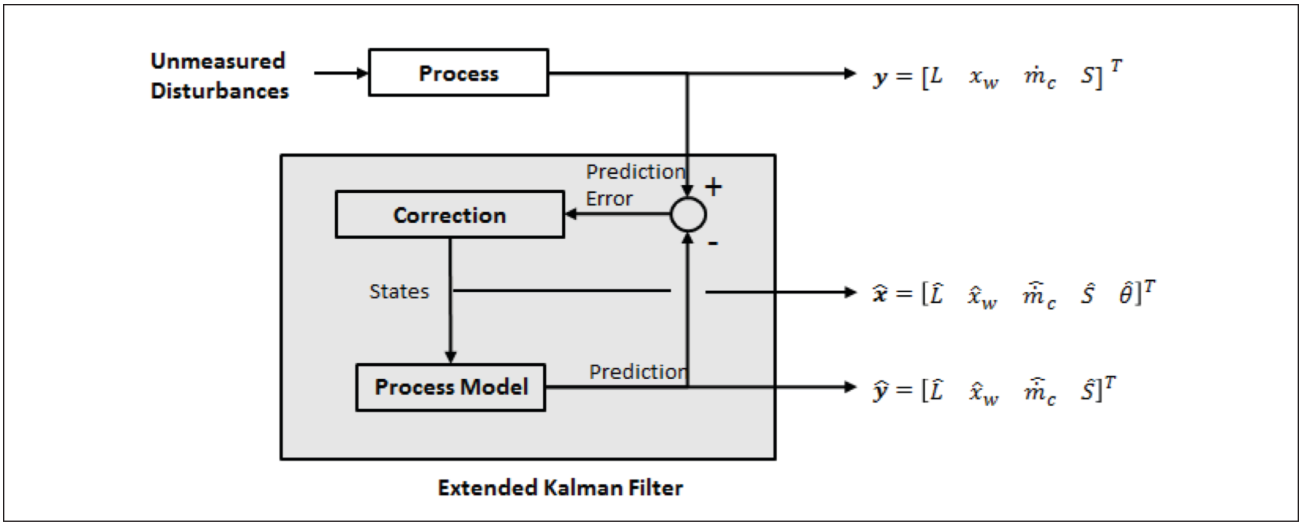
The EKF provides a mechanism to determine an estimate of the unknown parameter θ and to filter noisy measurements. Details of the EKF are provided in the Appendix. **Figure 4** is a schematic block diagram of the EKF showing the flow of information. In this implementation there are no inputs to the process model. Instead, the inputs are included as states so that the EKF can be used to filter those variables. The model runs in parallel with the process and is used to predict the outputs $\hat{y}$. At the sample times, the measured process outputs y are fed back to the EKF and are compared to the predicted outputs, which results in a prediction error. This error is then used to apply a correction to the state estimates that reduces the magnitude of future prediction errors. This prediction-correction process is repeated on an interval T_s.

Determination of covariance matrices

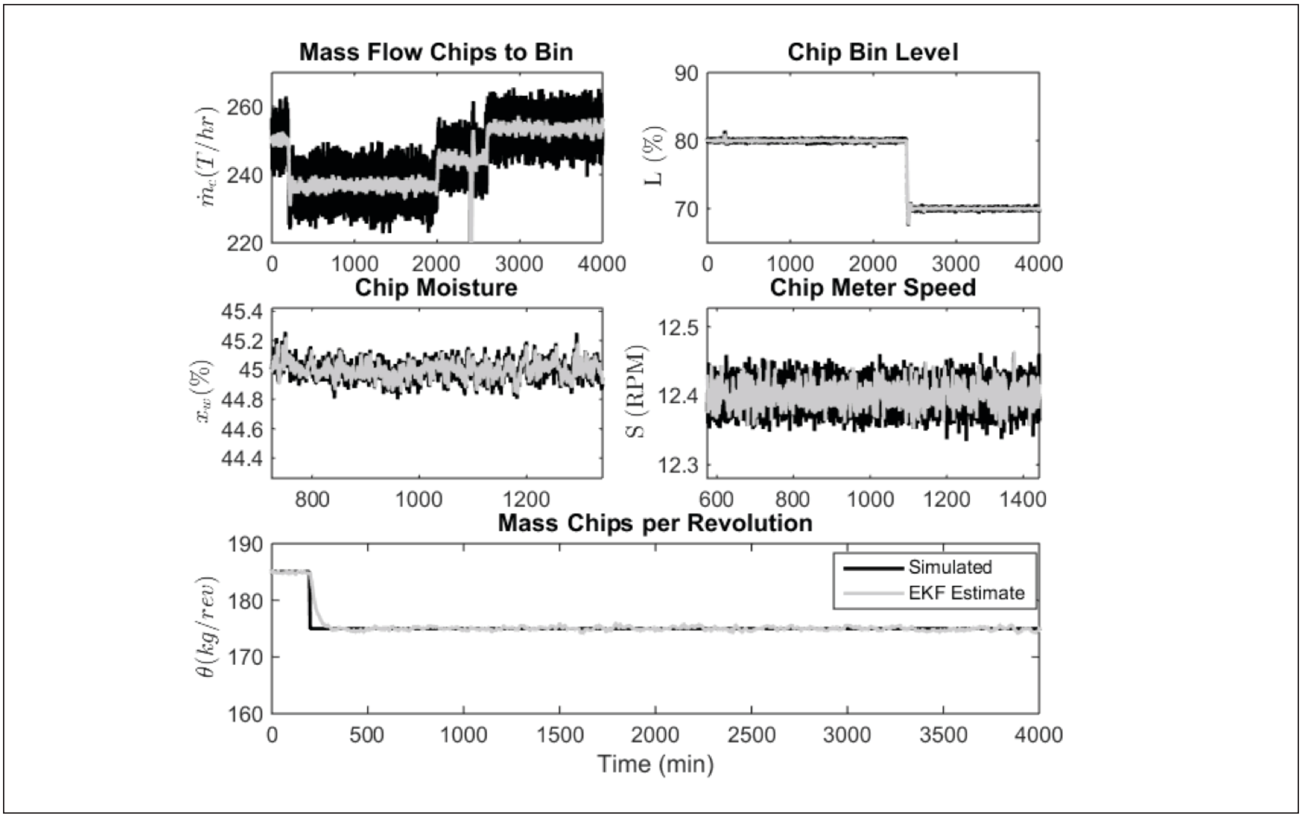
The filtered estimate from the EKF is influenced by two factors: (1) the model contribution (Eq. A8) and (2) the data contribution (Eq. A11). As the measurement error R_v is increased relative to the model error R_w, the EKF will weight the model more and the measurement less. Likewise, if R_v is decreased relative to R_w, the EKF will weight the model less and the measurement more. Thus, the elements of R_v and R_w are the tuning parameters of the EKF. Generally speaking, the covariance matrices are usually taken to be diagonal, both for convenience and for lack of information regarding covariances. Usually, R_v is easily obtained from knowledge of the measurement sensors or from measurement data. The diagonal elements of R_w (variances) are chosen to reflect the total error in predicting the state over the time interval t to $t + T_s$.

To estimate R_v, raw (unfiltered) time series data was obtained from the mill's data historian at a 1-min sampling interval. These values were subsequently fixed and the diagonal elements of R_w were then chosen via simulation to achieve the desired EKF response.

As shown in the following section, the parameter estimate $\hat{\theta}$ is used directly in the dry chip feedrate control calculation



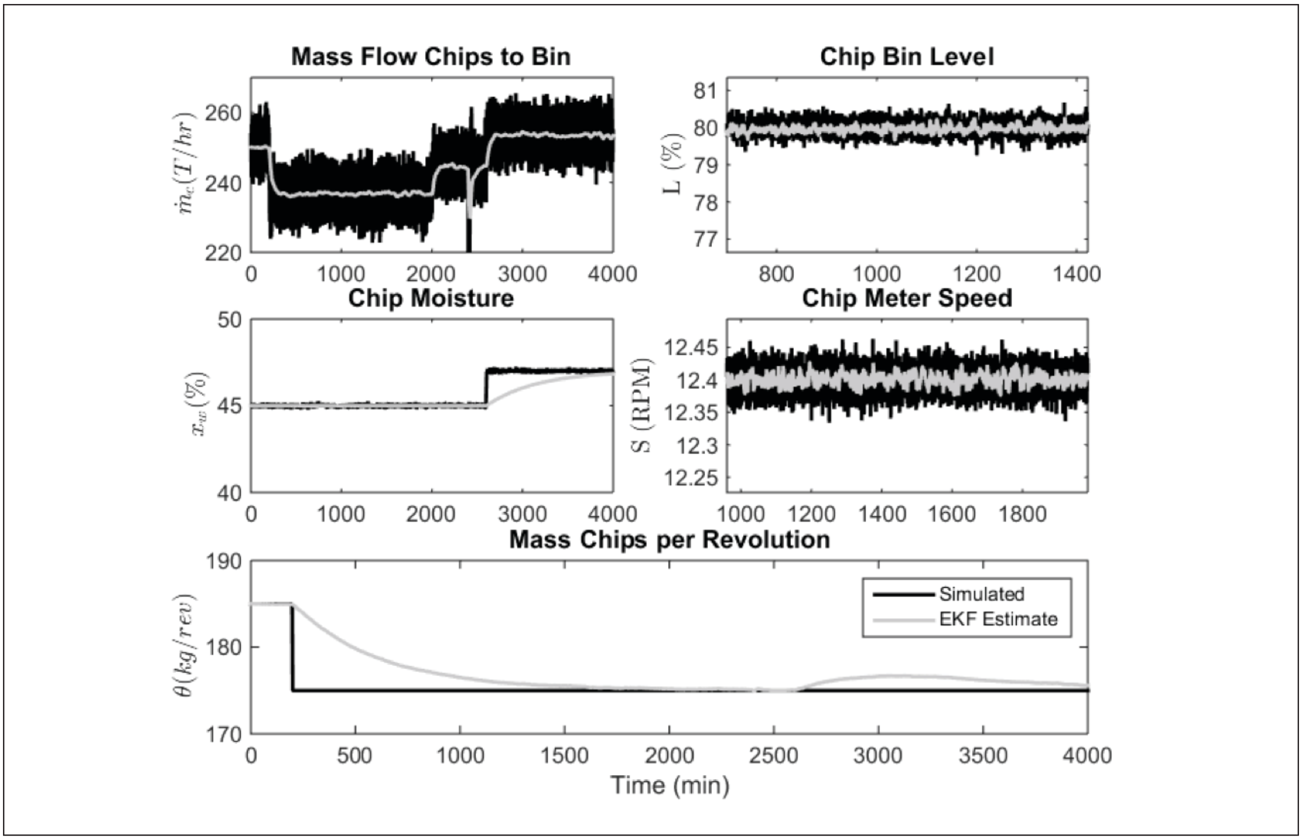
4. Block diagram of extended Kalman filter showing flow of information.



5. Extended Kalman filter response with nominal tuning to step changes in (1) θ, (2) chip meter speed, (3) chip bin level, and (4) chip moisture.

(Eq. 5). Therefore, the tracking error ($\theta - \hat{\theta}$) was of primary importance during tuning of the EKF. In addition, it was anticipated that the filtered state associated with the chip moisture $\hat{x}_w$, together with θ, would be needed for future EA-to-wood and liquor-to-wood control modifications. Finally, it was desirable that the filtered states be insensitive to chip level variability. The following three-step procedure was established to tune the EKF through the choice of R_w diagonal elements: (1) choose a nominal set of tuning criteria, (2) design a test sequence to evaluate the design against the criteria, and (3) fine-tune the design until the criteria are met.

Initial estimates of the state error variances, R_w, were taken as 1% of the nominal operating value. **Figure 5** shows the nominal response of each of the state estimates against the



6. Extended Kalman filter response with refined tuning to step changes in (1) θ, (2) chip meter speed, (3) chip bin level, and (4) chip moisture.

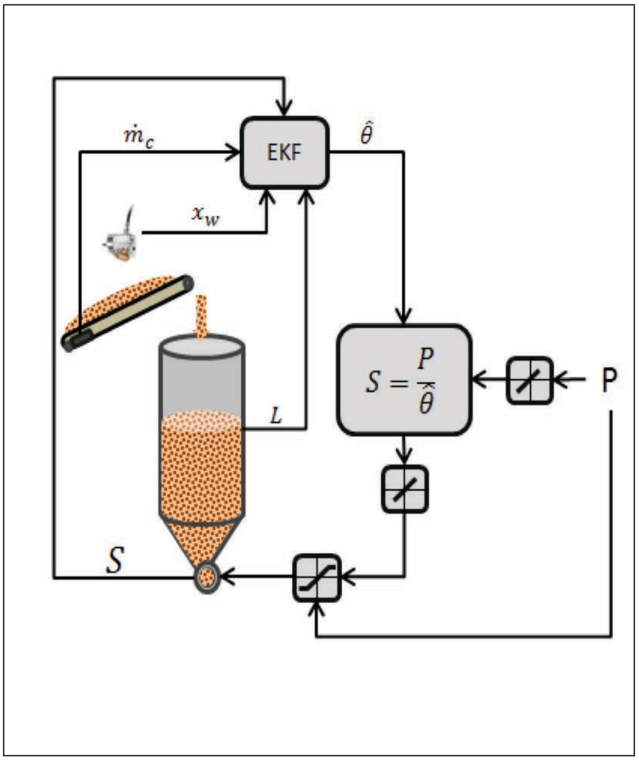
simulated values for step changes in θ, chip meter speed, chip bin level target, and chip moisture. In simulation, the EKF is able to completely remove the effects of changes to the chip meter speed, chip bin level target, and moisture, and it has a 1-h response to a step in unknown θ. However, the response of $\hat{\theta}$ and $\hat{x}_w$ was deemed too fast and it was determined that more filtering was required for practical application.

The desired response time of the estimator was based on the specified maximum allowable chip meter rate of change. To ensure compliance the rate was further reduced by 50%. The EKF was then tuned by trial and error until the desired performance was achieved.

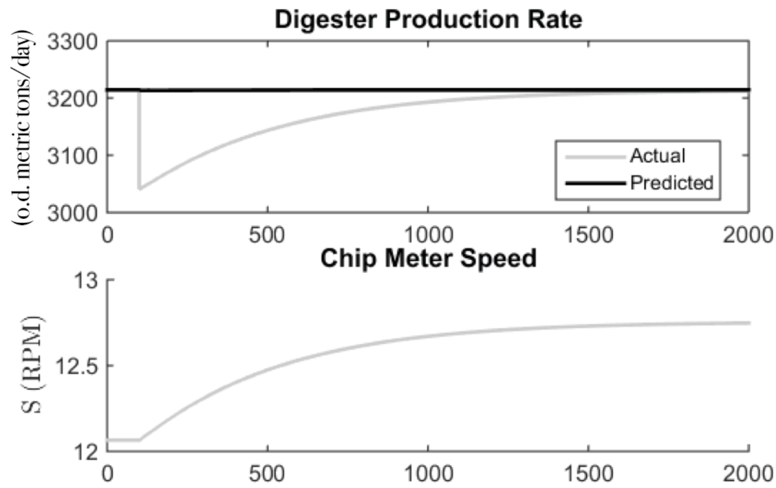
Figure 6 shows the response with the modified tuning to the same changes. No noticeable loss in performance for chip meter and level changes is noticed, and the desired response time in $\hat{\theta}$ is achieved. The step change in moisture affects the estimate of $\hat{\theta}$, as deviation from the actual value, x_w, is temporarily accounted for in the unmeasured state. The implications of this deviation and likelihood of a step disturbance are low. Typical disturbances in chip moisture occur over a similar time frame to the estimator response.

Dry chip feedrate control

The new dry chip feedrate control strategy is shown in **Fig. 7**. The output of the EKF is fed into the following static calculation (Eq. 5):



7. Online extended Kalman filter-based feedrate control.



8. Dry feed rate control response to 10 kg/rev step.

$$S = \frac{P}{\hat{\theta}} \tag{5}$$

where P is the desired chip feedrate in kg/min and is computed from the target pulp production rate through a yield factor. While the calculation of the chip meter speed itself seems trivial, (Eq. 5) effectively closes the loop.

Figure 8 shows the response of the controller to a 10 kg/rev step in θ. Note that the closed loop settling time of the control response is identical to the asymptotic tracking time of the EKF (compared with Fig. 6).

Practical implementation required that the control algorithm fit into the mills pre-existing digester control system, provide onsite tuning capabilities, and protect against unexpected events. Tuning of the EKF alone cannot guarantee prevention of excessive output manipulation. To alleviate this problem, the control algorithm was modified to include an output rate limiter, which allows for mill adjustment to the final control action. In addition, production rate changes traditionally are done using ramping on the digester. Ramping provides time for the digester and its operation to adapt. The production is tied to all the key flowrate and temperature targets of the digester via a multitude of ratio controllers. To ensure similar behavior, the new controller's target was tied to the existing one to ensure seamless integration with the digester control system. Finally, accuracy of the estimator is tied to the accuracy of the chip moisture and wet mass flow measurements. While short-term variation from the mean is inherently handled by the EKF, deviation from the true mean will bias the EKF estimates. Examples of this include instrument drift and failure. To help mitigate this risk, limits were added to the output of the controller. Linear limit constraints as a function of the current production target ensured that chip meter speed manipulations stay in an acceptable range for all operational regimes.

ONLINE APPLICATION RESULTS

The new dry chip feedrate controller was implemented on the digester of a 2000 a.d. metric tons/day Canadian hardwood kraft mill. Both the EKF and controller were implemented in the mill's distributed control system.

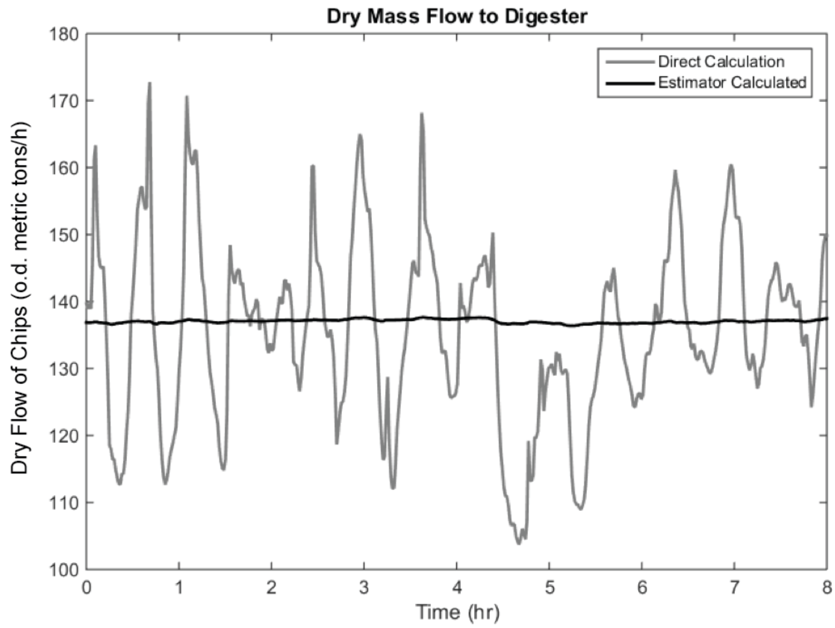
Estimator implementation

The key purpose of the estimator is to remove the short-term variability imposed on the wet chip mass flow measurement from the action of the chip bin level controller. Simulation results showed that the EKF performed very well, both with nominal and final tuning, to disturbances directly affecting the level. **Figure 9** shows an 8-h trend that compares the chip bin dry mass inlet (Fig. 3) and outlet flows. The outlet flow is estimated via the product $\hat{\theta}S$, from Eq. 3. The impact of the level control is effectively removed, providing better representation of the dry mass flow of chips fed to the digester.

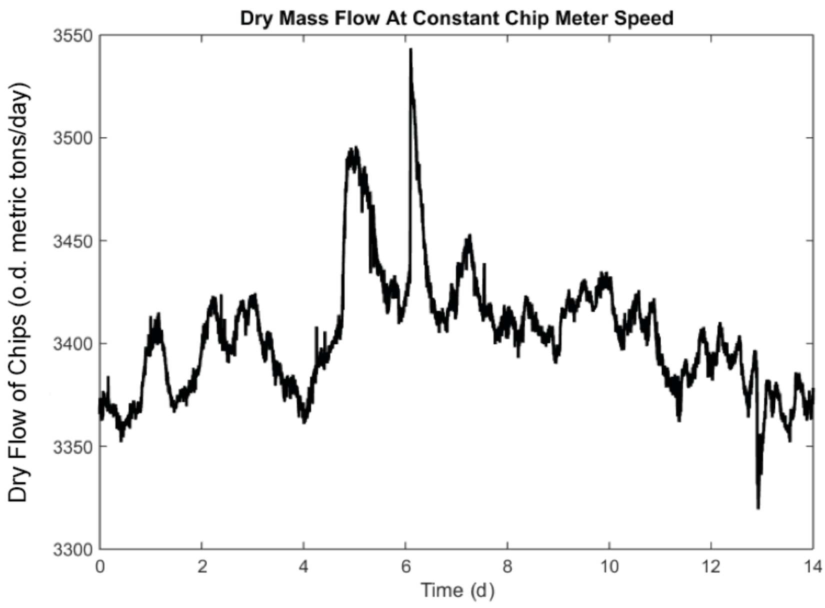
Data from the EKF output over a longer time frame, as shown in **Fig. 10**, reveal significant variation in the overall dry mass flow even though chip meter speed is constant. This demonstrates the weakness of the constant production to chip meter speed relationship traditionally used in the industry.

Control implementation

A 60-day trial was conducted with the final implementation of the chip feedrate controller shown in Fig. 7. The controller performance is evaluated against a 50-day period from the previous year. The results, shown in **Fig. 11**, are normalized by the feedrate target. For the period prior to the implementation of the EKF, the control feedrate was found to vary substantially during the period and typically resulted in an actual feedrate lower than targeted. Production rates greater than

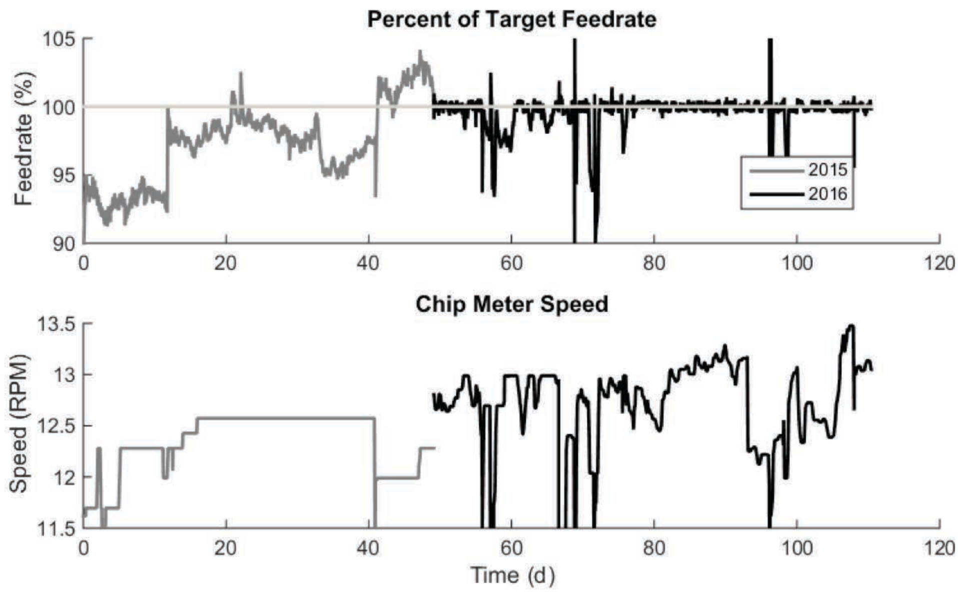


9. Eight-hour trend of dry mass inlet and estimated outlet flow.



10. Long-term trend of estimated dry mass flow at constant chip meter speed.

the target are still possible. After implementation the feedrate holds the target. Short periods of deviation from the target are the result of chip meter saturation. Comparison of the datasets suggests an overall increase in production of 2.5%. It is difficult to extrapolate these results on the basis of the relatively short run time to date, but if we assume that a 1% increase in production is sustainable, then for the February 2017 hardwood spot price of US$500/ton from the RISI database [9], this improvement would be worth US$3.5 million/year in increased revenue to the mill. Also, the feedrate to the digester is stabilized. Better control of the feedrate ensures cooking chemicals are consistently dosed (EA to wood). The liquid/solid or hydraulic balance of the vessel (liquor to wood) also becomes more consistent. This reduction in operational variation is expected to reduce pulp quality variation and alleviate operational issues.



11. Comparison of feedrate for constant chip meter versus extended Kalman filter control.

CONCLUSIONS

A new continuous digester dry chip feedrate control strategy was designed and implemented on a dual vessel digester. The new strategy uses a noncontacting NIR-based chip moisture sensor and a weightometer. One difficulty faced during the development is that the chip weight and moisture sensors are located on the chip belt on the inlet side of the chip bin, whereas what was needed was a measurement of the dry chip flowrate through the chip meter, on the outlet side of the bin. Because this quantity is unmeasured, a chip bin mass balance was used to devise an estimate of the dry mass per chip meter revolution θ via an extended Kalman filter. The new dry chip feedrate controller, based on this estimate, was implemented on the digester of a 2000 a.d. metric tons/day Canadian hardwood kraft mill. The results indicate that, under constant chip meter speed, the actual digester dry chip feedrate can be anywhere between -8% and +3% of the target value and, on average, is 2.5% below the target. Under the new control strategy, the actual dry chip mass flow was able to hold the target value and only showed deviations when the chip meter was saturated or when the digester was upset. Comparison of the datasets suggests an overall increase in production of 2.5%. This improvement is estimated to be worth roughly US$3.5 million/year in increased revenue to the mill. In addition, the removal of large swings in the dry chip feedrate is expected to improve overall digester operation and reduce pulp quality variability by providing more consistent control of chemical dosing and vessel hydraulic loading. **TJ**

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APPENDIX

Extended Kalman filter

State space representation of the model.

The EKF is used to estimate the unknown parameter θ and to filter noisy measurements in the model [4]. The model must first be converted into state space representation. All variables in the model, with the exception of θ, are measured. The state vector for the model is defined as:

$$x = [L \quad x_w \quad \dot{m}_c \quad S \quad \theta]^T \tag{A1}$$

Then, Eq. 4 can be rewritten as:

$$\dot{x}_1 = \frac{1}{\rho_{bd} A}\left((1 - x_2)x_3 - x_4 x_5\right) \tag{A2}$$

The remaining states are assumed to contain an unknown stochastic behavior. The time derivatives for these states are assumed equal to zero:

$$\dot{x}_i = 0, \quad i = 2,3,4,5 \tag{A3}$$

While states 2–4 could just as easily have been considered as inputs to the model, the decision to incorporate them as states was done to allow for filtering of the values in the EKF directly. The filtering employed helped to remove noise from the measurements, while also reducing responsiveness to short-term process upsets.

The measurements available for state estimation consist of states 1–4:

$$y = [L \quad x_w \quad \dot{m}_c \quad S]^T \tag{A4}$$

This leads to the linear observation matrix C:

$$y = \underbrace{\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \end{bmatrix}}_{C} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{bmatrix} \tag{A5}$$

The state space model is defined by Eqs. A2, A3, and A5.

<u>State estimation via an extended Kalman filter</u>

Consider the general nonlinear model for the process dynamics arising from unsteady-state material balances:

$$\begin{aligned} \dot{\boldsymbol{x}}(t) &= \boldsymbol{g}(\boldsymbol{x}(t), \boldsymbol{u}(t)) \\ \boldsymbol{y}(t) &= \boldsymbol{h}(\boldsymbol{x}(t), \boldsymbol{u}(t)) \end{aligned} \tag{A6}$$

where *g* and *h* are vectors of nonlinear functions. The idea behind EKF [8] is to extend linear Kalman filter theory to nonlinear systems. This is achieved by linearization of the system about the current state estimate, and by application of the Kalman filter to the resulting time-varying linear process. The nonlinear functions in Eq. A6 are linearized about the current conditions, $x(t)$ and $u(t)$, and discretized to yield a linear, discrete-time model of the form:

$$\begin{aligned} \boldsymbol{x}(k+1) &= \boldsymbol{A}\boldsymbol{x}(k) + \boldsymbol{B}\boldsymbol{u}(k) \\ \boldsymbol{y}(k) &= \boldsymbol{C}\boldsymbol{x}(k) + \boldsymbol{v}(k) \end{aligned} \tag{A7}$$

Here, the time argument k refers to the current discrete-time sampling instant corresponding to time tk and $k + 1$ refers to a time t_{k+1} one sampling instant into the future where $t_{k+1} = t_k + T_s$ and T_s is the sampling interval. The matrices A, B, and C are generally functions of the states $x(k)$ and controls $u(k)$. Vectors $w(k)$ and $v(k)$ are independent, normally distributed white noise vectors with covariance matrices $R_w = cov\{w(k)\}$ and $Rv = cov\{v(k)\}$, respectively, where $w(k)$ is introduced to account for errors in the one-step-ahead prediction of the state arising from modeling errors and errors due to linearization and $v(k)$ is measurement error.

At the k[th] sampling interval, the current estimate of the state vector, using all the available information at that time, is $\hat{x}(k|k)$, $\hat{x}(k|k)$, and the errors associated with this estimate have a covariance matrix $P(k|k)$. The EKF uses the linearized model to make a one-step-ahead prediction of the state estimate using the available information:

$$\boldsymbol{x}(k+1|k) = \boldsymbol{A}\big(\hat{\boldsymbol{x}}(k|k), \boldsymbol{u}(k)\big)\hat{\boldsymbol{x}}(k|k) + \boldsymbol{B}\big(\hat{\boldsymbol{x}}(k|k), \boldsymbol{u}(k)\big)\boldsymbol{u}(k) \tag{A8}$$

The errors associated with this prediction have a covariance matrix $P(k+1|k)$, that is given by:

$$\boldsymbol{P}(k+1|k) = \boldsymbol{A}\big(\hat{\boldsymbol{x}}(k|k), \boldsymbol{u}(k)\big)\boldsymbol{P}(\boldsymbol{k}|\boldsymbol{k})\boldsymbol{A}\big(\hat{\boldsymbol{x}}(k|k), \boldsymbol{u}(k)\big)^T + \boldsymbol{R_w} \tag{A9}$$

The observation functions are then linearized about this prediction to yield the linearized observation matrix, and this is used in the calculation of the Kalman gain matrix for correction of the one-step-ahead prediction:

$$\boldsymbol{K}(k+1) = \boldsymbol{P}(k+1|k)\boldsymbol{C}\big(\hat{\boldsymbol{x}}(k+1|k), \boldsymbol{u}(k)\big)^T \times \Big[\boldsymbol{C}\big(\hat{\boldsymbol{x}}(k+1|k), \boldsymbol{u}(k)\big)^T + \boldsymbol{R_v}\Big]^{-1} \tag{A10}$$

When the new measurement $y(k+1)$ becomes available, the prediction is corrected (filtered) using this new information and the Kalman gains:

$$\hat{\boldsymbol{x}}(k+1|k+1) = \hat{\boldsymbol{x}}(k+1|k) + \boldsymbol{K}(k+1)\big[\boldsymbol{y}(k+1) - \boldsymbol{C}\big(\hat{\boldsymbol{x}}(k+1|k), \boldsymbol{u}(k)\big)\hat{\boldsymbol{x}}(k+1|k)\big] \tag{A11}$$

The covariance matrix, $P(k+1|k+1)$, of this one-step-ahead filtered estimate is then computed:

$$\boldsymbol{P}(k+1|k+1) = \boldsymbol{P}(k+1|k) - \boldsymbol{K}(k+1)\boldsymbol{C}\big(\hat{\boldsymbol{x}}(k+1|k), \boldsymbol{u}(k)\big)\boldsymbol{P}(k+1|k) \tag{A12}$$

and both $\hat{x}(k+1|k+1)$ and $P(k+1|k+1)$ are stored for the next interval. The EKF is defined by Eqs. A8–A12.

ABOUT THE AUTHORS

This particular work was part of an overall program to increase digester yield. Inside this program, a new chip moisture measurement shed light into an opportunity for better control of production rate. This work helps improve overall chip management in a continuous digester. It can be used to supplement traditional digester control strategies.

Overcoming the impact of the chip bin level controller on the weightometer was the most difficult part of the work. We overcame this challenge using estimation/modeling techniques to transform the information to something more readily used for control.

Our research was the first application using extended Kalman filtering techniques and their use as part of a control algorithm. An interesting finding was the sheer size of the variability caused by the assumptions made using a constant chip meter speed for production rate control.

This information could be used to improve the overall feed of chips to the mill for control purposes. Benefits to mills could include stabilized and potentially increased production rates and better production quality when combined with existing liquor dosing controls.

The next step is to apply the method at a number of different mills to identify any differences about how it might be implemented in their control systems.

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