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, 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 non-contacting NIR-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.

INTRODUCTION

In kraft pulping, the primary goals are to manufacture uniform, high quality pulp, maximize production and minimize costs. This is a significant 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 know volume, or a rotating wheel with pockets designed to deliver a uniform volume of chips per revolution. The speed is very 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 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) affect 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 and liquor-to-wood ratios may vary quite substantially from the assumed values. The actual production rate will almost always be less than expected as the production rate calculation normally assumes full pockets. EA-to-wood and liquor-to-wood variability 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 t/d mill, a 1% loss of production reduces revenues by approximately $1M/y, assuming a marginal profit of $300/t. 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 ±8 units when pulping softwood to kappa 30 at an EA-to-wood of 15%. Similar observations have been reported elsewhere [[1], [2], [3]].

One way to compensate for variability in the wood chip feed entering a continuous digester is through feedback control via a liquor analyser [[2], [4]]. Feedback control of the residual effective alkali (REA) is, however, limited in its effectiveness by the extremely long process dynamics. REA 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, e.g. [[1], [5]], but most of these require a chip sampling system and are, therefore, difficult to maintain. Furthermore, as the measurements are most often made on the chip belt upstream of the chip bin, proper compensation must be made for variability caused by the chip bin level controller. This aspect of the problem has received little to no attention in the literature.

In this report a new continuous digester production rate control strategy is proposed that addresses these shortcomings. A new non-contacting 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. The remainder of the report is organized as follows. In Section 2, the continuous digester process where the new control strategy was applied is described in detail. 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, due to 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. Since 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 in Section 3. Finally, Section 4 details the results of applying the new measurements and control strategy to a dual vessel continuous digester.

PROCESS DESCRIPTION

A dual vessel hydraulic digester is depicted in Figure 1. Chips are fed up 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 flow to transfer the chips to the impregnation vessel. The majority of white liquor addition occurs at the feed to the impregnation vessel, and the high pressure drives the penetration of the liquor into the wood chip. Proper impregnation ensures cooking liquor fills all internal void space inside the chips, 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 and hemicellulose from the wood chips, leaving behind the cellulose fibres. The reaction is driven by pressure, temperature, and cooking chemicals. The top of the digester is called the bottom circulation (BC) zone, which circulates liquor from the 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 BC zone to ensure a required amount of effective alkali exists 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 bottom of the digester wash zone, where more liquor is extracted and cold blow is added to cool the bottom of the digester. The chips then pass out the blowline where the chips become pulp fibres 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 hemi-cellulose 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.
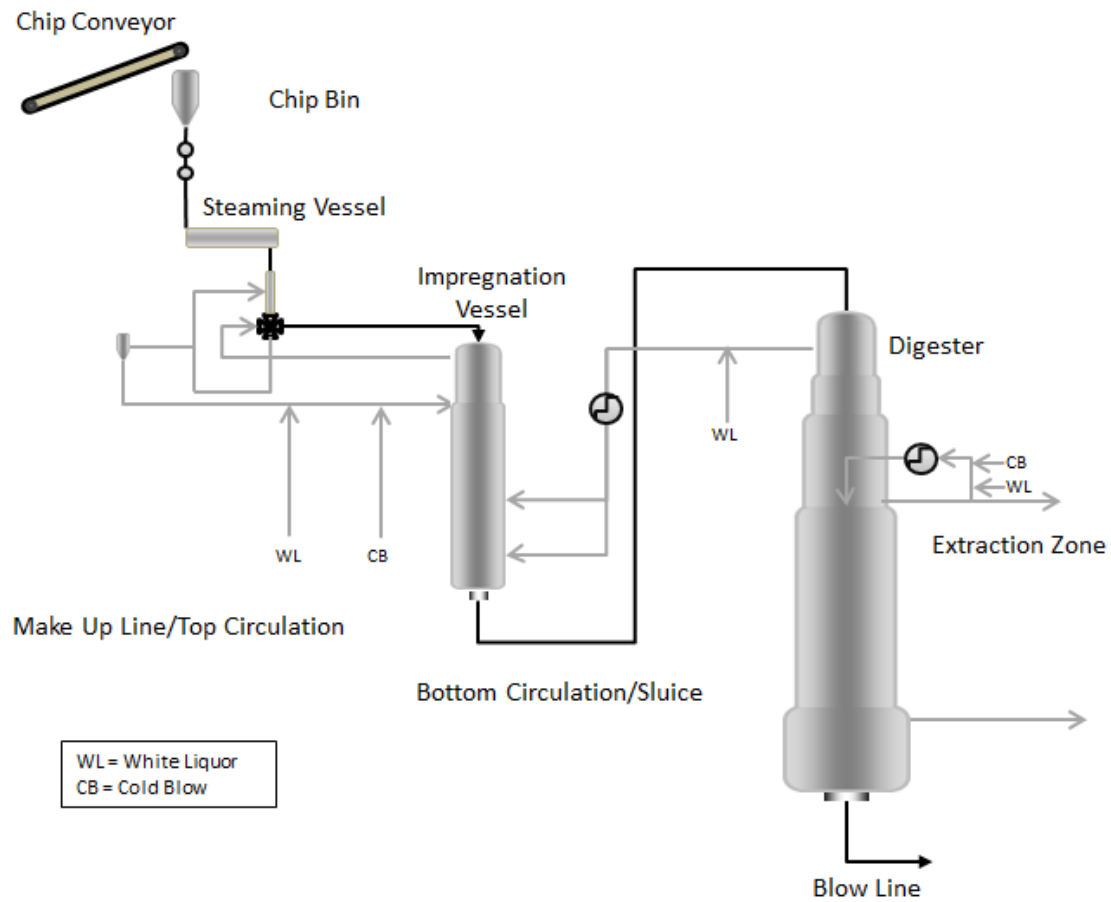
Figure 1: Continuous dual vessel hydraulic digester.

Figure 2 shows a more 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, as mentioned in the introduction, 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 weightometer (Kistler-Morse 1700) and a chip moisture sensor [5]. Both sensors are located on the chip belt upstream of the chip bin.
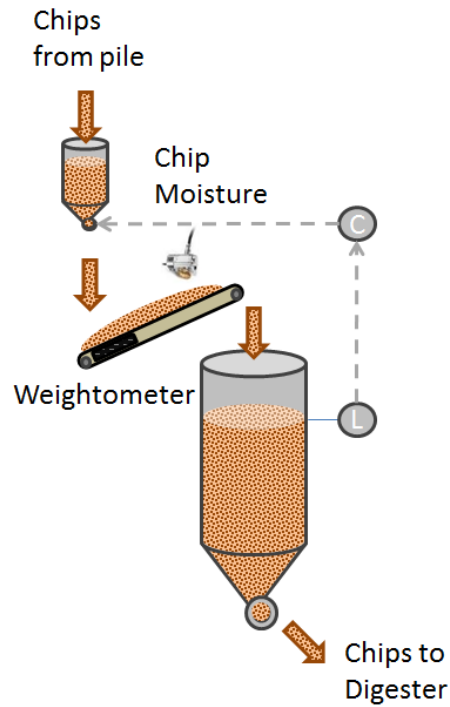
Figure 2: Chip feed handling system.

As mentioned in the introduction, 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 Figure 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 eight hour period. Note that 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 t/h 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. The purpose of the next section is to detail how this situation can be rectified.
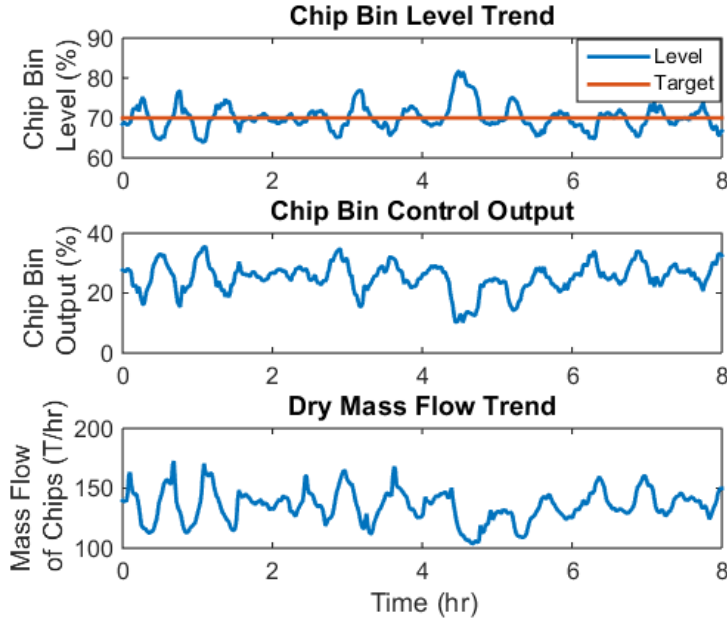
Figure 3: Response of weightometer to chip bin level controller.

DEVELOPMENT OF CHIP DRY MASS FEEDRATE CONTROL STRATEGY

What is needed is a measurement of the dry wood flowrate through the chip meter, on the outlet side of the chip bin. Since 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. The EKF is then discussed. The section concludes with the estimator based strategy for chip dry mass feedrate control.

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:

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

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):

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

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. Here it is assumed that the small transport delay between the locations of the weightometer and the chip sensor is small compared to 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:

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

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

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

The constants of Equation (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 known accurately the dry bulk density is known to vary as stated earlier. A steady state analysis of (4) implies that errors in the bulk density only impact 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 (4) for estimation, as discussed in the next section.

Extended Kalman Filter (EKF)

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.
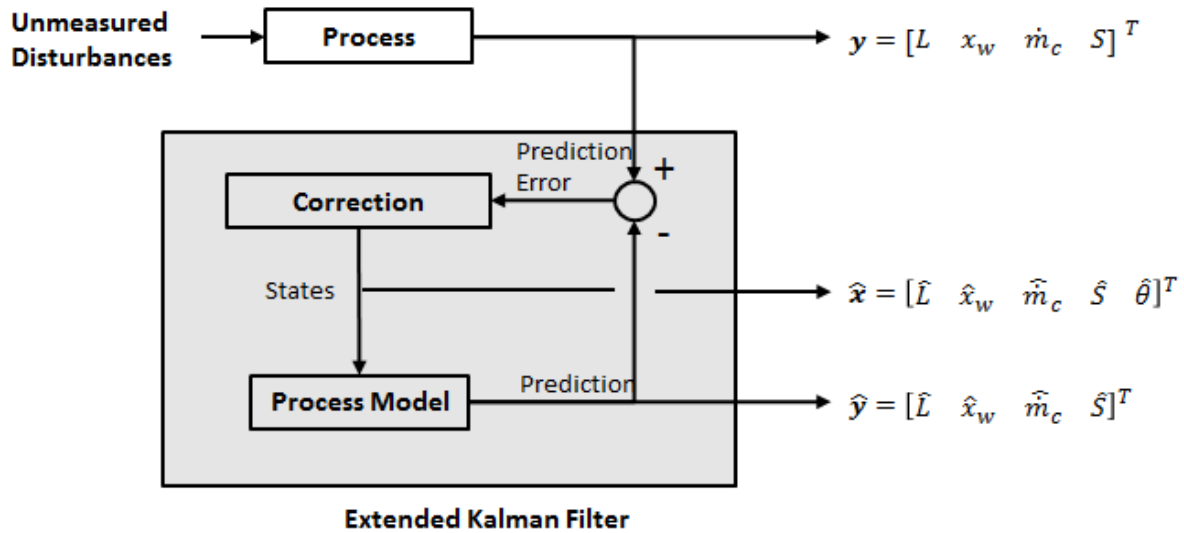

Figure 4: Block diagram of EKF showing flow of information.

Determination of Covariance Matrices.   The filtered estimate from the EKF is influenced by two factors; (i) the model contribution (A8), and (ii) the data contribution (A11), see Appendix. As the measurement error $\boldsymbol{R}_v$ is increased relative to the model error $\boldsymbol{R}_w$, the EKF will weight the model more and the measurement less. Likewise, if $\boldsymbol{R}_v$ is decreased relative to $\boldsymbol{R}_w$, the EKF will weight the model less and the measurement more. Thus, the elements of $\boldsymbol{R}_v$ and $\boldsymbol{R}_w$ 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. $\boldsymbol{R}_v$ is usually easily obtained from knowledge of the measurement sensors,

or from measurement data. The diagonal elements of $\boldsymbol{R}_w$ (variances) are chosen to reflect the total error in predicting the state over the time interval t to $t + Ts$.

In order to estimate $\boldsymbol{R}_v$, raw (unfiltered) time series data was obtained from the mill's data historian at a one minute sampling interval. These values were subsequently fixed and the diagonal elements of $\boldsymbol{R}_w$ were then chosen via simulation to achieve the desired EKF response.

As shown in the next section, the parameter estimate $\hat{\theta}$ is used directly in the dry chip feedrate control calculation, see Equation (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 $\hat{\theta}$, 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 procedure was established to tune the EKF through the choice of $\boldsymbol{R}_w$ diagonal elements;

1. Choose a nominal set of tuning parameters
2. Design a test sequence to evaluate the design against the criteria
3. Fine tune the design until the criteria are met

Initial estimates of the state error variances, $\boldsymbol{R}_w$, were taken as 1% of the nominal operating value as done in previous work [9].
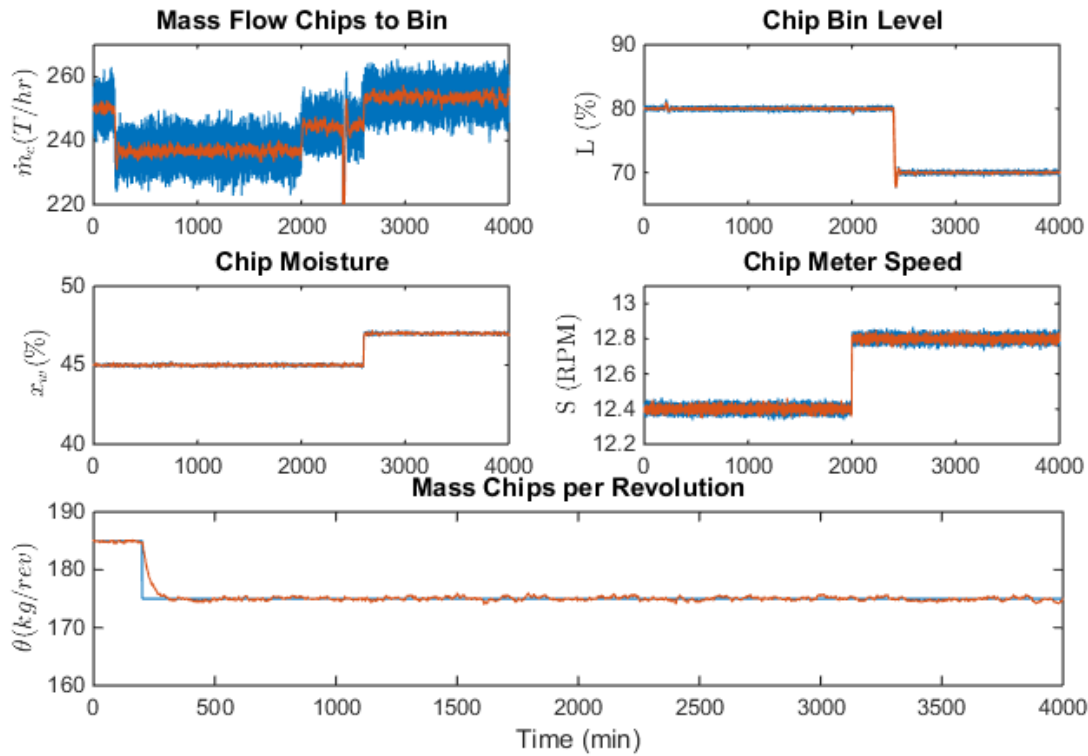
Figure 5: EKF response with nominal tuning to step changes in: 1) $\boldsymbol{\theta}$, 2) chip meter speed, 3) chip bin level and 4) chip moisture.

Figure 5 shows the nominal response of each of the state estimates against the 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 impacts of changes to the chip meter speed, chip bin level target and moisture and has a 1 hour 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. There is no noticeable loss in performance for chip meter and level changes, and the desired response time in $\hat{\theta}$ is achieved. The step change in moisture does impact 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.
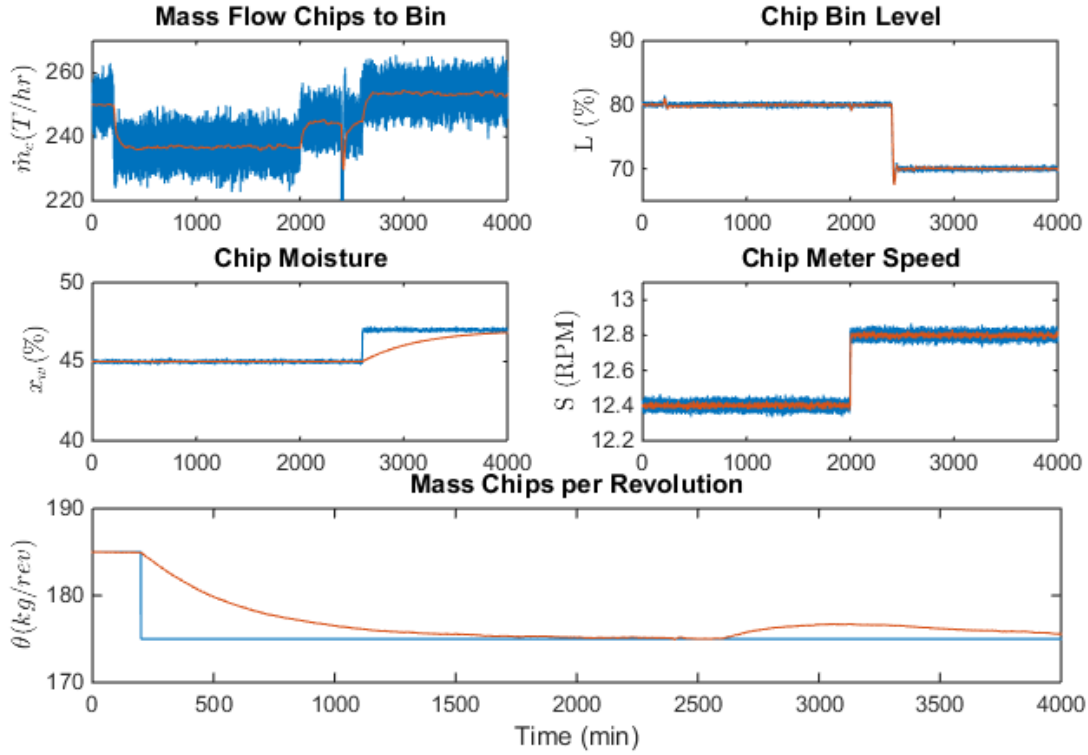
Figure 6: EKF response with refined tuning to step changes in: 1) θ, 2) chip meter speed, 3) chip bin level and 4) chip moisture.

Dry Chip Feedrate Control

The new dry chip feedrate control strategy is shown in Figure 7. The output of the EKF is fed into the following static calculation;

$$S = \frac{P}{\hat{\theta}} \qquad (5)$$

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, Equation (5) effectively closes the loop.
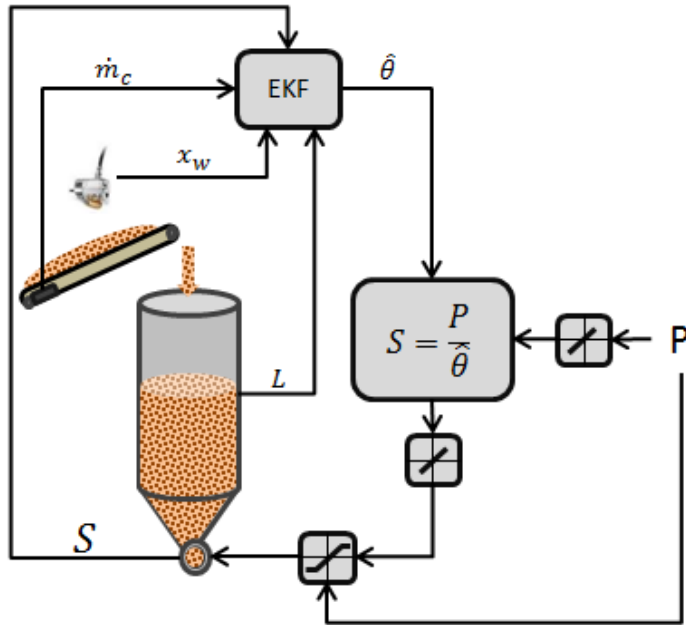
Figure 7: Online EKF based feedrate control.

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 to Figure 6).
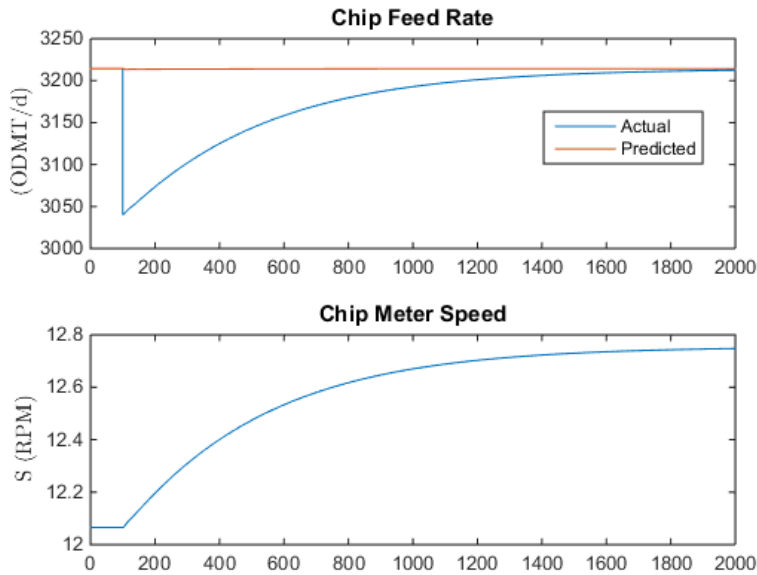

Figure 8: Dry feed rate control response to 10 kg/rev step.

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 issue 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 are traditionally 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 behaviour, 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 ADMT/d Canadian hardwood Kraft mill. Both the EKF and controller were implemented in the mills Honeywell DCS.

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 impacting the level. Figure 9 shows an 8 hour trend that compares the chip bin dry mass inlet (from Figure 3) and outlet flows. Note that the outlet flow is estimated via the product $\hat{\theta}S$ (see Equation (3)). The impact of the level control is effectively removed, providing a better representation of the dry mass flow of chips fed to the digester.
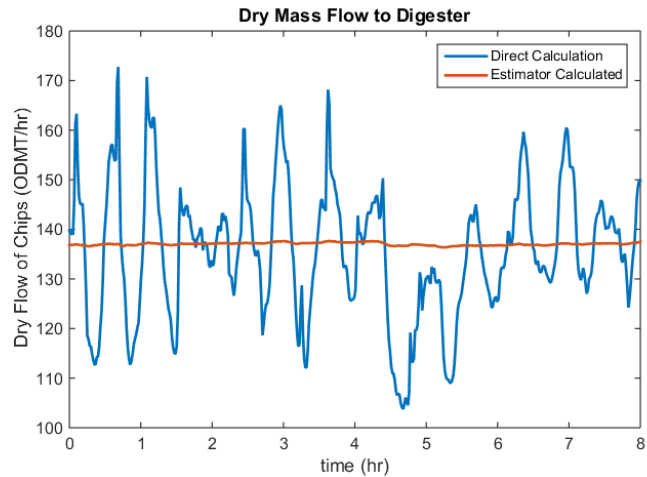

Figure 9: Eight hour trend of dry mass inlet and estimated outlet flow.

Data from the EKF output over a longer time frame, as shown in Figure 10, reveals 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.
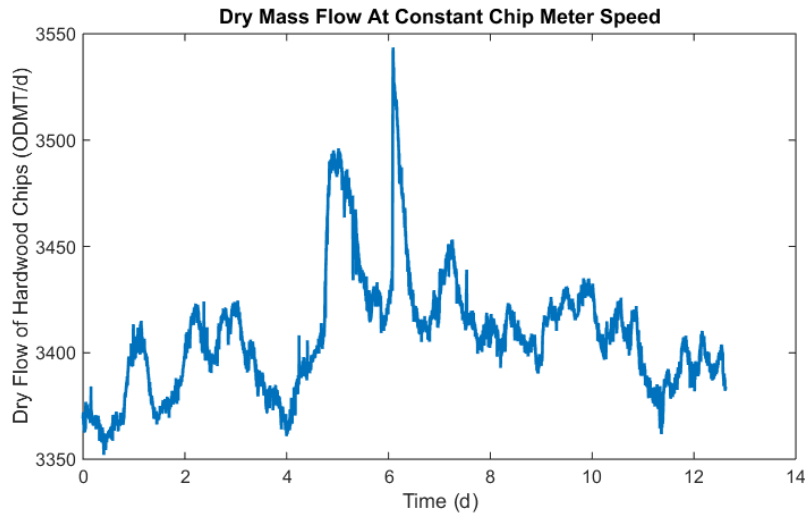
Figure 10: Long term trend of estimated dry mass flow at constant chip meter speed.

Control Implementation

A 60 day trial was conducted with the final implementation of the chip feed rate controller shown in Figure 7. The controller performance is evaluated against a 50 day period from the previous year. The results, shown in Figure 11, are normalized by the feed rate target. For the period prior to the implementation of the EKF the control feed rate was found to vary significantly during the period, and typically resulted in an actual feed rate lower than targeted. Production rates greater than 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 based on the relatively short run time to-date, but if we assume that a 1% increase in production is sustainable, then for the current hardwood spot price of $500US/t (RISI database – February 2017) this improvement would be worth $3.5M/y in increased revenue to the mill. Additionally the feedrate to the digester is stabilized. Better control of the feed rate 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.
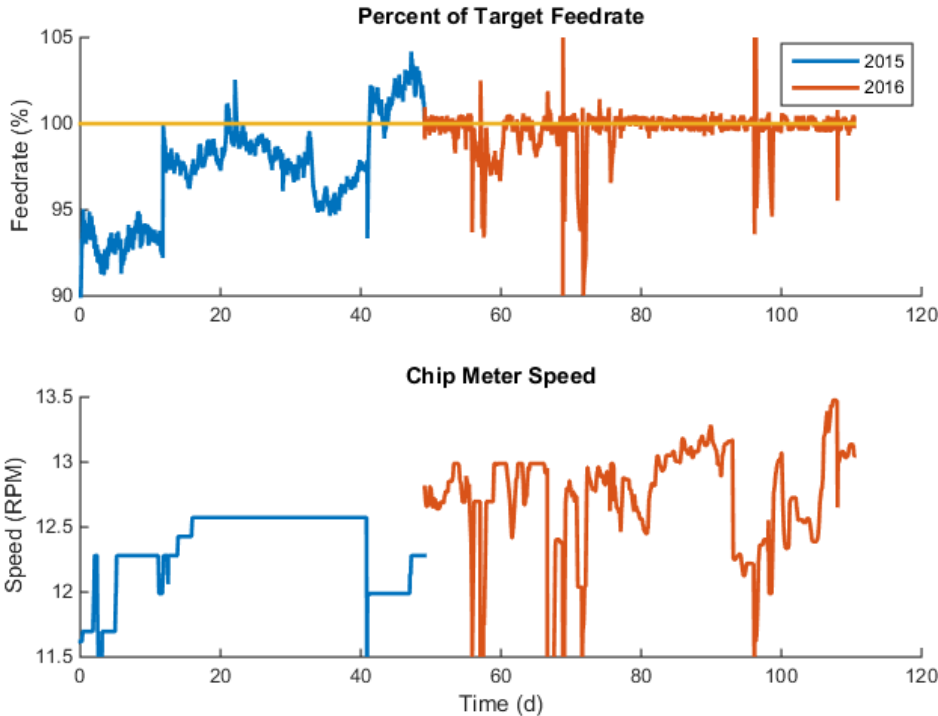
Figure 11: Comparison of feedrate for constant chip meter vs. EKF control.

CONCLUSIONS

In this report, a new continuous digester dry chip feedrate control strategy was designed and implemented on a dual vessel digester. The new strategy is based on a non-contacting 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. Since 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 ADMT/d 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 $3.5M/y 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.

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APPENDIX

Extended Kalman Filter (EKF)

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:

$$x = \begin{bmatrix} L & x_w & \dot{m}_c & S & \theta \end{bmatrix}^T \tag{A1}$$

Equation (4) can then 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 behaviour. 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:

$$y = \begin{bmatrix} L & x_w & \dot{m}_c & S \end{bmatrix}^T \tag{A4}$$

This leads to the linear observation matrix C:

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

(A5)

Equations (A2), (A3) and (A5) define the state space model.

State Estimation via an EKF. Consider the general nonlinear model for the process dynamics arising from unsteady-state material balances:

$$\dot{x}(t) = g\big(x(t), u(t)\big)$$
$$y(t) = h\big(x(t), u(t)\big)$$

(A6)

where g and h are vectors of nonlinear functions. The idea behind the 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 (A6) are linearized about the current conditions, x(t) and u(t), and discretized to yield a linear, discrete-time model of the form:

$$x(k+1) = Ax(k) + Bu(k) + w(k)$$
$$y(k) = Cx(k) + v(k)$$

(A7)

Here, the time argument k refers to the current discrete-time sampling instant corresponding to time t_k 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 $R_v = cov\{v(k)\}$, 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 kth sampling interval, the current estimate of the state vector, using all the available information at that time, is $\hat{x}(k|k)$, and the errors associated with this estimate have a covariance matrix $P(k \mid k)$. The EKF uses the linearized model to make a one-step ahead prediction of the state estimate using the available information:

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

(A8)

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

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

(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:

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

(A10)

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

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

(A11)

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

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

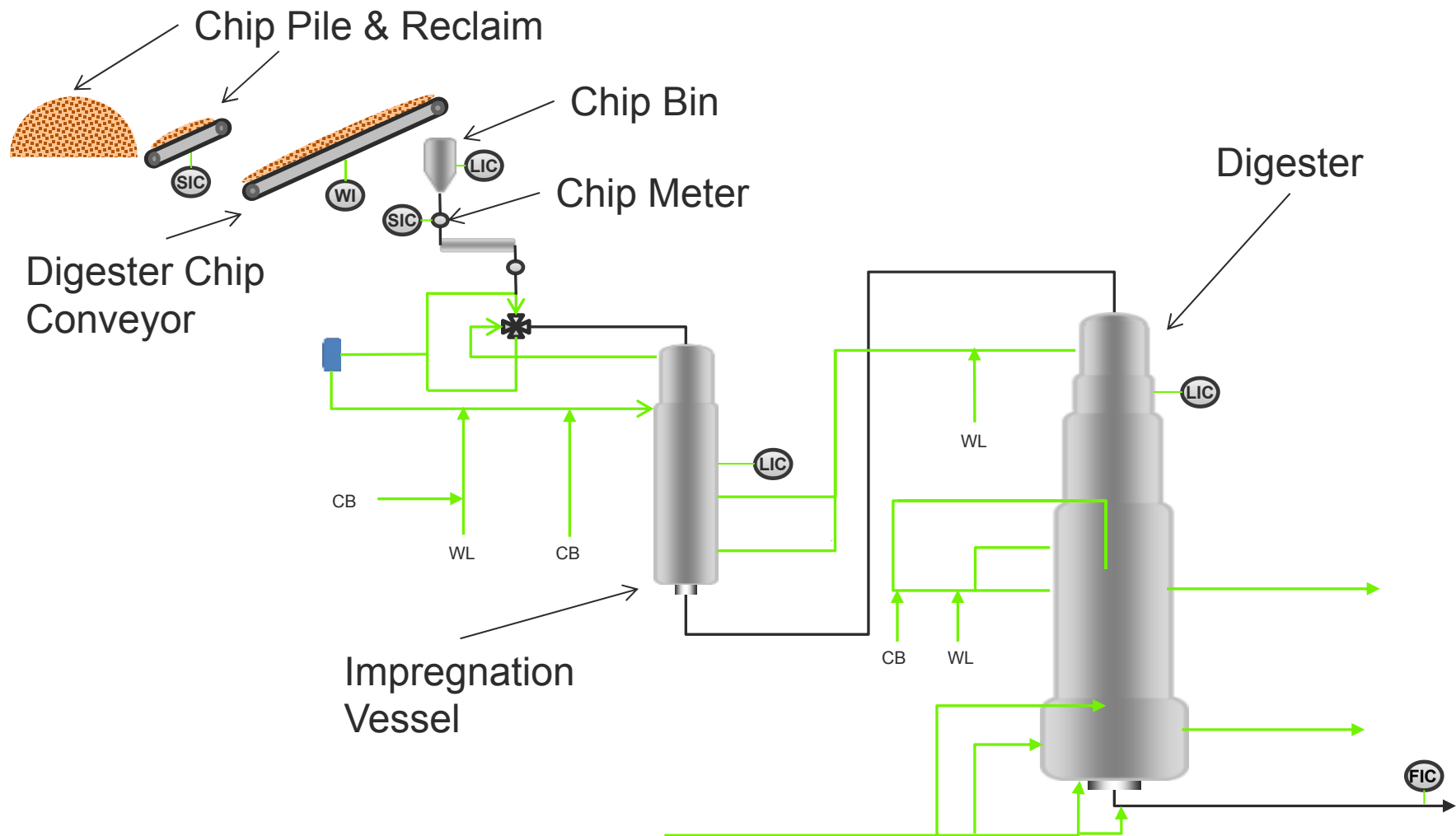and both $\hat{x}(k + 1|k + 1)$ and $P(k + 1|k + 1)$ are stored for the next interval. Equations (A8) to (A12) define the EKF.

Overview

- Review existing digester chip metering
- Discuss improvements based on new biomass sensing
- Results & discussion

Continuous Digester

Chip Pile & Reclaim

Chip Bin

Digester

Chip Meter

Digester Chip Conveyor

SIC

WI

LIC

SIC

LIC

WL

LIC

CB

WL

CB

CB

WL

Impregnation Vessel

CB

WL

FIC

Importance of Chip Feedrate

- Sets production rate
- Cooking chemical dosing
- H-Factor (or temperature profile)
- Relative chip/liquid flow profile

Conventional Feed Determination

- Chips are metered into the digester
  - Rotary star feeder
  - Screw
- Chip flow (T dry chips/d)
  - Chip meter speed (known)
  - Feed pocket size (fixed)
  - Pocket fill factor (assumed)
  - Wet bulk density (assumed)
  - Moisture (assumed)

Wood Room

Chip Meter RPM

To LPF
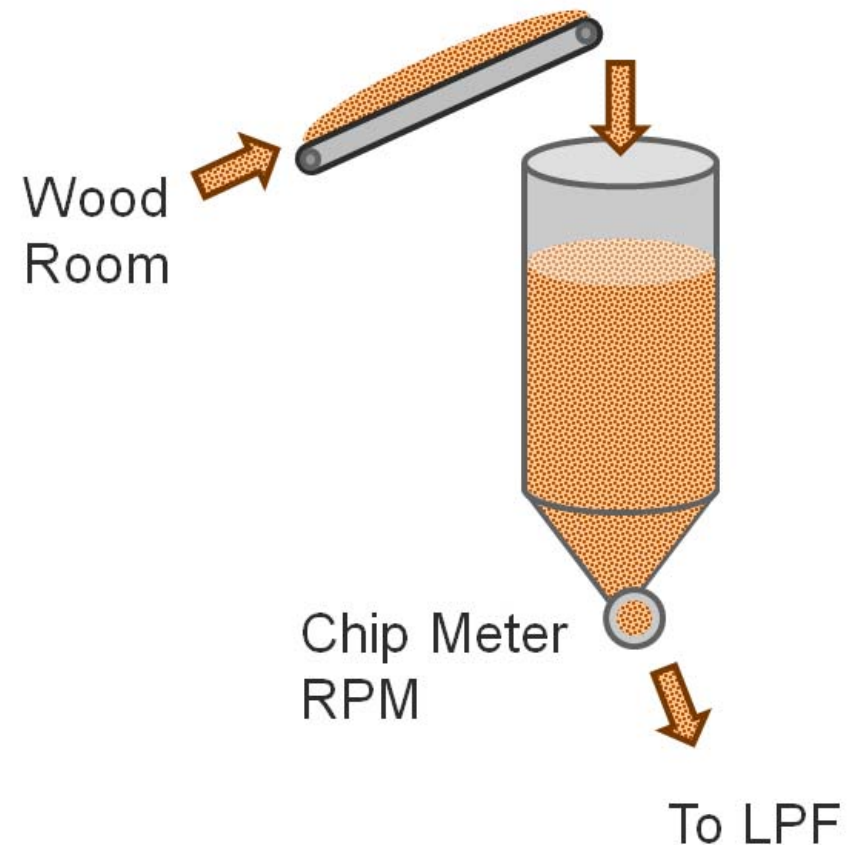
Validity of Assumptions?

- Wet Bulk Density/Fill factor
  - Chip size distribution
  - Chip shape
  - Moisture
  - Seasoning (Extractives)
  - Frozen/Thawed
- Moisture
  - Seasoning (Drying)
  - Frozen/Thawed

Impact of Assumptions

- Potential loss of production rate
- Increased pulp quality variability
    - EA to wood dosing
    - H-Factor
    - Liquor to wood
        - EA concentration
        - Hydraulics

New Opportunity

- Chip moisture no longer needs to be assumed

- Online dry mass flow

  - Chip conveyor weightometer
  - Chip moisture sensor

8
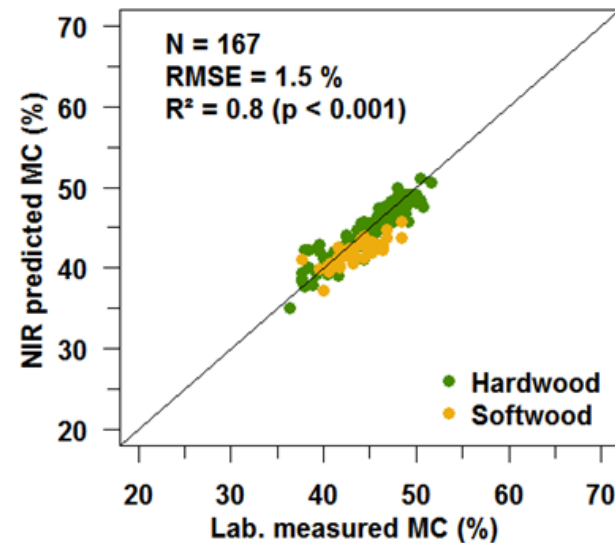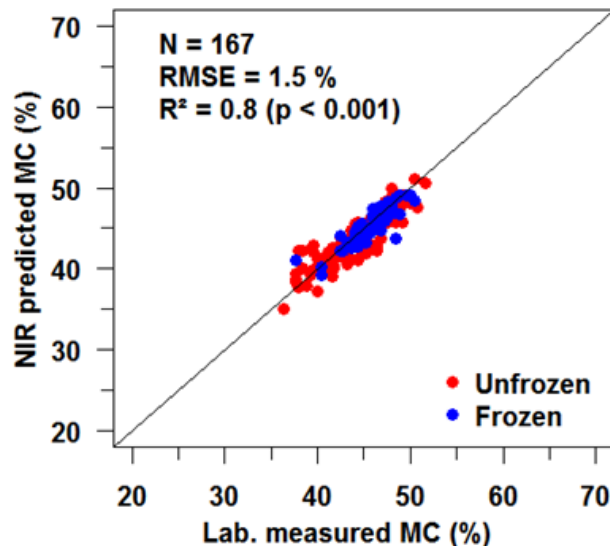
Calculating Dry Mass Flow

$$W \times \left(\frac{100 - \%M}{100}\right)$$

Dry Chip Flow

Direct Calculation of Dry Mass Flow

9
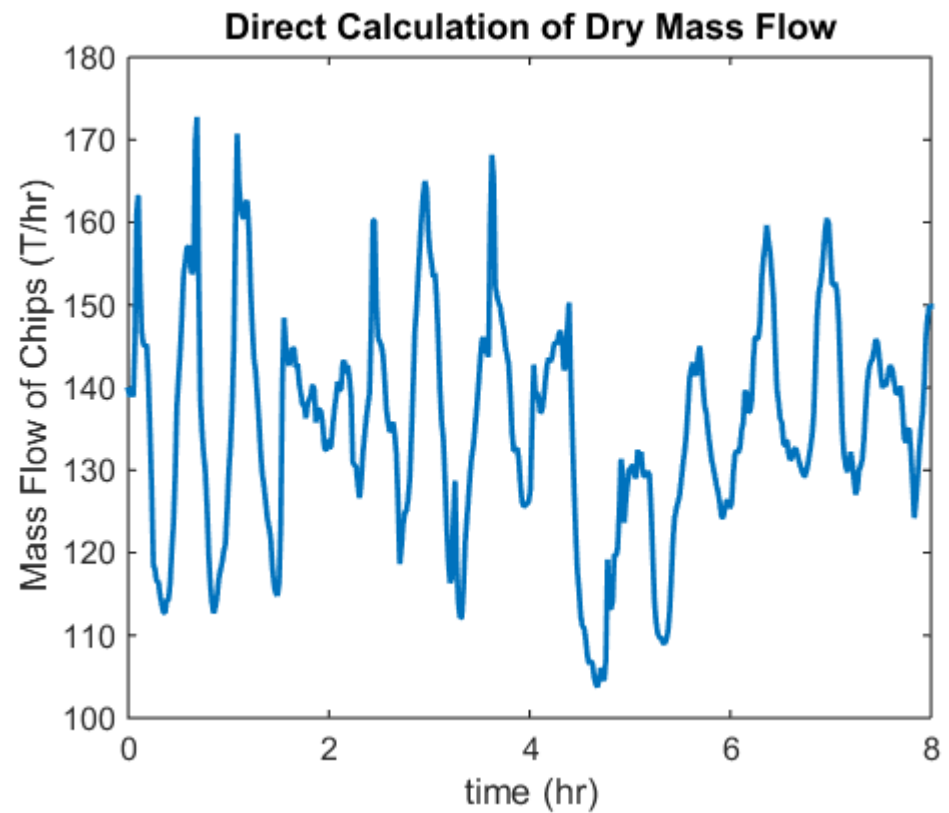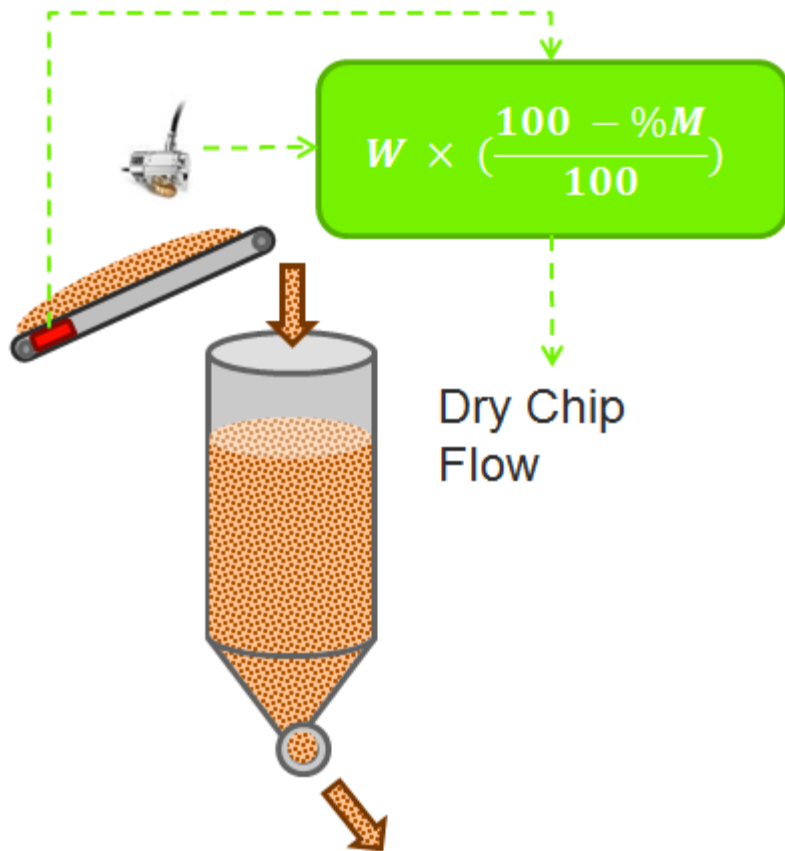
Impact of Chip Bin Level

Chips from pile

Chips to Digester?

Chip Bin Level Trend

Level
Target

Chip Bin Control Output

Dry Mass Flow Trend

Time (hr)
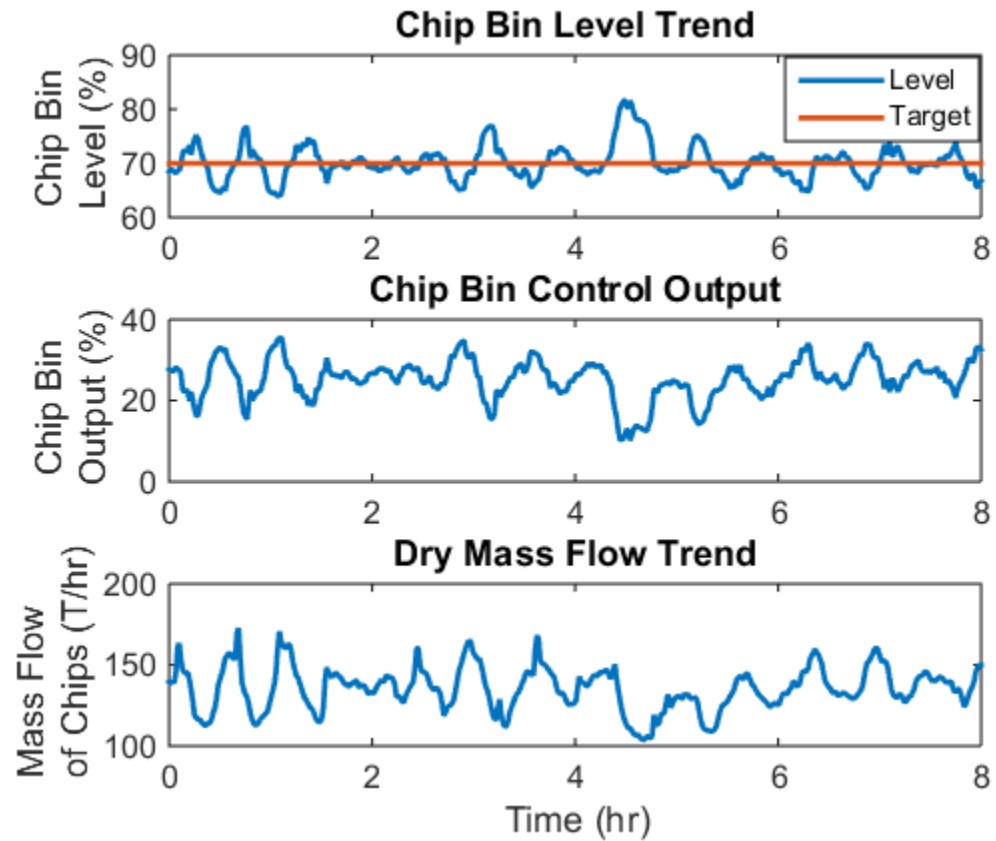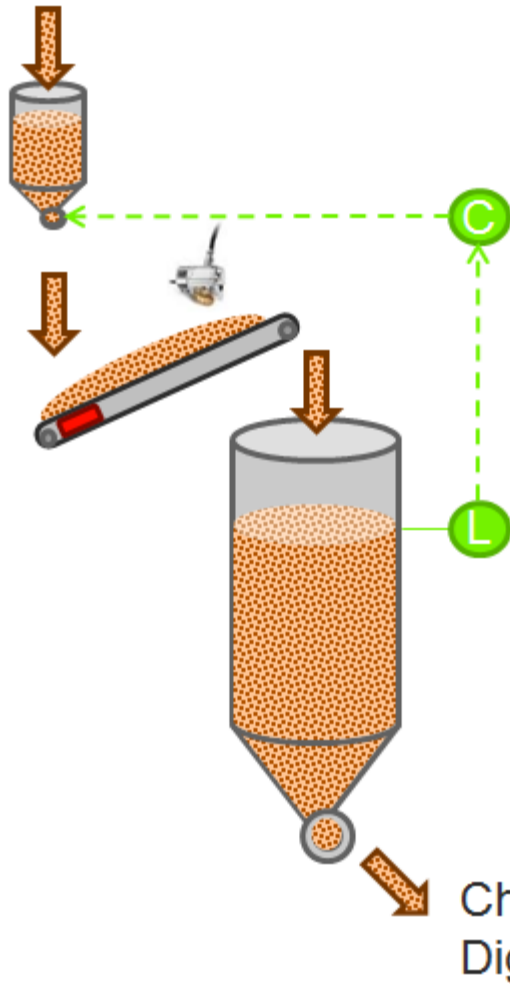
Problem

- Measurements are on wrong side of the chip bin
  - Weightometer is impacted by chip bin level controller
- Multiplication of noisy measurements

Solution

- Fusion of dynamic modeling techniques, filtering and estimation
- Outputs dry mass per revolution of chip meter (kg/CM rev)
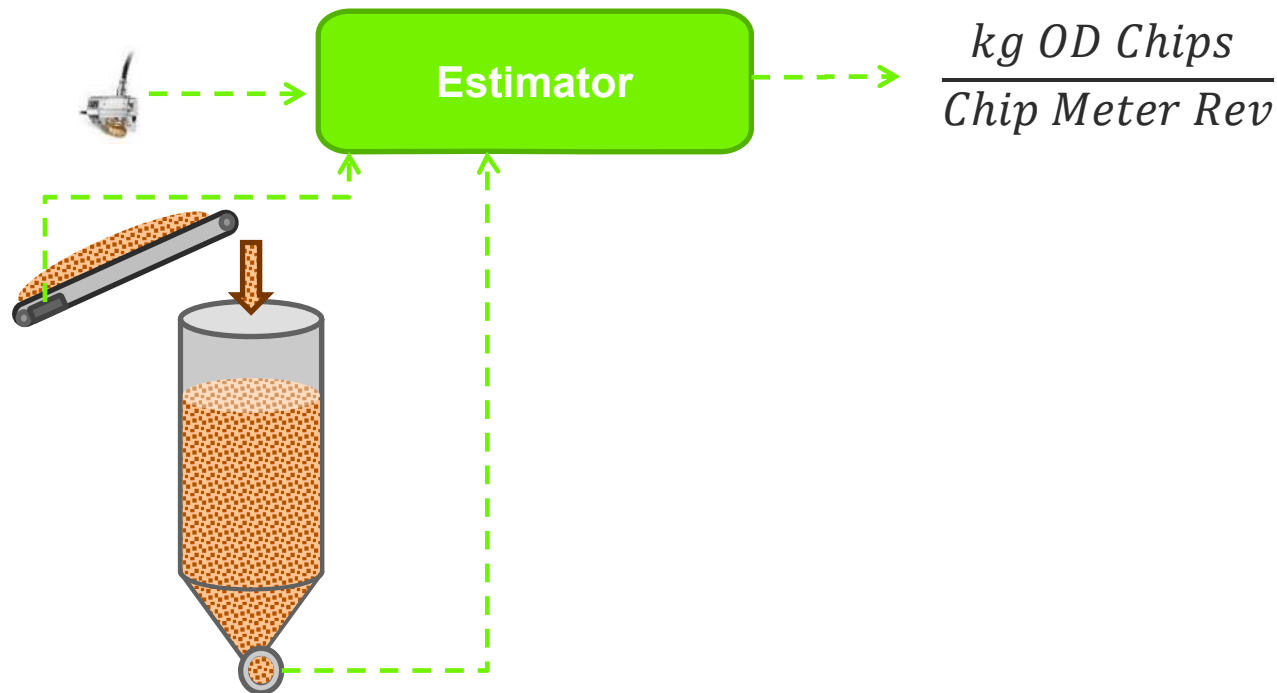
Solution Part 1 – Dynamic Model

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

Measure Variables

x_w = Mass fraction water

$\dot{m}_c$ = Mass flow wet chips

S = Chip meter speed

Unknown Variable

θ = Dry mass of chips per revolution

Constants

ρ_{bd} = Dry bulk density

A = Chip bin cross section areas

Solution Part 2 - Kalman Filter

Extended Kalman Filter
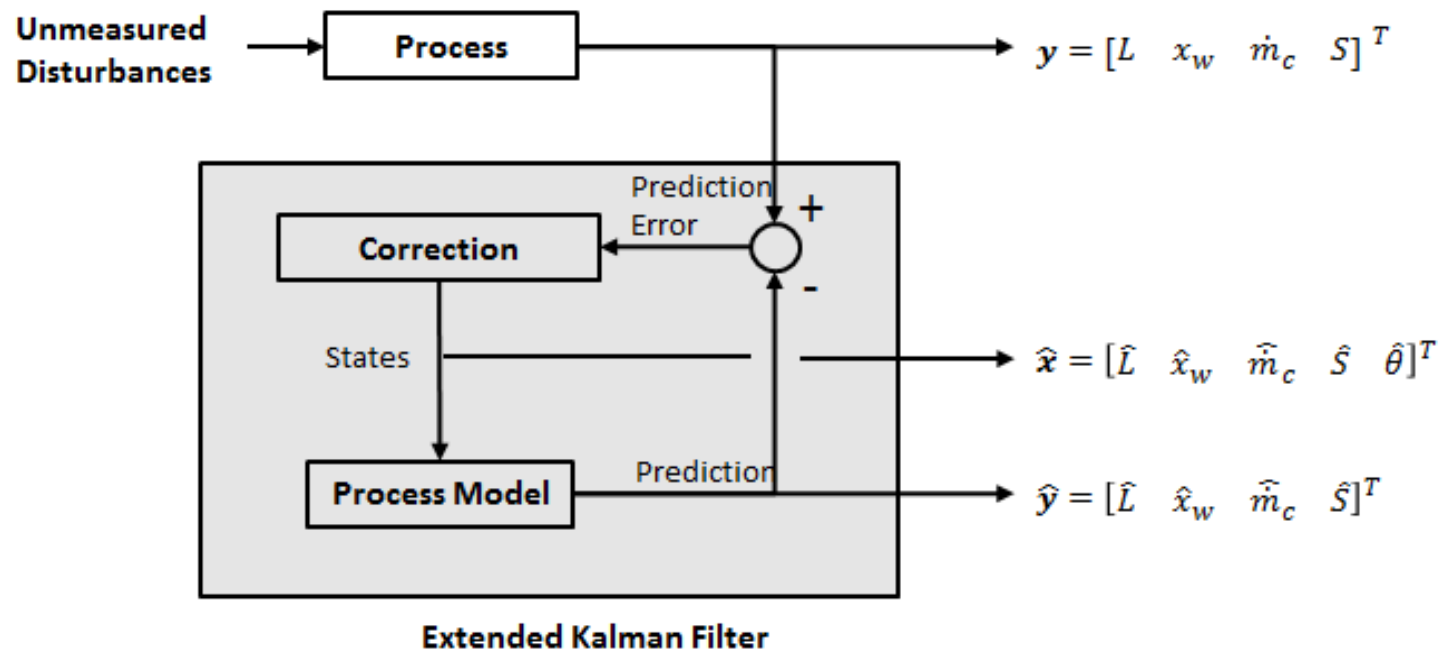
Solution
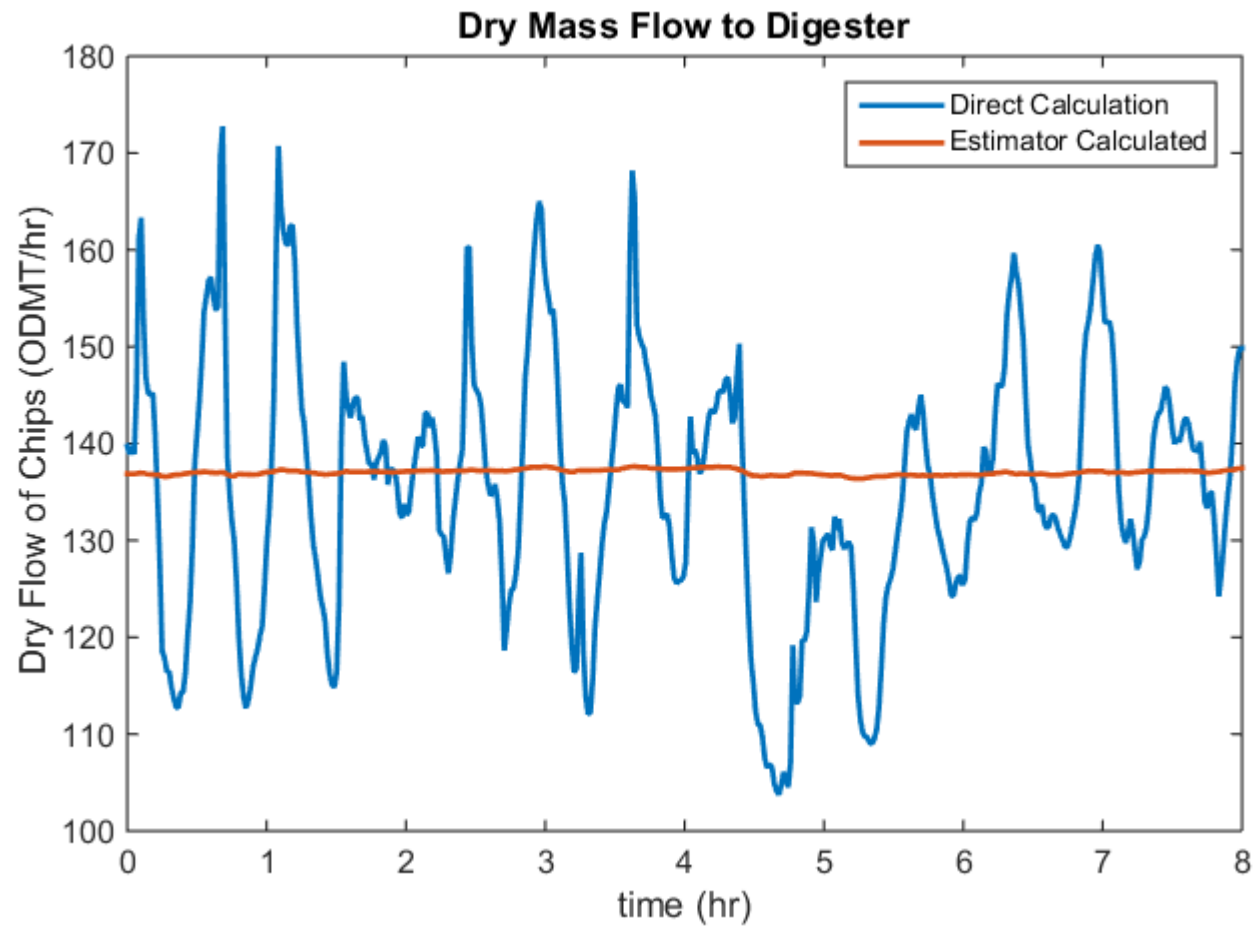
Validation of Assumptions
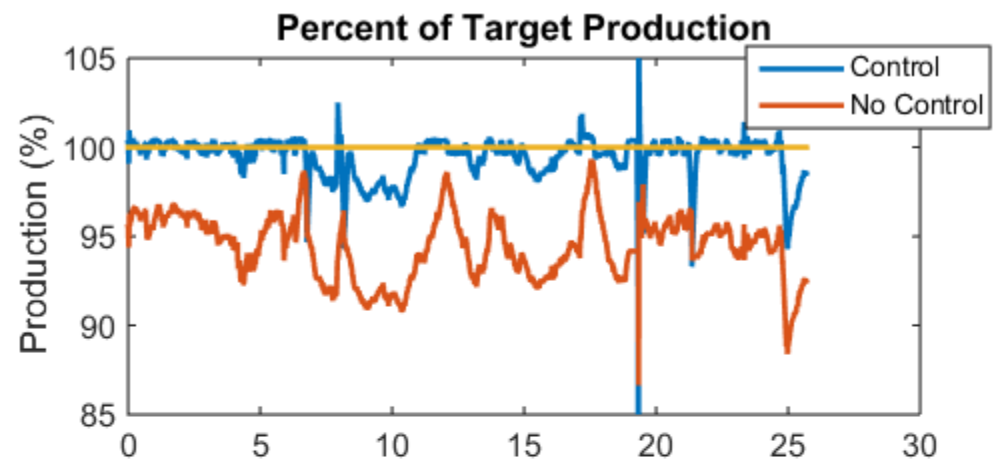

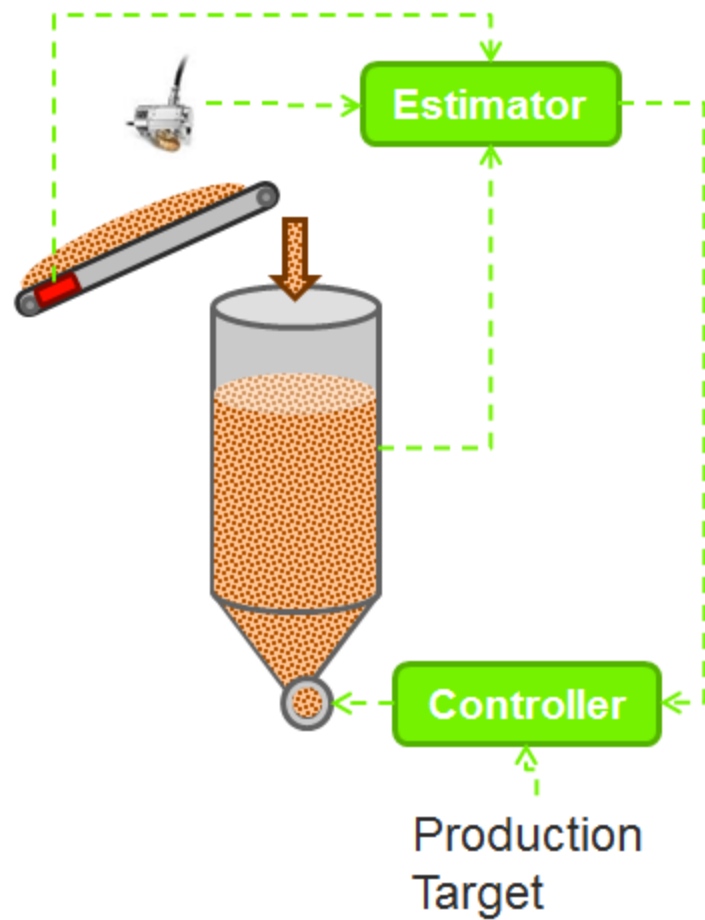Dry Mass Flow At Constant Chip Meter Speed
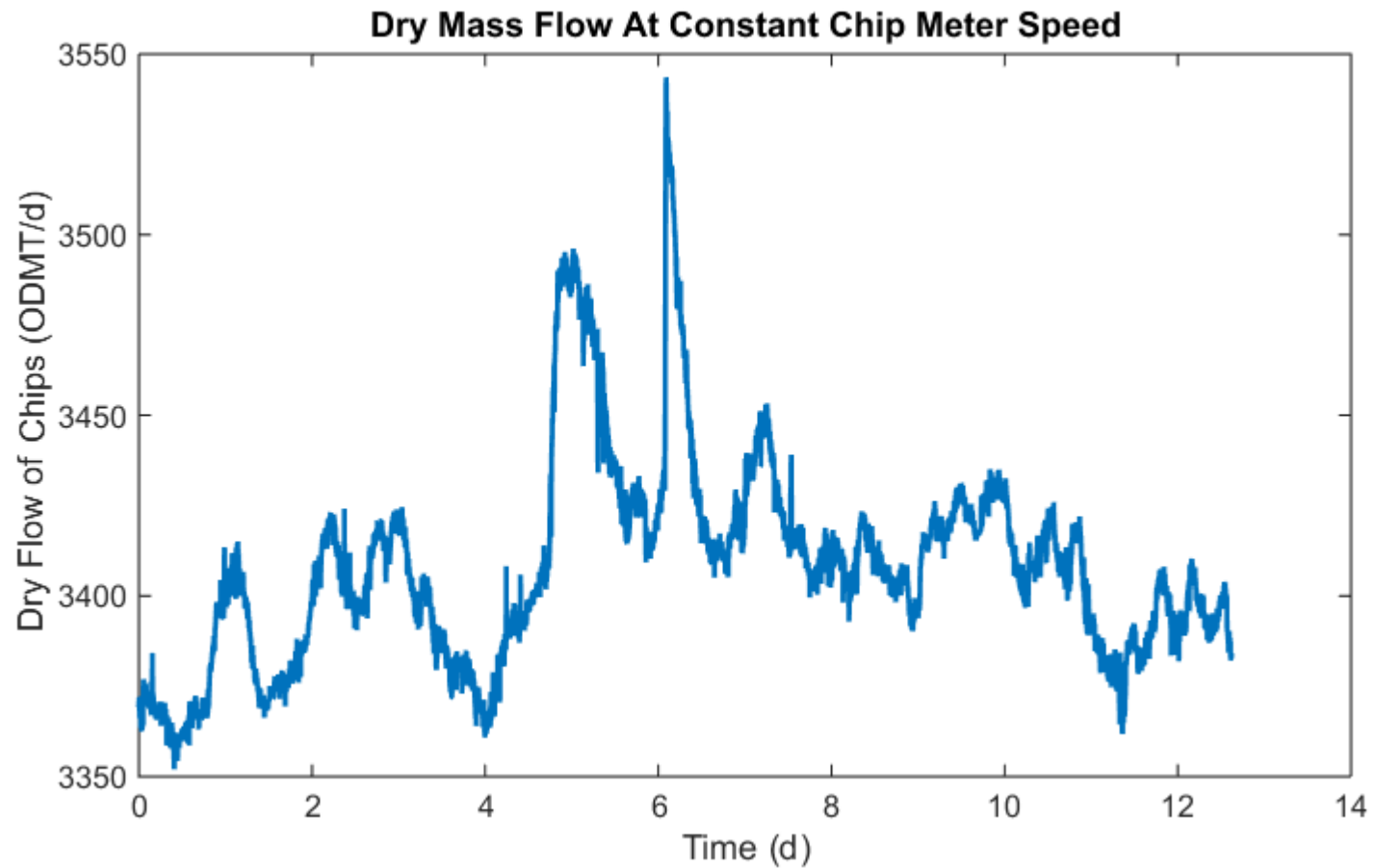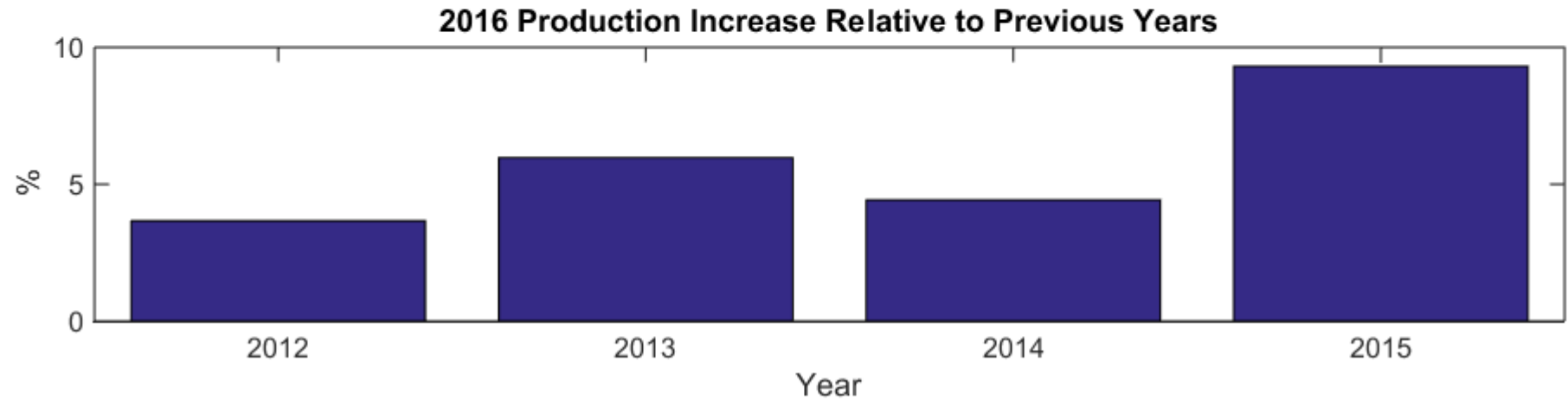
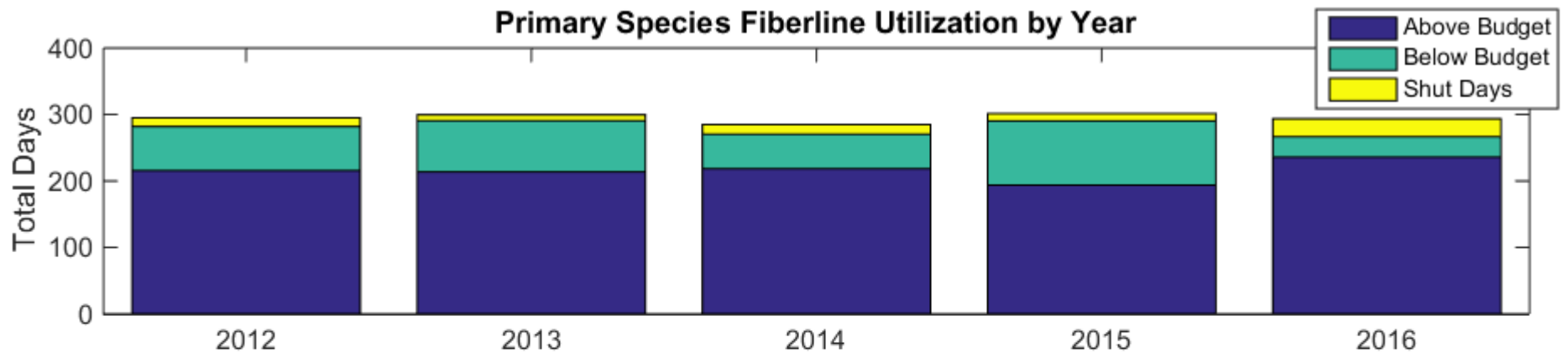**Assumptions are poor!**

Comparison of Control
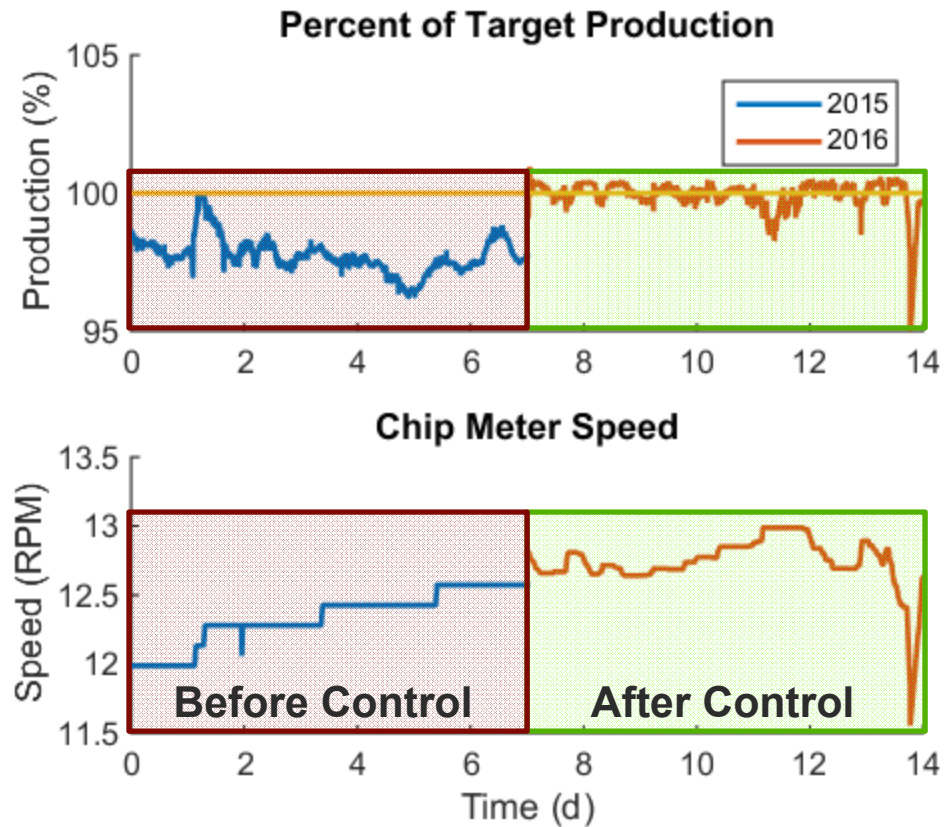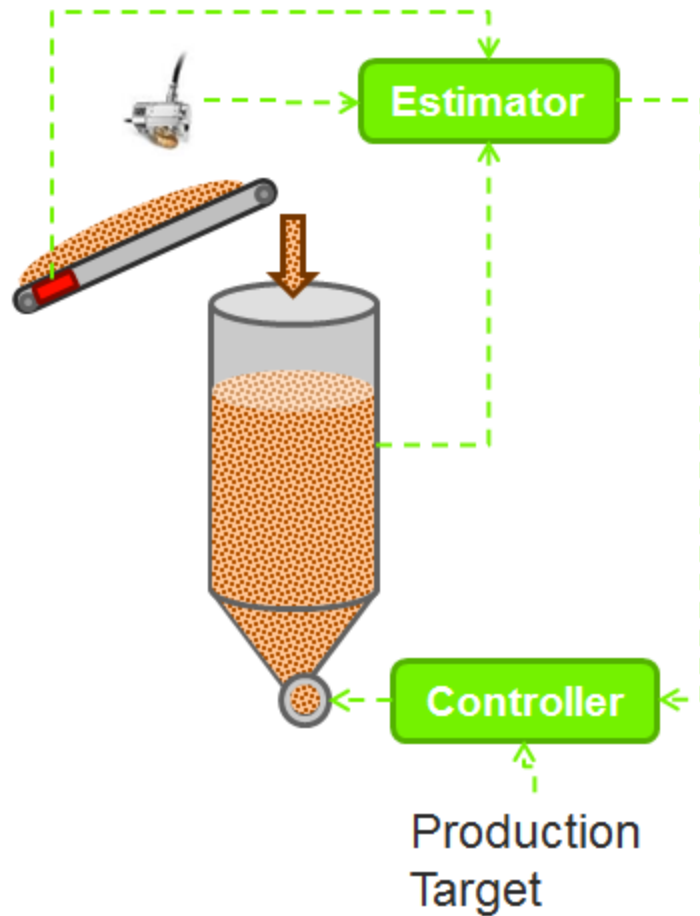
Dry Mass Flow Control
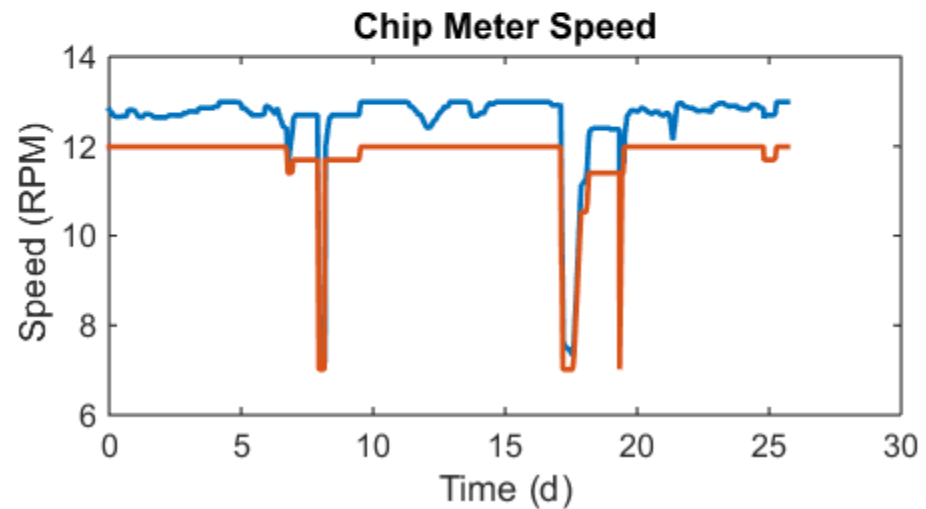
Machine Rate

Summary

- Chip meter fill factor is continuously changing
    - Potential loss of production
    - Increased product/process variability
- Determination of online dry flow of chips is done using a weightometer and chip moisture measurement
- Use estimation techniques to compensate for measurement location
- 1 year trial benefits
    - ~4% production increase
    - Improved fiberline operation

PEERS
November 5-8, 2017
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