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A MODEL OF A BUBBLING FLUIDIZED BED COMBUSTOR FOR THE ESTIMATION OF THE CHAR MASS VIA EXTENDED KALMAN FILTER

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Abstract: The carbon load is one of the key variables for the description of the behaviour of a fluidized bed coal combustor (FBC). In this paper, the problem of estimating such a variable is addressed by the development of a suitable model and then by resorting to Extended Kalman Filter (EKF) techniques.

Keywords: Power plants; Fluidized bed combustor; Extended Kalman filter; State estimation; Modelling.

1. INTRODUCTION

The fluidization technique is often used in processes where a non-homogeneous reaction takes place, because of the wide contact surface between solid and gas. Known since the 20's, the fluidized bed technology was applied mostly in the chemical and petroleum industry. Only in the 70's it made its appearance in the power plant realm. With respect to a conventional power plant equipped with pollutant abatement systems (DENOX, DESOX), a fluidized bed combustor (FBC) has the advantages of a simpler operation and the possibility of using low quality fuel (non-pulverized coal, mine residues, waste) with a comparable efficiency. The pollutant reduction is intrinsically contained in this type of process. Indeed, the low operating temperature of FBC (around 850°C), leads to a lower emission of NO_x and to an improvement of the desulphurization process (the limestone present in the fluidized bed reacts with SO_2 to produce gypsum).

While in conventional combustion chambers the pulverised coal take less than a second to burn out, in a FBC the burning time of a coal particle is remarkably higher, mainly because the temperature is lower and the particles are bigger. After the release of its volatile matter and water content, the coal takes the name of *char*. The peculiar behaviour of the coal combustion in FBC's above described implies that a significant supply of char is always present in the bed (char loading).

The char loading is one of the key variables in the FBC process, because it describes the potential amount of heat available in the bed. A real-time knowledge of the char loading is useful for the plant operation. The char loading affects the combustion efficiency and the emission of NO_x. In fact, the losses in combustion efficiency derive mainly from the presence of unburned carbon in the flue gases. The main source of unburned carbon are the fines produced by the attrition of the coal particles in the bed. Experimental results indicate that fines production rates and char loading are linearly correlated (Donsi et al., 1981). Furthermore, char acts as a catalyst in the conversion of NO_x to molecular nitrogen.

The measurement of this variable can be done in steady state conditions, withdrawing and analysing a sample of

bed content. An accurate real-time measurement, on the other hand, appears to be impracticable.
The purpose of this paper is to present the results of an activity jointly developed by the Centro di Ricerca di Automatica (CRA) of ENEL S.p.A. (the Italian electricity board) and the Dipartimento di Elettronica e Informazione (DEI) of the Politecnico di Milano. An estimation technique of the char mass in the FBC starting from the available plant measurements was developed adopting the Extended Kalman Filter (EKF) algorithm. The joint work CRA-DEI mainly refers to a pilot bubbling FBC plant (1 MW of power) located at the ENEL research station in Livorno, put into operation in 1990.
After a brief presentation of the structure and of the operating conditions of the plant (Sect. 2), a lumped parameters model of Livorno FBC, is described (Sect. 3); this model is based on the physical description of the plant, but it is simple enough to enable the application of real time estimation algorithms. The tuning of the model (Sect. 4), the presentation of the EKF technique (Sect. 5) and the results obtained in char loading estimation (Sect. 6) are the concluding arguments shown in this paper.

2. DESCRIPTION OF THE PLANT

Consider a bed of small diameter particles, such as sand. When a gas is uniformly injected from the bottom with speed overtaking a threshold value, called minimum fluidization speed (u_{mf}), a rising of bed level is observed. The mixture between air and solid has a homogeneous physical behaviour, comparable to the one of a liquid. At the same time air bubbles rise from the bottom to the top of the bed. This particular condition is named bubbling fluidization. For more details about fluidization dynamics see, e.g. (Halow, 1995).
The combustor of the FBC plant in Livorno (Fig. 1) is about 7m high and has a circular section of about $1 m^2$. Air is pressurised, preheated and injected in the bed through a distributor, which is designed to yield a uniform air flow. The injected air passes through the bed constituted by sand, limestone and fuel (usually coal) and takes part in the chemical reactions of combustion. Thermal power is absorbed by bed heat exchangers and wall pipes. The residuals of combustion are exhausted gases blowing out from the chimney. The desulphurization reaction between limestone ($CaCO_3$) and SO_2 produces $CaSO_4$, discharged from the bottom of the combustor, and CO_2.
Usually, at the operating steady state conditions of the plant, the temperature is 850°C to allow maximum desulphurization efficiency.
There are four main sub processes to which the coal particle is subjected. As soon as the particle is introduced in the combustor, due to high temperature, it dries up. Then the volatile matter (H_2, CO, hydrocarbons, etc.) is released and the coal particles break into fragments (char).

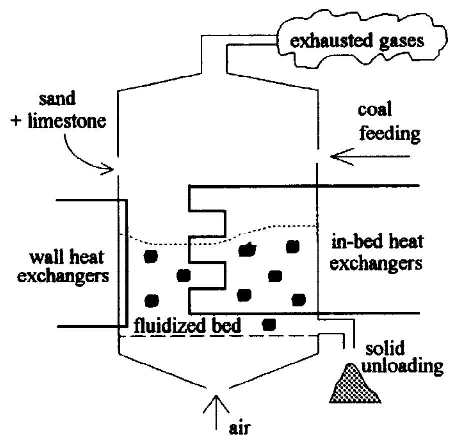

Fig. 1 - The FBC combustor.

At the temperature of 850°C and in presence of oxygen the carbon oxidises to produce mainly carbon dioxide and marginally carbon monoxide. Lastly, the attrition between sand and char leads to the production of particles of very small diameter (the fines).
A thorough model of the plant based on physical description of the plant was developed in (De Marco et al., 1991). It is a nonlinear model with distributed parameters able to describe the operating condition of the combustor with high precision. In the sequel, this model will be referred to as the simulator.

3. THE ESTIMATION ORIENTED MODEL

The application to the mass estimation problem of the EKF requires the development of a simplified model of the plant, preferably with lumped parameters and reduced complexity. Our research aimed at developing a 3rd order model having the char mass (m), the solid mass (M_s) and the average bed temperature (T) as state variables.
In order to simplify the model, the coal particles were considered of uniform diameter. Moreover the dynamics associated with drying and devolatilization processes were neglected. The coal temperature and the bed temperature, uniform in the whole bed, were supposed to evolve with the same dynamics (Bardelli et al., 1994).
The model structure is modular, as shown in Fig. 2, where w_{ci} is the coal flow rate, w_a the air flow rate, T_a the input air temperature, T_w the wall pipes temperature, T_{ser} the in-bed heat exchangers temperature, w_{si} the input solid flow rate and w_{so} the output solid flow rate.
A description of the three state equation is in order.

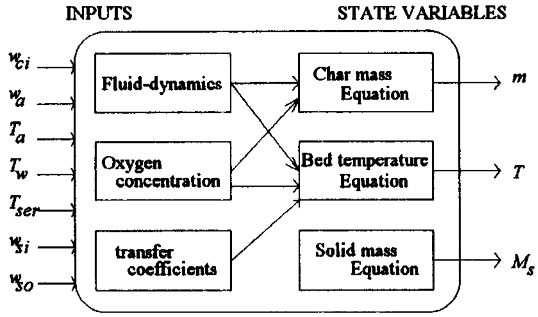

Fig. 2 - Structure of the model

3.1. The Bed Mass Conservation equation

By ignoring the consumption of limestone in the desulphurization reaction we obtain that

$$\frac{d}{dt}M_s = w_{si} - w_{so} \tag{1}$$

3.2. The Char Mass Conservation equation

The diameter of the char particles decreases progressively with a shrinking velocity depending on combustion and attrition with adjacent solid particles. The global char mass conservation equation is given by

$$\frac{d}{dt}m = w_{ch} - w_{abr} - w_{br} \tag{2}$$

where w_{ch} is the char feed rate, w_{abr} the mass flow rate of char consumed by attrition and w_{br} the mass flow rate of burning char.
The char feed rate w_{ch} is given by

$$w_{ch} = (1 - x_w - x_{vol})w_{ci} \tag{3}$$

where x_w is the fraction of evaporating water and x_{vol} the fraction of volatile matter.
The attrition flow rate w_{abr} is roughly proportional to the excess of inlet air velocity u with respect to u_{mf} and to the particles total surface (Davidson et al., 1985). If D_{abr} is the average abrasion diameter, then

$$w_{abr} = k_{abr}\frac{m}{D_{abr}}(u - u_{mf}) \tag{4}$$

The burning flow rate mainly depends on the size of the coal particle, the amount of char available in bed and the average oxygen concentration C_{O2}. So

$$w_{br} = \frac{12h_c}{32h_c + 12h_m}\frac{1}{1 - x_{cn}}\frac{6h_m m}{\rho_{ch}D_{br}}C_{O2} \tag{5}$$

where D_{br} is the average burning diameter, ρ_{ch} the char density, x_{cn} is the fraction of unburned residues. h_c is the chemical kinetic constant, and h_m is the oxygen mass transfer coefficient.

3.3. The Energy Conservation equation

The energy balance takes the following form:

$$(c_s M_s + c_{ch}m)\frac{d}{dt}T = P_{br} + P_{vol} + P_{brf} - -(P_{ser} + P_w + P_a) \tag{6}$$

where $c_{ch}m$ is the char heat capacity, $c_s M_s$ the solid heat capacity. The inlet energy is given by the burning char (P_{br}), the burning fines (P_{brf}) and burning volatile gases (P_{vol}), while the outlet energy is absorbed by in-bed (P_{ser}) and wall (P_w) heat exchangers and air flowing through the bed (P_a). More precisely P_{br} represents the thermal power released by char combustion

$$P_{br} = w_{br}H_{ch} \tag{7}$$

where H_{ch} is the combustion heat.
The energy rate released by the volatile matter combustion is proportional to the mass flow of volatiles, being H_{vol} the combustion heat of volatiles:

$$P_{br} = w_{ci}x_{vol}H_{vol} \tag{8}$$

The combustion of fines is a very complex process, depending on the availability of oxygen in bed. It is described by the following correlation

$$P_{brf} = (1 - x_{cn})w_{abr}\frac{M_{fin}C_{O2}}{1 + M_{fin}C_{O2}}H_{ch} \tag{9}$$

where M_{fin} is a parameter that has to be tuned.

The term P_a is the power delivered for heating the air mass flow rate from the inlet temperature (enthalpy h_{ai}). to the bed temperature (enthalpy $h(T)$). Then

$$P_a = w_a(h(T) - h_{ai}) \tag{10}$$

Finally, P_w+P_{ser} is the thermal power transferred to the cooling surfaces:

$$P_w + P_{ser} = \gamma_w S_w(T - T_w) + \gamma_{ser}S_{ser}(T - T_{ser}) \tag{11}$$

S_w and S_{ser} are the heat exchange surfaces which depend on the bed height; $\gamma_w(F_w)$ and $\gamma_{ser}(F_{ser})$ are the heat transfer coefficients. They depend on two parameters, F_w and F_{ser}, that have to be tuned. For more details see (Bardelli and Carugati, 1993) and (Panseri and Poncia, 1994).

Remark

The model defined by equations (1)-(11) is a third order one, the state variables being M_s (eq. (1)), m (eq. (2)) and T (eq. (6)). It can be further simplified by making reference to those operating conditions where the input and output solid flow rates coincide ($w_{si}=w_{so}$), so that eq. (1) can be dropped.

4. MODEL PARAMETER SELECTION

In the model equations there is a large number of parameters whose precise value is *a priori* unknown. The parameters are the diameters D_{abr}, D_{br}, the fines burning constant M_{fin} and finally F_w and F_{ser}. These parameters were tuned so as to impose that the simplified model behaves as the simulator in a steady state condition (Tab. 1) which will be named *RS1* by short.

w_{ci} = 0.12kg/s w_a = 1.3kg/s
T_a = 400K T_w = 333K T_{ser} = 368K

Tab. 1 - Inputs of steady state condition *RS1*

The behaviour of the obtained 2nd order model is compared to that of the simulator in Tab. 2, when the parameters are tuned as in Tab. 3.

With the aim of validating the model, several tests in different steady and transient conditions were made.

a) Starting from *RS1*, the model was tested matching the state variables transients of simulator and model when a step of input variables w_a or w_{ci} was imposed. These tests show that, in a neighbourhood of the *RS1* condition, the dynamic behaviour of the simplified model is quite similar to the simulator one. (See Fig. 3)

	SIMULATOR	MODEL	% ERROR
m (kg)	107.3	107.315	0.01%
T (K)	1367.0	1367.01	0.00%
u_{mf} (m/s)	0.1015	0.1007	0.80%
P_{br} (MW)	0.8972	0.9021	0.55%
P_{brf} (MW)	1.0849	1.0669	1.67%
P_w (MW)	0.2422	0.2425	0.14%
P_{ser} (MW)	0.9588	0.9084	5.26%

Tab. 2 - Matching between model and simulator

D_{abr} = 0.00225 F_w = 0.8050 M_{fin} = 230
D_{br} = 0.005562 F_{ser} = 0.5526

Tab. 3 - Parameters values

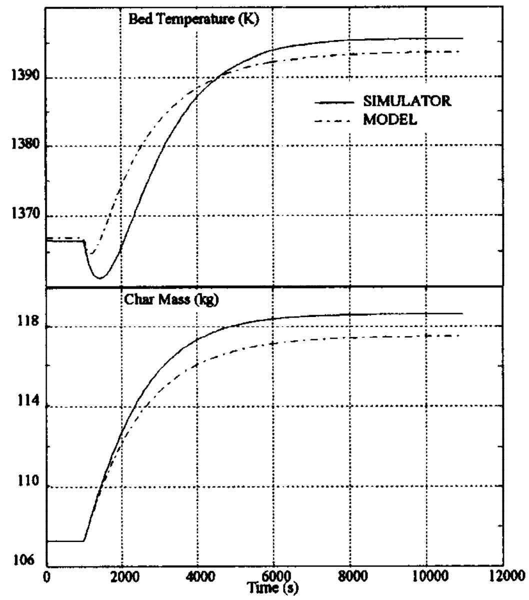

Fig. 3 - Decreasing step of 10% of w_a

b) The model behaviour was tested around two new steady state conditions (*RS2* and *RS3*). The comparison between the simulator and the model obtained for *RS1* was carried out. The disagreement is now not negligible: about 8% for the char mass and 7% for the bed temperature. This was confirmed when transient tests were made starting from the new conditions.

Among other things, from the above discussion it follows that the model is sensitive to the specific operating condition, as such it should be tuned accordingly. As for the problem of estimating the char mass, however, we will show how the use of the EKF applied to the model for *RS1* alleviates this effect and leads to fair estimates, even in different operating conditions (Sect. 6).

5. THE EKF ESTIMATION TECHNIQUE

In this section we concisely outline the EKF algorithm for a system represented by the non linear lumped parameters model:

$$\dot{x}(t) = f(x(t), u(t)) + v(t) \tag{12}$$

$$y(t) = h(x(t), u(t)) + w(t) \tag{13}$$

where $x(t)$ and $u(t)$ are the state and the input vector respectively. The uncertainty that the model has in interpreting the system and the measuring error are described by two variables $v(t)$ and $w(t)$, which are modeled as white gaussian noises (WGN) with

$E[v(\cdot)]=0$ $E[w(\cdot)]=0$

$$E\left[\begin{vmatrix} v(t) \\ w(t) \end{vmatrix} \begin{vmatrix} v(\tau)' & w(\tau)' \end{vmatrix}\right] = \begin{vmatrix} Q & 0 \\ 0 & R \end{vmatrix} \delta(t-\tau)$$

where $Q \geq 0$ and $R>0$. The system has the initial condition $x(t_0)=x_o$, with $E[x_o]=\bar{x}_0$, $E[(x_o-\bar{x}_o)(x_o-\bar{x}_o)']=P_0 \geq 0$ and gaussian distribution.

The EKF is a dynamic system that gives the state estimation $\hat{x}(\cdot)$ on the basis of the measurement of $u(\cdot)$ and $y(\cdot)$. The equation of EKF are

$$\dot{\hat{x}}(t) = f(\hat{x}(t), u(t)) + K(t)(y(t) - \hat{y}(t)) \tag{14}$$

$$\hat{y}(t) = h(\hat{x}(t), u(t)) \tag{15}$$

where $K(t)$ is the gain of the filter

$$K(t) = P(t)H(\hat{x}(t), u(t))' R^{-1} \tag{16}$$

and $P(t)$ is the solution of the differential Riccati equation (DRE)

$$\dot{P}(t) = P(t)F(\hat{x}(t),u(t))' + F(\hat{x}(t),u(t))P(t) - P(t)H(\hat{x}(t),u(t))'R^{-1}H(\hat{x}(t),u(t))P(t) + Q \tag{17}$$

with $\hat{x}(t_0)=\bar{x}_0$ and $P(t_0)=P_0$.

The matrices $F(\hat{x}(t),u(t))$ and $H(\hat{x}(t),u(t))$ have to be calculated at every time instant from the state and output functions of the model.

$$F(\hat{x}(t), u(t)) = \left.\frac{\partial f(x,u)}{\partial x}\right|_{\substack{x=\hat{x}(t) \\ u=u(t)}} \tag{18}$$

$$H(\hat{x}(t), u(t)) = \left.\frac{\partial h(x,u)}{\partial x}\right|_{\substack{x=\hat{x}(t) \\ u=u(t)}} \tag{19}$$

It is demonstrated that $P(t)$ is the variance of the estimation error. For more details, see e.g. (Gelb, 1974).

The EKF algorithm was applied to solve the char mass estimation problem. The model considered was the 2nd order simplified one described in Sect. 3, with the bed temperature T as measured variable.

6. THE CHAR LOADING ESTIMATION

The most delicate phase in the project of the estimation algorithm is to set the values for the matrices Q, R and P_0, because it is through these matrices that the information about the model and the measure uncertainties is passed to the filter.

R describes the measurement error of the temperature transducer: the higher is R the lower is the confidence in the measurements. Based on experimental data obtained from tests on the plant in Livorno, the value R=10 was taken.

P_0 is the initial value of the variance of the error estimation and it affects the convergence speed of the filter. P_0 can be seen as an index of the extent to which the initial state value of the filter is reliable. As we consider $\hat{x}(t_0)$ close to $x(t_0)$, P_0 will have small components.

Q can be tuned with the aim of optimising the estimation. In this connection, observe that Q characterises the discrepancy between model description and real system. As is well known among the EKF theorists and pratictioners, the problem of choosing a value for Q is extremely complex. In our problem, we made use of the char mass given by the simulator as if it were the true one and we selected a value for Q so as to render the char mass estimation $\hat{m}$ as close as possible to the simulator value m. Briefly, two goal functions were calculated over a large number of transient tests:

$$J_1 = \left|\overline{m} - \overline{\hat{m}}\right| \tag{20}$$

$$J_2 = \frac{1}{T}\int_0^T \left|m(t) - \hat{m}(t)\right| dt \tag{21}$$

where $\overline{m}$ and $\overline{\hat{m}}$ are considered in steady state condition.

The average values $\bar{J}_1$ and $\bar{J}_2$ over the transients were then found. The Q value corresponding to minimum $\bar{J}_1$ and $\bar{J}_2$ was at the end chosen as $Q = \mathrm{diag}(10^{-5}, 10^{-1})$.

The estimation algorithm was tested in steady state and transient conditions, repeating the tests presented in Sect. 4 with the EKF tuned as shown previously.

a) Starting from *RS1*, new transients were calculated when a step of the inputs was imposed. Fig. 4 shows the matching between simulator, model and EKF for a specific transient.

When the model is well tuned around a steady condition, one can observe that the filter and the model have the same behaviour in mass estimation. The char mass estimation is, in this case, similar when it is obtained either with EKF or with the model.

b) In the *RS2* condition, when the model is tuned in *RS1*, the model badly interprets the behaviour of the simulator. When the filter is applied the mass estimation improves noticeably. Fig. 5 shows that the estimation, starting from the model *RS2* condition, gets closer to the simulator value. Several transient tests starting from *RS2* condition with step inputs of w_{ci} or w_a attest that the char mass estimation with the model is completely different from the simulated value, while the Kalman filter based algorithm allows a more precise prediction (see Figs. 6 and 7).

In conclusion, the estimation algorithm, based on the measured temperature information, can alleviate the influence that the modelling error has on the state variables.

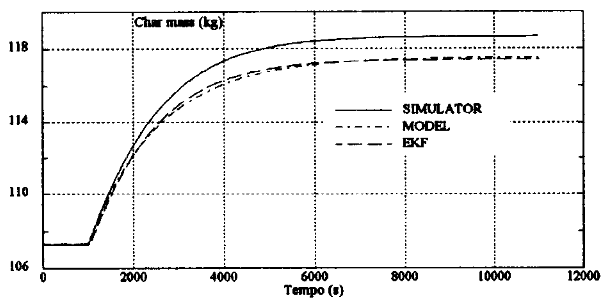

Fig. 4 - Decreasing step of 10% of w_a

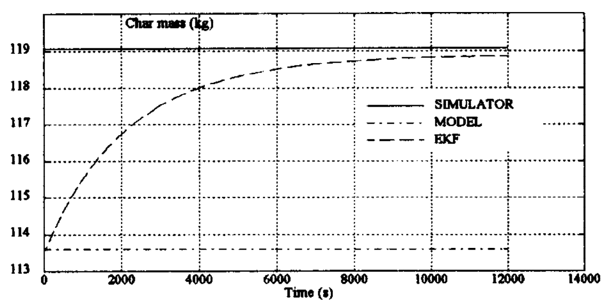

Fig. 5 - Steady state condition *RS2*

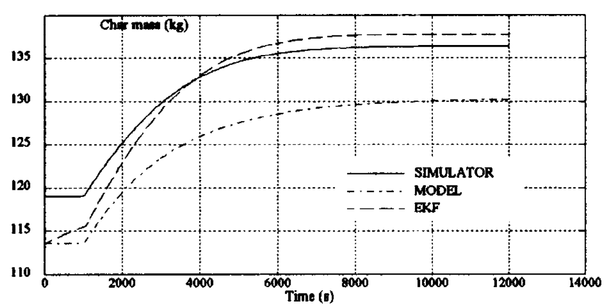

Fig. 6 - Decreasing step of 10% of w_a starting from *RS2*

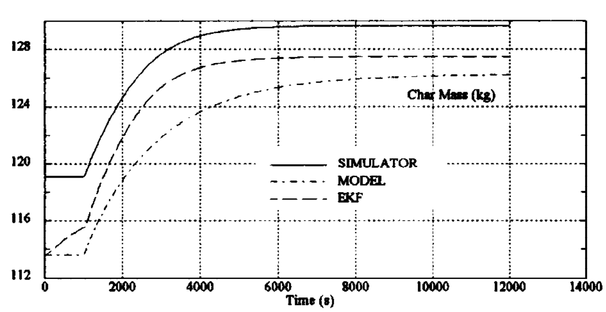

Fig. 7 - Increasing step of 10% of w_{ci} starting from *RS2*

Furthermore, the application of the algorithm allows to avoid the tuning of the model parameters every time there is a change in the plant operational point. We can explain this observing that most part of the uncertainty is due to the oversimplification of the temperature state equation and in particular of the description of heat transfer coefficients. The measure information partly replaces the temperature model description, so that the char mass estimation is more precise.

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