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ESTIMATION OF MOISTURE CONTENT IN COAL IN COAL MILLS

Peter Fogh Odgaard * **Babak Mataji** **

* *Department of Control Engineering, Aalborg University, Fredrik Bajers Vej 7C, DK-9220 Aalborg, Denmark, odgaard@control.aau.dk*
** *Elsam Engineering A/S, Kraftværksvej 53, DK-7000 Fredericia, Denmark, bama@elsam-eng.com*

Abstract
For coal-fired power plants information of the moisture content in the coal is important to determine and control the dynamical behavior of the power plants. E.g. a high moisture content in the coal can result in a decreased maximum load gradient of the plant. In this paper a method for estimating the moisture content of the coal is proposed based on a simple dynamic energy model of a coal mill, which pulverizes and dries the coal before it is burned in the boiler. An optimal unknown input observer is designed to estimate the moisture content based on an energy balance model. The designed moisture estimator is verified on a couple sets of measurement data, from which it is concluded that the designed estimator estimates the real coal moisture content.

Keywords: Moisture estimation, Coal-fired Power Plants, Optimal Unknown Input Observer

1. INTRODUCTION

During the late years production of Danish power plants has been regulated more and more depending on the energy market, which results in variating load requirements. Simply due to the fact that the plant production is depending more on the prices on the market as well as the demands for power. This again results in higher focus on better dynamical performance of the power plants. In this regard it is of importance to monitor the performance, e.g. monitor if the required performance is gained or can be gained. One of the variables influencing the performance of a coal-fired power plant is the moisture content of the raw coal. In other words it would be useful to know the moisture content in order to make an assessment and prediction on the plant performance, unfurtunately, the moisture content is not measurable. In order to understand this, the attention is addressed on the coal mill. Before the coal is burned in the furnace, it is preprocessed in the coal mill. The main purpose of the coal mill is to dry and pulverize the coal. The primary air flow is used to dry and carry the pulverized coal to the furnace. It is therefore important that the primary air has sufficient energy at all loads. During a load increase of the power plant the coal flow is increased together with the primary air flow. When the moisture content of the coal is higher than assumed it would take longer time to dry the coal, resulting in changed dynamics of the coal mill, and accumulation of coal in the coal mill. This will evidently change the possible performance of the power plant in general.

It is not possible to measure the coal moisture content online for use in a real time control system.

However, static estimates of the coal moisture content is delivered by the mill control system.

The focus of research in control of coal mills has not been addressed on moisture estimation. Instead, dynamic modeling and nominal control of these coal mills have been the topic of numerous of publications. Some examples dealing with modeling of coal mills are (Rees and Fan 2003), (Zhang *et al.* 2002) and (Tigges *et al.* 1998). Controllers for the coal mill are designed in (Rees and Fan 2003) and (Hasselbacher *et al.* 1992). High order dynamic models and observer design for coal mills are the topics in (Fukayama *et al.* 2004).

In (Rees and Fan 2003) a non-linear dynamic energy balance model is given. In this paper the model is simplified and adapted to the specific coal mill Babcock MPS 212, which is used in Elsam's Nordjyllandsværktet Unit 3. The model is subsequently linearized. An optimal unknown input observer, see (Chen and Patton 1999), is subsequently designed in order to estimate coal moisture content of the coal feed into the coal mill.

The outline of this paper is as follows: the coal mill is first described and modeled, including a state representing the moisture content. In the subsequent section the observer is designed, it is subsequently applied to data from a coal mill, from which it can be concluded that the designed observer estimates the coal moisture content.

2. THE COAL MILL

The work presented in this paper, is based on a Babcock MPS 212 coal mill used at Elsam's Nordjyllandsværktet Unit 3. However, the method proposed in the paper is so generic that it can be applied to other types of coal mills. The coal mill is illustrated in principles in Fig. 1. The coal is fed to the coal mill through the central inlet pipe. The coal is pulverized on the rotating grinding table by the rollers. The pulverized coal is subsequently blown up and the moisture content of the coal dust is evaporated by the hot primary air. The primary air is mixed by cold outside air and heated outside air, which is heated by hot air from the furnace. The ratio of these air flows are used to control the temperature of the primary air flow. Coal particles which in the pulverizing have been small enough will pass through the classifier and out through the outlet pipes into the boiler. On the other hand if the coal particles are not dried enough they cannot be lifted out of the coal mill by the primary air flow, since these particles are too heavy.

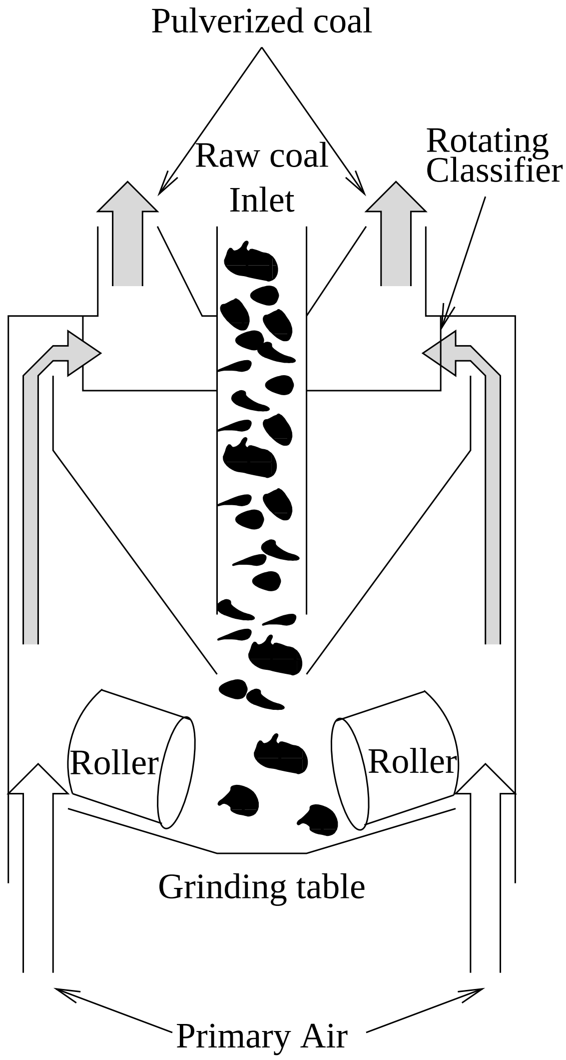

Figure 1. An illustration of the principals of the coal mill. The raw coal is pulverized by the rollers and the grinding table, the pulverized coal is subsequently dried and lifted by the primary air. If these particles are small enough they will be lifted through and into the power plant furnace.

2.1 Control and measurements

References to the coal flow and the primary air flow are given by the general power plant controller, as well as speed for the classifier. The temperature of the primary air is used to control the temperature in the coal mill at the classifier. The temperature controller is often required to keep temperature constant at 100°C in order to evaporate the moisture in the coal. A coal mill is a harsh environment in which it is difficult to perform measurements, this means that all the variables are not measurable. E.g. the actual coal flow into the coal mill is only estimated. The coal flow out of the coal mill is not measurable. However, the primary air flow and temperature are, as well as the temperature of the coal dust at the classifier.

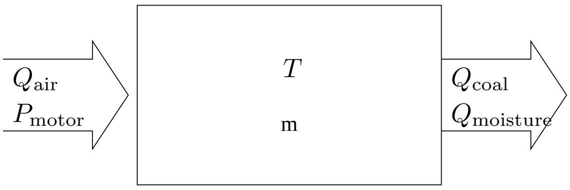

Figure 2. An illustration of energy balance in the coal mill, where T is the temperature in the mill, $Q_{\rm air}$ is the energy in the primary air flow, $P_{\rm motor}$ denotes the power delivered by the roller motors, $Q_{\rm coal}$ is the energy in the coal flow, and $Q_{\rm moisture}$ is the energy in the coal moisture.

3. ENERGY BALANCE MODEL OF THE COAL MILL

A simple energy balance model of the coal mill is derived based on (Rees and Fan 2003). (Rees and Fan 2003) includes more details, but these are neglected in this work. In this model the coal mill is seen as one body with the mass $m_{\rm m}$, as illustrated in Fig. 2, in which T is the temperature in the mill, $Q_{\rm air}$ is the energy in the primary air flow , $P_{\rm motor}$ denotes the power delivered by the roller motors, $Q_{\rm coal}$ is the energy in the coal flow, and $Q_{\rm moisture}$ is the energy in the coal moisture. It is also assumed that the input coal flow is equal the output coal flow. Even though this assumption is only entirely true for steady state, it is assumed in this paper for simplifying the model. A more detailed model which takes different coal flows into account might result in more precise estimation of the moisture content. The energy balance illustrated in Fig. 2 is given by (1)

$$m_{\rm m}\cdot C_{\rm m}\cdot \dot{T}(t) = Q_{\rm air}(t) - Q_{\rm coal}(t) - Q_{\rm moisture}(t) + P_{\rm motor}(t). \quad (1)$$

The heating and evaporation of the moisture in the coal is modeled by a combined heating coefficient. The temperature is due to the control loop is kept at 100°C. The latent energy of the evaporation dominates the energy required for a few degrees heating of the moisture. The combined heat coefficient, $H_{\rm st}$, is following defined as $H_{\rm st} = C_{\rm w} + L_{\rm steam}/100$, where $C_{\rm w}$ is the specific heat of the water, and $L_{\rm steam}$ is the latent heat. This combined heat coefficient does not deal with the fact that the specific heat of water and steam are different, however the model error due to heat of steam to a couple of degrees above 100°C is negligible in this context.

The dynamic non-linear model is subsequently given by

$$\begin{aligned} m_{\rm m}C_{\rm m}\dot{T}(t) =& \dot{m}_{\rm pa}(t)C_{\rm air}\left(T_{\rm PA}(t) - T(t)\right) \\ &+ \dot{m}_{\rm c}(t)C_{\rm c}\left(T_{\rm s} - T(t)\right) \\ &+ \gamma(t)\dot{m}_{\rm c}(t)C_{\rm w}T_{\rm s} \\ &- \gamma(t)\dot{m}_{\rm c}(t)H_{\rm st}T(t) \\ &+ P_{\rm motor}(t), \end{aligned} \quad (2)$$

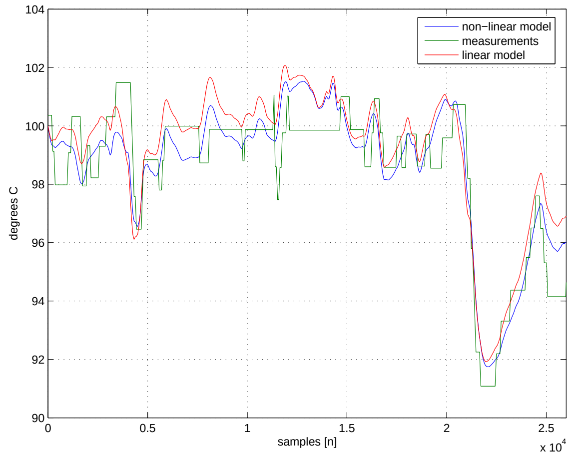

Figure 3. A plot of the non-linear and linear model response compared with measurements of a step response on the coal mill.

where: $C_{\rm m}$ is the specific heat of the mill, $T(t)$ is the mill temperature, $\dot{m}_{\rm pa}(t)$ is the primary air mass flow in and out of the mill, $C_{\rm air}$ is the specific heat of air, $T_{\rm PA}(t)$ is the temperature of the inlet primary air, $\dot{m}_{\rm c}(t)$ is the coal mass flow, $C_{\rm c}$ is the specific heat of the coal, $T_{\rm s}$ is the surrounding temperature, $\gamma(t)$ is the ratio of moisture in the coal, $C_{\rm w}$ is the specific heat of the moisture, $H_{\rm st}$ parameter combining the latent heat of the steam and specific heat of the water, and $P_{\rm motor}(t)$ is the power delivered by the mill motor.

All parameters in this model are found in data books except $m_{\rm m}\cdot C_{\rm m}$ which is identified based on measurements of a step response on the coal mill. The model response is compared with measurements as well as a response of a linearized model in Fig. 3. From this figure it can be seen that the responses of both models are quit similar to the large dynamical changes as the measurements show. However, it is difficult to validate the details in the response due to the way the signals are sampled. A dead band on one per cent is applied to these measurements meaning that the signals shall have changes of a given size before this change is sampled. The non-linear model (2) is subsequently linearized and transformed into a state space representation, see (3), the motor power is also neglected from this state space model since it is much smaller than the other powers in the equation.

$$\dot{\bar{T}}(t) = \mathbf{A}\bar{T}(t) + \mathbf{B}\cdot\begin{bmatrix}\bar{\dot{m}}_{\rm PA}(t)\\ \bar{T}_{\rm PA}(t)\\ \bar{\dot{m}}_{\rm c}(t)\\ \bar{\gamma}(t)\end{bmatrix} + \mathbf{q}(t), \quad (3)$$

$$\bar{T}_{\rm m}(t) = \mathbf{C}\bar{T}(t) + \mathbf{r}(t), \quad (4)$$

where a given signal $\circ$ is linearized by $\bar{\circ} = \circ - \circ_{\rm o}$, $\circ_{\rm o}$ is the operation point of $\circ$, $\mathbf{q}(t)$ is the normal distributed process disturbances, $\mathbf{r}(t)$ is the normal distributed measurement noises, $T_{\rm m}(t)$ is the measured temperature and

$$\mathbf{A} = \left[\frac{-\dot{m}_{\text{PA,o}} \cdot C_{\text{air}} - \dot{m}_{\text{c,o}} \cdot (C_{\text{c}} + \gamma_o \cdot H_{\text{st}})}{m_{\text{m}} \cdot C_{\text{m}}} \right], \tag{5}$$

$$\mathbf{B} = \begin{bmatrix} \frac{C_{\text{air}} \cdot (T_{\text{PA,o}} - T_o)}{m_{\text{m}} \cdot C_{\text{m}}} \\ \frac{C_{\text{air}} \cdot \dot{m}_{\text{PA,o}}}{m_{\text{m}} \cdot C_{\text{m}}} \\ \frac{C_{\text{c}} \cdot (T_{\text{s}} - T_o) + \gamma_o \cdot (C_{\text{w}} \cdot T_{\text{s}} - H_{\text{st}} \cdot T_o)}{m_{\text{m}} \cdot C_{\text{m}}} \\ \frac{\dot{m}_{\text{c,o}} \cdot (C_{\text{w}} \cdot T_{\text{s}} - H_{\text{st}} \cdot T_o)}{m_{\text{m}} \cdot C_{\text{m}}} \end{bmatrix}^T, \tag{6}$$

$$\mathbf{C} = \mathbf{I}. \tag{7}$$

3.1 Model with moisture

This linear model is subsequently modified for the estimation of the coal moisture content. An additional state is introduced for representing the coal moisture content, $\gamma[n]$, instead of the input. This state is driven by the unknown input, denoted $\gamma_{\text{n}}[n]$. In addition the static estimate of the moisture content is considered as a very noisy measurement, $\bar{\gamma}_{\text{m}}[n]$, (8-13).

$$\begin{bmatrix} \dot{\bar{T}}(t) \\ \dot{\bar{\gamma}}(t) \end{bmatrix} m = \mathbf{A}_{\text{q}} \begin{bmatrix} \bar{T}(t) \\ \bar{\gamma}(t) \end{bmatrix} + \mathbf{B}_{\text{q}} \begin{bmatrix} \bar{\dot{m}}_{\text{PA}}(t) \\ \bar{T}_{\text{PA}}(t) \\ \bar{\dot{m}}_{\text{c}}(t) \end{bmatrix} + \mathbf{E}_{\text{q}} \gamma_{\text{n}}(t) + \mathbf{q}(t), \tag{8}$$

$$\begin{bmatrix} \bar{T}_{\text{m}}(t) \\ \bar{\gamma}_{\text{m}}(t) \end{bmatrix} = \mathbf{C}_{\text{q}} \begin{bmatrix} \bar{T}(t) \\ \bar{\gamma}(t) \end{bmatrix} + \mathbf{r}(t), \tag{9}$$

where $\gamma_{\text{n}}(t)$ is the generic unknown input which is low-pass filtered in order to represent the coal moisture content, and

$$\mathbf{A}_{\text{q}} = \begin{bmatrix} \mathbf{A} & \frac{\mathbf{B}_4}{p} \\ 0 & -p \end{bmatrix}, \tag{10}$$

$$\mathbf{B}_{\text{q}} = \begin{bmatrix} \mathbf{B}_{(1\cdots3)} \\ \mathbf{0} \end{bmatrix}, \tag{11}$$

$$\mathbf{C}_{\text{q}} = \mathbf{I} \in \mathcal{R}2 \times 2, \tag{12}$$

$$\mathbf{E}_{\text{q}} = \begin{bmatrix} 1 \\ 1 \end{bmatrix}, \tag{13}$$

where p is the pole of internal fault model. The model is discretizied before any further use, I.e. ($\mathbf{A}_{\text{q}}$, $\mathbf{B}_{\text{q}}$, $\mathbf{C}_{\text{q}}$, $\mathbf{E}_{\text{q}}$) are transformed to ($\mathbf{A}_{\text{d}}$, $\mathbf{B}_{\text{d}}$, $\mathbf{C}_{\text{d}}$, $\mathbf{E}_{\text{d}}$).

3.2 Optimal unknown input observer

The optimal unknown input observer is described in (Chen and Patton 1999). For discrete time systems with unknown inputs and disturbances which can be represented by

$$\mathbf{x}[n+1] = \mathbf{A}_n \mathbf{x}[n] + \mathbf{B}_n \mathbf{u}[n] + \mathbf{E}_n \mathbf{d}[n] + \mathbf{q}[n], \tag{14}$$

$$\mathbf{y}[n] = \mathbf{C}_n \mathbf{x}[n] + \mathbf{r}[n], \tag{15}$$

an optimal unknown input observer of the following form can be derived.

$$\mathbf{z}[n+1] = \mathbf{F}_{n+1} \mathbf{z}[n] + \mathbf{T}_{n+1} \mathbf{B}_n \mathbf{u}[n] + \mathbf{K}_{n+1} \mathbf{y}[n] \tag{16}$$

$$\hat{\mathbf{x}}[n+1] = \mathbf{z}[n+1] + \mathbf{H}_{n+1} \mathbf{y}[n+1]. \tag{17}$$

The basic idea in this observer is to eliminate the dependency of the unknown input from the estimation error by matrix transforms, and subsequently design a Kalman estimator for the transformed system. A positive side effect of this, is that the estimator gain is recomputed at each sample, meaning the model can be changed such that the point of operation can updated. The schemes for computing the matrices in the optimal unknown input observer can be seen in Appendix A.

The variance of the disturbance and measurement noises $\mathbf{Q}[n]$ and $\mathbf{R}[n]$, as well as the internal fault model parameter p are all found by trial and error, based on experimental data, in the way that the observer estimates the moisture content in the coal. The results can be seen in Section 4. From Fig. 4-7 in Section 4 it can be seen that the observer estimates the fault signal due to the coal moisture content well, and it is hereby concluded that the observer and model are well tuned.

4. RESULTS

The designed moisture estimator is applied to measured data from the coal mill described in Section 2. Since the moisture content is not measured it is impossible to compare the estimated moisture content with the real moisture content. However it can be compared with a static estimate, as well as a low pass filtered version of the static estimate. This comparison has been done for four different sets of measurements and can be seen in Fig. 4-7.

The first example shown in Fig. 4 contains two changes of the plant load at sample 66 and 450, these load changes are influencing the static measured but not the one estimated by the use the proposed scheme. Except from the the plant load changes both methods are following the increases and decreases of the moisture content.

The second example shown in Fig. 5 contains one load change approximately at sample 900. Again the static measurement/estimate reacts on the load changes whereas the proposed scheme does not. Both estimates follow the increased moisture content well.

The third example shown in Fig. 6 contains a load change approximately at sample 1230. The observer estimated coal moisture content shows

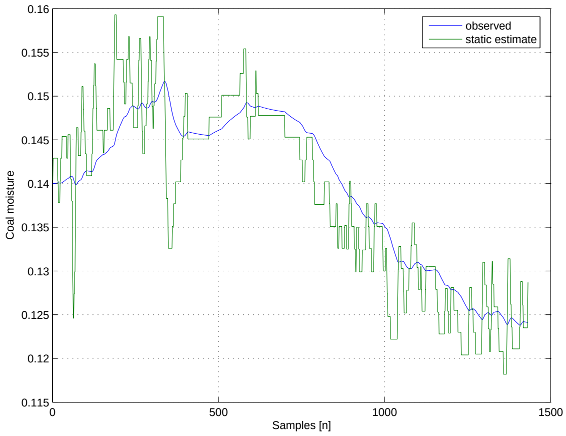

Figure 4. Example 1, comparison of observer estimated and static measured/estimated coal moisture content. Notice the static measurement is influenced by a plant load change at sample 66 and 450.

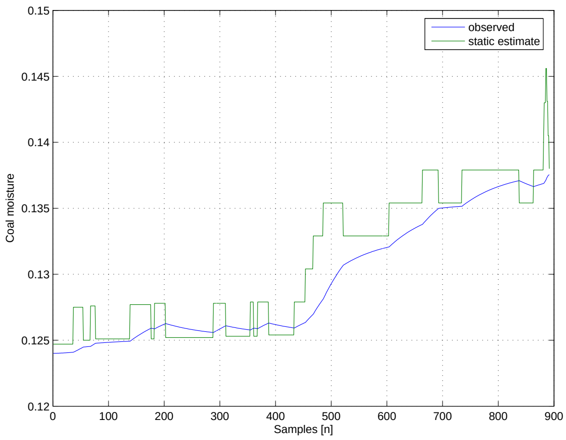

Figure 5. Example 2, comparison of observer estimated and static measured/estimated coal moisture content. The observer estimate does not react on the load change at sample 900, which the static estimate does.

the increase in coal moisture content without reacting on the load change at sample 1230, which the static estimated moisture content, on the other hand, does.

The fourth example which is illustration by Fig. 7, has a variating moisture content and plant load change approximately at sample 146. The conclusion which can be made of this example is similar to the three others. The observer based estimation gives the moisture content without reacting on the plant load changes, which the static estimate, on the other hand, does.

From these four examples illustrated by Figs. 4-7 it can be seen that the observer estimates the moisture content of the coal well in all four cases, on the other hand this estimate does not react on load changes as the static estimate does. It can hereby be concluded that the observer and model

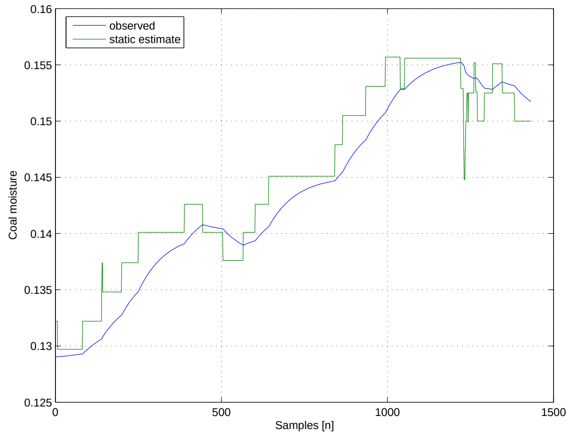

Figure 6. Example 3, comparison of observer estimated, static measured/estimated coal moisture content. The static estimate reacts on the load change at sample 1230, which the observer estimate does not.

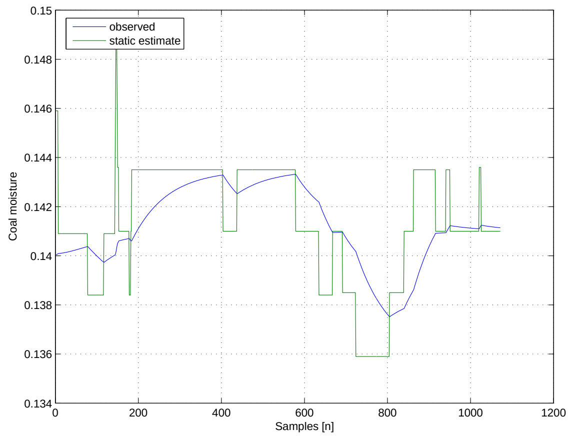

Figure 7. Example 4, comparison of observer estimated, static measured/estimated moisture content.

are well tuned, and the estimator can be used to estimate the moisture content dynamically.

5. CONCLUSION

This paper introduces a method for estimating coal moisture content in the coal in coal mills used in power plants. The estimation is performed by using a simple linearized dynamic energy balance model, and an optimal unknown input observer. The designed observer is tested on four sets of experimental data from a coal mill, and it is concluded that the observer estimates the coal moisture content very well in all these cases, with different moisture content.

6. ACKNOWLEDGMENT

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Appendix A. OPTIMAL UNKNOWN INPUT OBSERVER

A necessary and sufficient condition for the existence of a solution to the given observer problem is in (Chen and Patton 1999) given as: An optimal unknown input observer solution exists if and only if: rank $(\mathbf{C}_{n+1}\mathbf{E}_n) = $ rank $(\mathbf{E}_n)$.

The computation of the matrices in the observer is also given in (Chen and Patton 1999) as:

(1) Set initial values: $P_0 = P(0)$, $\mathbf{z}_0 = \mathbf{x}_0 - \mathbf{C}_0\mathbf{E}_0\left(\mathbf{C}_0\mathbf{E}_0\right)^+\mathbf{y}_0$, $\mathbf{H}_0 = 0$.
(2) Compute $\mathbf{H}_{n+1} = \mathbf{E}_n\left(\mathbf{C}_{n+1}E_n\right)^+$.
(3) Compute
$\mathbf{K}^1_{n+1} = \mathbf{A}^1_{n+1}\mathbf{P}_n\mathbf{C}_n^T\left(\mathbf{C}_n\mathbf{P}_n\mathbf{C}_n^T + \mathbf{R}_n\right)^{-1}$,
and $\mathbf{P}'_{n+1} = \mathbf{P}_n - \mathbf{K}^1_{n+1}\mathbf{C}_n\mathbf{P}_n\left(A^1_{n+1}\right)^T$
(4) Compute $T_{n+1} = \mathbf{I} - \mathbf{H}_{n+1}\mathbf{C}_{n+1}$,
$\mathbf{F}_{n+1} = \mathbf{A}_n - \mathbf{H}_{n+1}\mathbf{C}_{n+1}\mathbf{A}_n - \mathbf{K}^1_{n+1}\mathbf{C}_n$,
$\mathbf{K}^2_{n+1} = \mathbf{F}_{n+1}\mathbf{H}_n$, and $\mathbf{K}_{n+1} = \mathbf{K}^1_{n+1} + \mathbf{K}^2_{n+1}$.
(5) Now compute
$\mathbf{z}[n+1] = \mathbf{F}_{n+1}\mathbf{z}[n] + \mathbf{T}_{n+1}\mathbf{B}_n\mathbf{u}[n] + \mathbf{K}_{n+1}\mathbf{y}[n]$
and $\hat{\mathbf{x}}[n+1] = \mathbf{z}[n+1] + \mathbf{H}_{n+1}\mathbf{y}[n+1]$.
(6) Compute $\mathbf{P}'_{n+1} = \mathbf{P}_n - \mathbf{K}^1_{n+1}\mathbf{C}_n\mathbf{P}_n\left(\mathbf{A}^1_{n+1}\right)^T$,
and following
$\mathbf{P}_{n+1} = \mathbf{A}^1_{n+1}\mathbf{P}'_{n+1}\left(\mathbf{A}^1_{n+1}\right)^T + \mathbf{T}_{n+1}\mathbf{Q}_n\mathbf{T}^T_{n+1} + \mathbf{H}_{n+1}\mathbf{R}_{n+1}\mathbf{H}^T_{n+1}$.
(7) Set $n = n + 1$ and jump to step 2.