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***Abstract*—Knowledge of moisture content in raw coal feed to a power plant coal mill is of importance for efficient operation of the mill. The moisture is commonly measured approximately once a day using offline chemical analysis methods; however, it would be advantageous for the dynamic operation of the plant if an on-line estimate were available. In this paper we such propose an on-line estimator (an extended Kalman filter) that uses only existing measurements. The scheme is tested on actual coal mill data collected during a one-month operating period, and it is found that the daily measured moisture content agrees with the estimates.**

I. Introduction

On the liberalized power market in the European Union, dynamic operation of fossil fuel power plants is of ever-increasing importance. Fast and efficient control of the power output from such plants relies to a large degree on being able to control the coal mills feeding fuel into the furnace well. The operation range of a power plant coal mill depends among other things on the moisture content of the incoming raw coal. In fact, the moisture content imposes limits on the minimum load at which the coal mill may be operated and how fast the mill may change its operating point. However, as the moisture is bound within the raw coal, offline chemical analysis is required to measure the water content reliably; typically, only one daily offline measurement is made of the moisture in the raw coal, preventing the measurement from being used in control.

In this paper, we propose an on-line coal moisture estimator to be used by power plant operating personnel, so that they may take the moisture into consideration when planning the plant operation. The proposed estimator uses already existing measurements near the coal mill along with a dynamic coal mill model to estimate the moisture content—see Figure 1. Dynamic models of coal mills are treated in numerous papers e.g. [1], [2], [3] and [4]. In these papers it is generally assumed that all moisture evaporates within the coal mill; in practice, however, this assumption does not always hold, as it requires a high inlet primary air temperature (typically at least 95°C).

Models for evaporation flow in similar processes may be found in literature, see for instance [5], where evaporation is treated as a combination of diffusion from the internal of particles to the surface and evaporation from the surface. The driving force for the evaporation is the difference between partial pressure of water at the particle surface and the partial pressure of water in the gas. Here, it is assumed that the internal diffusion is dominated by the grinding, such that the evaporation from the surface is the only interesting mechanism.

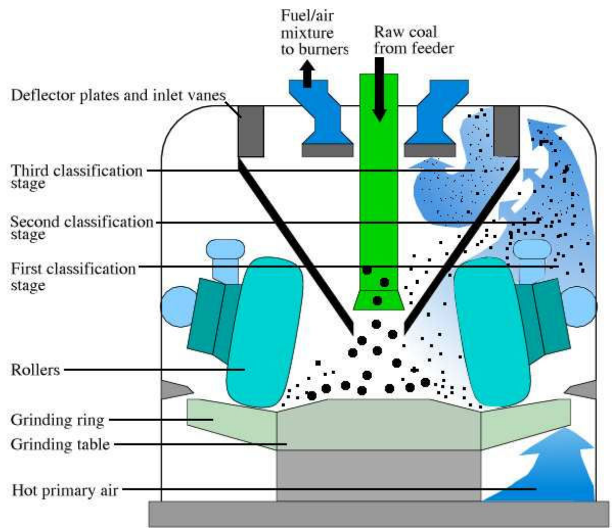

Fig. 1. Sketch of vertical spindle coal mill. The measured quantities in the mill are the inlet primary air flow m_{pa} and temperature T_{pa}, the raw coal flow from the feeder, m_c and the temperature inside the mill, T_m.

In the design presented here, we address the incomplete evaporation by identifying the evaporation flow as a function of the mill temperature and coal input flow, both of which are measured variables. The determination of this function is not straightforward, since the moisture content is not measured at neither the inlet nor the outlet of the mill. In order to find the evaporation function, we exploit the fact that there are several coal mills operating in parallel, which over a period of time are assumed to have approximately the same moisture content. Furthermore, it is assumed that when dynamic model inputs such as the hot air flow change quickly, the moisture content is unlikely to change. Carefully selected data sequences are used to find a parameter estimate for the desired function, which is then used in an extended Kalman filter-based design.

The outline of the rest of this paper is as follows: As a motivation for estimation of coal moisture, we first discuss the influence of coal moisture on the power plant load and load gradient. Then the model used in the estimator is presented, and the determination of the evaporation function is described.

Finally the Kalman estimation algorithm is explained and results are shown.

II. Moisture Influence on Plant Production

As mentioned above, the coal moisture content imposes bounds on the possible power plant load as well as the allowable load gradient.

As shown in Figure 1, hot primary air is used to transport sufficiently finely ground coal particles out of the coal mill, while too coarse particles are circulated back to the grinding table within the mill. This separation of particles is achieved by exploiting different air velocities within the mill as well as a rotating classifier, which acts roughly like a sieve. The primary air also provides heat for drying out the coal particles. The primary inlet temperature is controlled by merging cold air and air preheated in a heat exchanger using flue gas near the flue gas outlet. The ratio is controlled to keep a reference mill temperature near $100°$C. However, as also mentioned above, it may occur that the reference mill temperature cannot be maintained due to insufficient air heater power.

It is assumed that the available heat in the primary air depends on the power plant load, for instance given by the boiler power P_b, an expression of the actual power plant operation mode and the quality of the coal, whereas the coal moisture itself has little influence on the available power. The available power in the primary air may be calculated from temperature and flow measurements.

Let γ represent the current percentage of moisture in the coal and let γ_{res} denote the residual moisture in the coal leaving the coal mill and entering the plant furnace. With a given available power from the air heater, P_{ah}, the coal flow m_c must obey the inequality

$$P_{ah}(P_b) \geq P_{evap}(P_b, \gamma) = (\gamma - \gamma_{res,max}) m_c L \tag{1}$$

where $P_{ah}(P_b)$ is the power in the primary air at the plant boiler power P_b, L is the latent heat of water (a material constant) and $\gamma_{res,max}$ is the maximum residual moisture allowed into the furnace.

Assuming all the energy from the air heater is used for evaporation, we have $P_{ah} = c_a(T_{pa} - T_m)m_{pa}$, where c_a is the specific air heat capacity, T_{pa} is the primary air temperature and m_{pa} is the primary air flow. In normal operation the obtainable temperature level T_{pa} will decrease at lower plant load, meaning that the available power P_{ah} will decrease faster than the power P_{evap} that is necessary to evaporate the coal moisture at low load. Clearly, this implies that there will be a minimum load (depending on coal moisture and plant operation mode), where the residual moisture reaches $\gamma_{res,max}$.

Figure 2 illustrates this principle; $P_{ah}(P_b)$ is shown together with graphs for $P_{evap}(P_b, \gamma)$ at different values of γ. As can be seen, less moisture content in the coal allows lower load operation of the plant. An estimate of the coal moisture thus provides an opportunity to predict the lowest possible low boiler load if the residual moisture of the coal entering the boiler furnace should not exceed a certain maximum value.

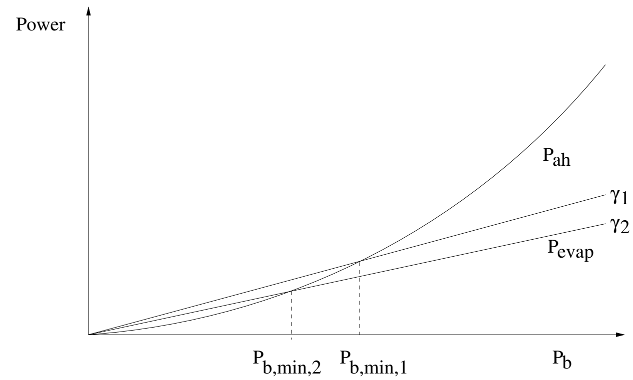

Fig. 2. Available power, P_{ah}, and evaporation power at moistures γ_1, γ_2.

Power plants often operate with more than one coal mill active at a time (typically up to four). This implies that if N mills are active, (1) should be rewritten as

$$P_{ah}(P_b) \geq \sum_{i=1}^{N} (\gamma_i - \gamma_{res,max}) m_{c,i} L \tag{2}$$

which indicates that a lower load may be reached for the coal mills with the lowest coal moisture (the mills are not filled with coal at the same time meaning that there may be different coal moistures in the different coal mills).

As mentioned in the previous section, the moisture also influences the dynamical properties of each mill. This is because a variation in the coal flow will not be reflected in the accessible power in the primary air heater until after some time. The dynamics from a change in coal flow to a change in primary air temperature thus depends on the dynamic properties of the boiler. To illustrate this effect, we consider the coal flow at time t and assume the boiler dynamics can be described as a time delay t_d. Then we have (with $N = 1$ for simplicity):

$$P_{ah}(P_b(t)) = P_{ah}(m_c(t - t_d)) \geq (\gamma - \gamma_{res,max}) m_c(t) L$$

Assuming that $P_{ah}(m_c)$ and t_d are known, we may be approximate $P_{ah}(m_c(t - t_d))$ by

$$P_{ah}(m_c(t - t_d)) \approx P_{ah}(m_c(t)) - \frac{dP_{ah}}{dm_c} \frac{dm_c}{dt} t_d$$

Inserting and rearranging gives

$$\frac{dm_c}{dt} \leq \frac{P_{ah}(m_c(t)) - (\gamma - \gamma_{res,max}) m_c(t) L}{t_d \frac{dP_{ah}}{dm_c}}$$

which clearly imposes a γ-dependent upper limit on the power plant boiler's admissible production gradient.

III. Dynamic Coal Mill Model

The model employed for the estimator is based on an energy balance for the total coal mill combined with a mass balance for the water (moisture) contained in the coal in the mill.

$$\begin{aligned} M_m C_m \frac{dT_m}{dt} &= m_{pa} c_a (T_{pa} - T_m) \\ &\quad + m_c c_c (T_a - T_m) + \gamma m_c c_w T_a \qquad (3) \\ &\quad - \gamma_{res} m_c c_w T_m - m_{evap} H(T_m) \\ M_c \frac{d\gamma_{res}}{dt} &= \gamma m_c - m_{evap} - \gamma_{res} m_c \qquad (4) \end{aligned}$$

where c_a, c_c and c_w denote the specific heat of air, coal and water, respectively, and T_a is the coal inlet temperature, which is considered equal to the ambient temperature. $M_m C_m$ is the heat capacity of the matter heated to the mill temperature T_m including the air, coal particles and some parts of the mill metal. The term $m_{pa} c_a (T_{pa} - T_m)$ is the net power supplied by the primary air, $m_c c_c (T_a - T_m)$ is the net power from the coal flow, and $\gamma m_c c_w T_a$ is the inlet power originating from the moisture in the raw coal. $\gamma_{res} m_c c_w T_m$ is the power leaving the coal mill contained in the coal particles. Finally, $m_{evap} H(T_m)$ is the power from the evaporation of the moisture, where $H(T_m)$ is the water outlet enthalpy. M_c denotes the coal mass.

The model parameters c_a, c_c, c_w are well known physical constants, while $H(T_m)$ is known from water and steam properties. In the lumped parameter heat balance the heat capacity $M_c C_m$ represents heat capacity of coal and air as well as metal parts with good thermal contact with coal and air; this quantity can be considered as a design parameter, which can be tuned to fit data series where the primary air temperature and/or primary flow is changing.

The most difficult term to evaluate is m_{evap}, since it depends on the mill temperature, the moisture partial pressure, as well as the coal and air flow. In the following, it is assumed that it may be expressed on the form

$$m_{evap} = \gamma_{res} m_c f(T_m) \qquad (5)$$

where the function $f(T_m)$ will be parameterized and found from coal mill measurements as described in the following section.

IV. Determination of the Evaporation Function

We first make the following observations.

- Since the pressure in the mill is close to atmospheric pressure, we can expect full evaporation at a mill temperature just below 100°C.
- If the temperature in the mill drops below a saturation temperature T_{sat}, no evaporation occurs.
- No on-line measurements the real coal moisture content are available the evaluation of the evaporation must rely on secondary observations.
- Since the moisture content in inlet coal is independent of m_c and m_{pa}, the moisture content can be expected to be roughly constant during short periods where one or both of these quantities change.
- During time intervals where the plant operates at approximately steady state conditions, the coal moisture contents in each of the active coal mills is assumed to be roughly equal.

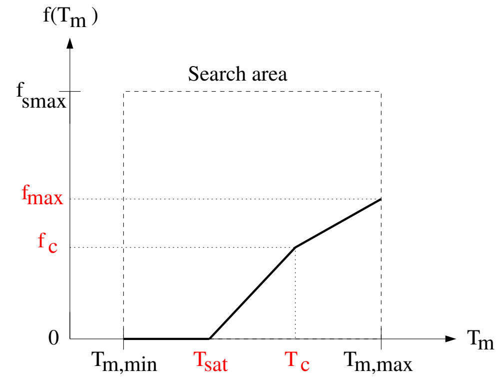

Fig. 3. A candidate for the evaporation flow function $f(T_m, \theta)$

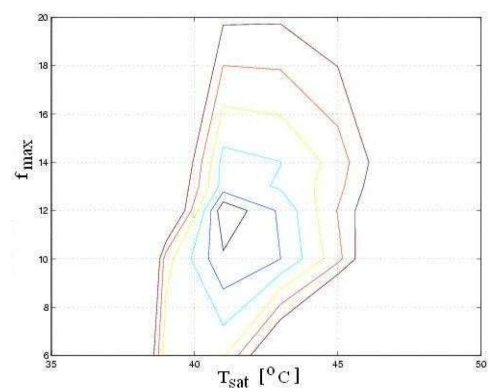

Fig. 4. Contours of best values varying T_{sat} and f_{max} in a grid

We parameterize $f(T_m)$ as a continuous piecewise affine function described by three connected lines, as follows.

$$f(T_m) = \begin{cases} 0 & \text{if } T_{m,min} < T_m < T_{sat} \\ f_c \frac{T_m - T_{sat}}{T_c - T_{sat}} & \text{if } T_{sat} < T_m < T_c \\ \frac{(f_{max} - f_c)(T_m - T_c)}{T_{m,max} - T_c} + f_c & \text{if } T_c < T_m < T_{m,max} \end{cases} \qquad (6)$$

The function $f(T_m)$ is sketched on Figure 3. The value of T_{sat} must necessarily be close to the dew point at the corresponding partial pressure (around 30 °C). The value of f_{max} should reflect the evaporation function at high temperatures. $T_{m,max}$ is near the boiling temperature in the mill.

As can be seen, the function has 4 parameters. We collect these in the parameter vector $\theta = [T_{sat}, T_c, f_c, f_{max}]^T$, which is restricted to belong to the hypercube $\Theta = [T_{m,min}; T_{m,max}]^2 \times [0; f_{s,max}]^2$.

Inspired by the observations above, the evaporation function $f(T_m)$ is determined from a series of time-matched data intervals in which the coal mill operation is roughly steady state. More specifically, define a number of sample intervals $\mathcal{T}_i = [\underline{t}_i \; ; \; \bar{t}_i], 0 \leq \underline{t}_i < \bar{t}_i \leq t_{max}, i = 1, 2, \ldots, \nu$, and collect samples $(T_m(t), T_{pa}(t), m_c(t), m_{pa}), t \in \cup_{i=1}^{\nu} \mathcal{T}_i$ for each of the coal mills in the power plant where the plant is operating in steady state.

Given a candidate evaporation function it is possible to determine a value of the moisture content $\gamma_{i,j}$ for the j'th mill for each time interval $\mathcal{T}_i$, which satisfies the combined steady state energy and mass balances (3) and (4):

$$0 = Q_a - \gamma_{i,j} Q_b, \qquad i = 1, \ldots, \nu, j = 1, \ldots, N \quad (7)$$

where Q_a and Q_b are defined by

$$\begin{aligned} Q_a &= m_{pa} c_a (T_{pa} - T_m) + m_c c_c (T_a - T_m) \\ Q_b(\theta) &= -m_c c_w T_a + \frac{m_c (c_w T_m + f(T_m, \theta) H(T_m))}{1 + f(T_m, \theta)} \end{aligned}$$

A value of γ found for one mill in one time interval cannot be expected to satisfy the corresponding energy balances for the other mills or for any of the mills in other time intervals. However, as the observations above suggest, this imbalance should be as small as possible for different mills in the same interval or for the same mill at time intervals immediately before and after a transient. Let $\gamma_{i,j}$ denote the moisture content obtained for the j'th mill during $\mathcal{T}_i$. We then introduce the following performance measures:

$$\tilde{J}_j(\theta, t) = \sum_{j=1}^{N} \sum_{\kappa=1}^{N} (Q_{a,j}(t)) - \gamma_{i,\kappa} Q_{b,j}(\theta, t))^2, j \neq \kappa$$

which measures the deviation from the energy balance between mill j and the other active mills at sample time $t \in \mathcal{T}_i$ (indices j and κ denote individual coal mills), and

$$\begin{aligned} \breve{J}_{i,j}(\theta) &= \sum_{t \in \mathcal{T}_{i-1}} (Q_{a,j}(t)) - \gamma_{i,j} Q_{b,j}(\theta, t))^2 \\ &\quad + \sum_{t \in \mathcal{T}_i} (Q_{a,j}(t)) - \gamma_{i-1,j} Q_{b,j}(\theta, t))^2 \end{aligned}$$

which measures the deviations from the energy balance for mill j between intervals $\mathcal{T}_{i-1}$ and $\mathcal{T}_i, i = 2, \ldots, \nu$.

Then we can formulate the following optimization problem in order to estimate the evaporation function given a set of data from N different coal mills operating at one plant:

$$\min_{\theta \in \Theta} J(\theta) = \sum_{j=1}^{N} \left(\sum_{t \in \cup_{i=1}^{\nu} \mathcal{T}_i} \tilde{J}_j(\theta, t) + \sum_{i=2}^{\nu} \breve{J}_{i,j}(\theta) \right) \quad (8)$$

V. Kalman Estimation

To estimate the coal moisture γ using Kalman filter techniques (see e.g.[6]), γ must appear as a state variable in the model, which implies that a model for dynamic behaviour of γ should be included. In order to ensure that the estimate converges to the correct value integral action is included in the estimator by introducing a model of moisture assuming this to be constant. Discretizing the dynamic model (3), (4) with expressions for m_{evap} from (5) and (6), using the sample time T_s in Euler's method and including the integrated γ state, we obtain the following discrete-time model, where k denotes sample number:

$$\begin{aligned} T_m(k+1) &= T_m(k) + T_s \frac{m_{pa}(k) c_a (T_{pa}(k) - T_m(k))}{M_m C_m} \\ &\quad + m_c(k) c_c (T_a - T_m(k)) + \gamma(k) m_c(k) c_w T_a \\ &\quad - \gamma_{res}(k) m_c(k) (c_w T_m(k) + f(T_m(k)) H(T_m(k))) \\ \gamma(k+1) &= \gamma(k) \\ \gamma_{res}(k+1) &= \gamma_{res}(k) + T_s \frac{\gamma(k) m_c(k)}{M_c} \\ &\quad - T_s \frac{\gamma_{res}(k) m_c(k)}{M_c} (f(T_m(k) + 1) \end{aligned}$$

where T_s is the simulation step size.

Defining the state vector $x = [T_m \ \gamma \ \gamma_{res}]^T$ and input vector $u = [T_{pa} \ m_{pa} \ m_c]^T$ and adding noise, the coal mill may be described by the nonlinear equations

$$\begin{aligned} x(k+1) &= g(x(k), u(k)) + w(k) && (9) \\ y(k) &= C x(k) + v(k) && (10) \end{aligned}$$

where y is the temperature of the mill, $C = [1 \ \ 0 \ \ 0]$, v is mill temperature noise, w is state noise.

Let $\hat{x}(k+1|k)$ denote the prediction of the state vector given samples up to and including sample k. The algorithm to estimate the moisture is then given by

$$\begin{aligned} \hat{x}(k+1|k) &= g(\hat{x}(k|k-1), u(k)) + L(y(k) - C\hat{x}(k|k-1)) \\ \begin{bmatrix} \hat{y}(k|k) \\ \hat{x}(k|k) \end{bmatrix} &= \begin{bmatrix} C(I - MC) \\ I - MC \end{bmatrix} \hat{x}(k|k-1) + \begin{bmatrix} CM \\ M \end{bmatrix} y(k) \end{aligned}$$

While the steady state value of the estimate is determined by $f(T_m)$, the behavior of the estimate in transient is heavily influenced by $M_c C_m$, which has been adjusted such that minimum variation is seen in the estimate of moisture.

The model function $g(x(k), u(k))$ in equation 9 is nonlinear having bilinear terms and the piecewise affine function $f(T_m)$. In order determine the Kalman gain matrices L and M a linearized version of the system model found by Jacobian based method in an operating point is used. The covariance matrices for w and v may be used as design parameters for the Kalman filter. Since this approach does not automatically ensure stability in the entire operating range, stability is investigated in selected operating points.

VI. Results

All results shown in this section is from the Danish power plant "Studstrupværket A/S", situated near Aarhus. On the power plant there are four identical coal mills. In order to estimate the evaporation function $f(T_m)$ an initial function was used. The results from this function is shown on figure 5. The data is from one month containing 30 days. It is seen that in some time intervals the power plant is not operating, in other time slots some of the mills are shut down, because of a limited power plant load. The estimates are omitted when a mill is not operating.

Since no on-line measurements of the coal moisture content are available, the optimization is based on other observations as quantified in (8). The minimization is solved by selecting

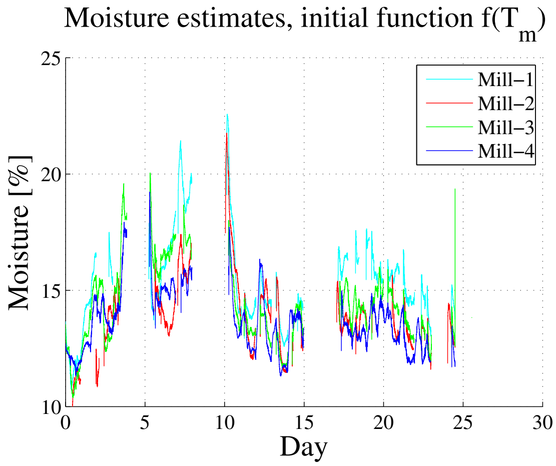

Fig. 5. Estimates of the moisture in the four coal mills using an initial evaporation function

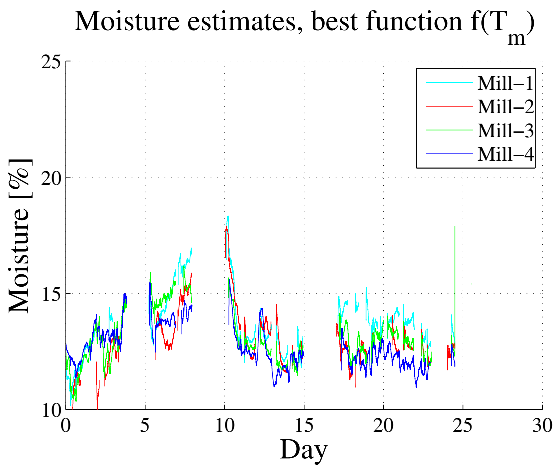

Fig. 6. Moisture estimates for the four coal mills using the best function $f(T_m)$

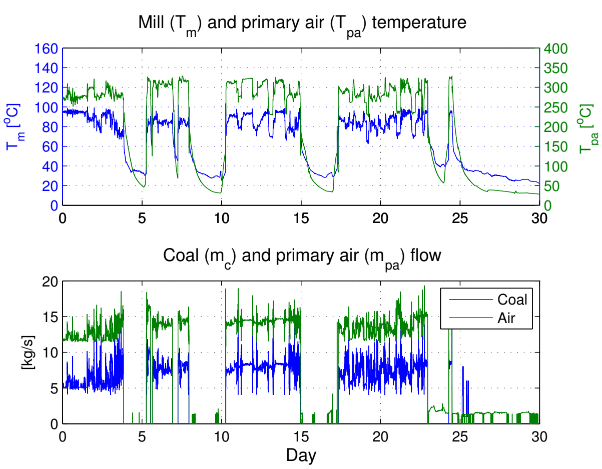

Fig. 7. The four inputs to the estimation algorithm for coal mill no. 4.

T_{sat} and f_{max} from a grid and computing the optimal values of f_c and T_c for each grid point by numerical search.

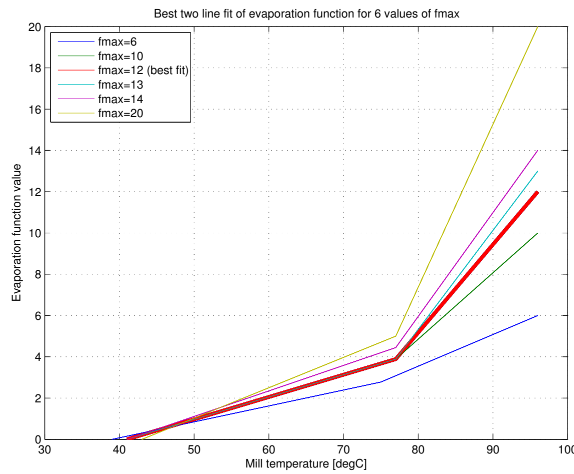

Fig. 8. Best fit function $f(Tm)$ and optimal functions for other values of f_{max}

The result of the minimization is shown at figure 4. The optimal value of parameters are found to $T_{sat} = 41$, $f_c = 3.88$, $T_c = 77$ and $f_m = 12$. On figure 8 the optimal $f(T_m)$ is shown as the bold red. Optimal graphs for other fixed values of f_{max} are also shown on the figure. The moisture estimation with the optimal function $f(T_m)$ is shown on Figure 6.

As stated above, the elements of $E(ww^T)$ and $E(vv^T)$, which are actually variances of disturbances on the individual states and measurement noise, respectively, may be used as design parameters to obtain an estimator that reacts 'reasonably fast.' Reasonably fast here is considered to be in the same order of magnitude as the dynamics of the coal mill determined by 3 and 4. The following parameter values were used:

$$E(ww^T) = \mathrm{diag}\left(1, \left(\frac{0.09}{100}\right)^2, \left(\frac{0.09}{100}\right)^2\right) \text{ and } E(vv^T) = 1$$

The determination of L and M is furthermore dependent on the linearized version of the model which requires determination of an operating point. In this work, we found the operating point from the recorded data; however, it should be noted that the operating point only influences the response time of the estimates, as the steady state values are determined by the nonlinear model. It should be noted that no stability problems have occured in simulations with data from the power plant coal mills, but some stability problems have been seen with other evaporation functions, particularly with large function values at high temperatures. This is considered to be a numerical problem, since with a large $f(T_m)$ one pole in the continuous-time linearized description will be very large and negative, which is known to cause problems for Euler discretization.

Using the operating point, model parameters and covariances the following values of L and M were found:

$$L = \begin{bmatrix} 1.355 \\ -0.000695 \\ -0.00177 \end{bmatrix} \text{ and } M = \begin{bmatrix} 0.999 \\ -0.000695 \\ -0.00241 \end{bmatrix}$$

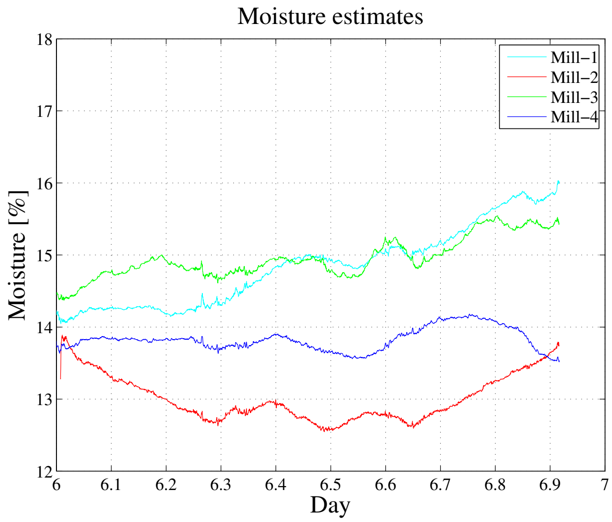

Fig. 9. A zoom in fig. 6 showing the variations in day six.

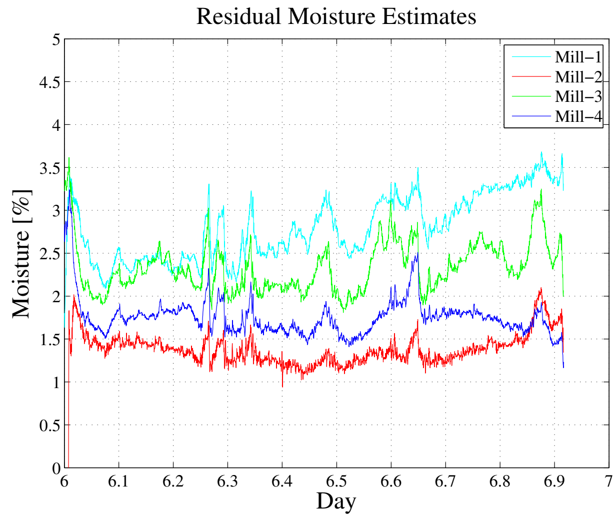

Fig. 10. The residual moisture estimates for day six

On fig. 7 the four input sequences to the estimation algorithm for one of the coal mills are shown.

It is seen that in order to fulfill the performance criteria the observed moisture was lower than when using the initial function. Smaller transients in the moisture estimate are observed near transients in m_c and m_{pa}. Furthermore, it is seen that the coal moistures in the four mills at the same time are closer than with the initial function. They are not identical since the mills have separate inflow tank which may have different filling times. Another phenomenon is the estimated moisture when a coal mill is restarted. Here, it seems that a too high moisture is estimated, which may indicate that lumping all coal, air and metal into one control volume is insufficient to describe a mill restart, where the entire metal needs to be heated to the operating value from ambient temperature. In a one-volume model the heating of outer metal part during start up may be interpreted as heat needed to evaporate moisture and thus result in a too high value of the moisture estimate. The model may be improved by increasing the order of the model using an extra control volume for energy. This would require determination of heat capacities and internal heat transfer models.

Finally, on fig. 9 and fig. 10 the estimates for day six are shown as well as the estimates of the residual coal moisture content.

VII. Conclusion

In this paper coal moisture estimation using an extended Kalman filter has been developed and tested on power plant data. The coal moisture influence on the power plant energy production has been explained, showing that the moisture gives rise to a minimum value of the production rate and an upper limit of the production gradient. The main problem to be solved is the presence of moisture in the coal leaving the coal mill, because insufficient energy available for preheating the primary air at low load leaves unevaporated moisture in the coal dust entering the boiler.

An algorithm for on-line estimation of moisture in inlet coal from measurements of inlet air temperature, inlet air flow, coal flow and mill temperature is presented. Unlike earlier attempts to estimate moisture the estimator takes unevaporated moisture into consideration. It turns out that the key to solving this problem is to find the evaporation as a function of the mill temperature and the coal flow. Since no on-line measurements of coal moisture exists a special performance function is designed to evaluate the evaporation from sequences with approximate steady state. Based on this, a Kalman estimator for the moisture was designed. The next step will be to implement the estimator on-line in the plant control system in order to gain experience about the relation between coal moisture and operation conditions of the mills.

Acknowledgment

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References

[1] N. W. Rees and F. Q. Fan, "Modelling and control of pulverised fuel coal mills." *In D. Flynn (Ed.) Thermal power plant simulation and control*,1st ed., Institution of Electrical Engineers, 2003.

[2] Y.G. Zhang,Q.H. Wu, J. Wang, G. Oluwande, D. Matts and X.X. Zhou "Coal Mill Modeling by Machine Learning on Onsite Measurements", *IEEE Transactions on Energy Conversion*, vol. 17, no. 4, December 2002

[3] P. F. Odgaard and B. Mataji, "Estimation of moisture content in coal in coal mills", *Proceedings of the IFAC symposium on control of power plants and power systems*, Kananaskis, Canada, 2006.

[4] R. Jankowski, P. D. Domanski and K. Swirski "Optimization of a coal mill control" *2003 ASME international mechanical engineering congress*,pp 223-243, Washington, DC, USA, 2003.

[5] H. Didriksen, "Model based predictive control of a rotary dryer", *Chemical Engineering Journal*, vol. 86, pp 53-60, 2002

[6] Mohinder S. Grewal and Angus P. Andrews, "Kalman Filtering, Theory and Practice Using MATLAB" ,3rd ed., John Wiley & Sons., 2008