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Kalman Filter Estimation of the Coal Flow in Power Plants

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Abstract—**In this paper the Kalman filtering method is used to estimate the fuel flow in a coal-fired power plant. The results obtained with a standard Kalman approach based on a mill-boiler-turbine black box model and the ones obtained with an extended Kalman filter based on a furnace nonlinear physical model have been compared. A detailed nonlinear real time simulator of an Italian power plant is used as test bench. The simulations show that a good fuel flow estimation can be achieved allowing a substantial improvement of the regulation performances.**

I. Introduction

THE use of coal in power plants has been gradually increasing through recent years thanks to its cheapness, to the possibility of its use with low polluting emissions (excepted CO_2) by means of denitrification/desulphurization systems and to the fact that it can be safely transported and stocked. This, combined with the growing control needs of the electric grid due to the electrical market liberalization process, has renewed the interest in the analysis of coal-fired power plants control in order to improve their poor dynamic performances. However, unlike other kinds of thermoelectric power plants, coal-fired power plants are affected by significant technological difficulties in measuring the fuel mass flow that enters the furnace. This has led to the unavailability of such measure in most operating plants hence to the impossibility of controlling in closed loop this important plant variable. The only available measure is the mill input coal mass flow that represents a good estimation of the coal mass flow to the furnace in steady state, but during the transients they may differ significantly.

Many studies have concerned the coal mass flow measurement [1], [2], [3] however it is important to note that, in order to accomplish a more robust control, the heat flux input to the furnace is the main needed information but, since different kinds of coal have different calorific values, a mere coal mass flow measure is a poor index for that value.

Software solutions have been developed too, see the online coal mass flow measuring [4] and applications of Kalman filtering [5], [6].

This paper presents a comparative study between two different approaches to the coal mass flow estimation using Kalman filtering. The former is based on a standard Kalman filter using a black box model of mill-boiler-turbine system whereas the latter is based on an extended Kalman filter using a nonlinear physical model of the furnace. Both of them fit well with a customization for other kind of boilers and, as simulation results show, they allow a clear improvement of the plant dynamic response to load changes and disturbances if used in closed loop as a substitution of the missing coal flow measure.

II. Reference Plant and Simulation Environment

The adopted reference plant is a conventional once-through 660 MW supercritical coal fuelled power plant reproducing an actual unit located in Italy. The dynamic simulator of such plant, that has been used as test bench, includes all the water-steam systems (boiler, steam turbine, balance of plant), the air-gas system, the mills and all the control loops.

The adopted simulation environment is ALTERLEGO [7], [8], a powerful simulation and modelling tool developed by CESI (Centro Elettrotecnico Sperimentale Italiano) and validated through the years in many applications. Indeed, ALTERLEGO is the standard environment used for the operators training as well as for the design and validation of the regulation and automation systems of real power plants.

III. The Coal Flow Control and Possible Enhancements

In Fig. 1 the original control scheme of the pulverized coal flow to the furnace is represented. The scheme includes a PI master controller driven by the error between the coal flow request (coming from the power plant load controller) and an estimation of the total ground coal exiting the mills. The output of the controller represents the mill feeder speed request for all the mills in operation (max 6 mills).

The feeder speed gives a good representation of the coal flow entering the mills and is controlled, for each mill, by a dedicated PI regulator. As for the coal flow estimation exiting each mill, its dynamic behavior is represented by means of two transfer functions taking into account the contribution of the grinding time delay (f_2) of the coal entering the mill and the contribution of the lead effect (f_1) of the air flowing inside the mill and carrying the pulverized coal flow to the furnace (in the following this estimation will be referred to as *previous estimation*).

The two transfer functions used for coal flow estimation

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have been identified on the basis of a trial and error procedure, leading to the following functions:

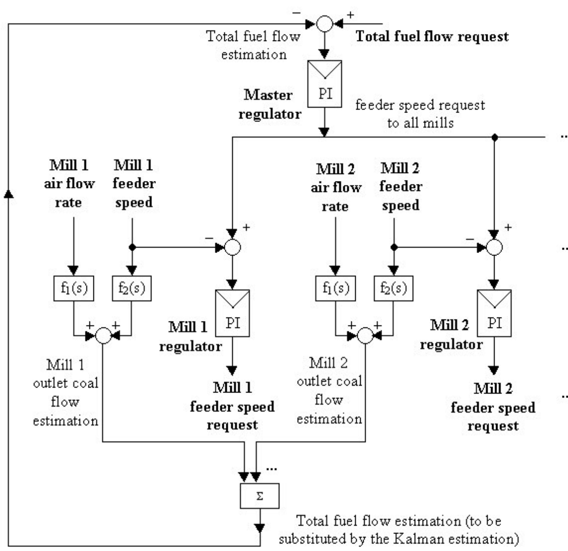


Fig. 1. Control scheme of the pulverized coal flow to the furnace

$$f_1(s) = \frac{80s}{(1+200s)}; \qquad f_2(s) = \frac{1-60s}{(1+60s)(1+200s)}$$

and consequently to tune the master PI controller $PI(s) = Kp\frac{1+sTi}{sTi}$ with Kp=1 and Ti=200 s.

Fig. 2 shows the error between the total fuel flow request and the flow obtained in response to a step variation of the plant load request. In particular, case 1) refers to the standard

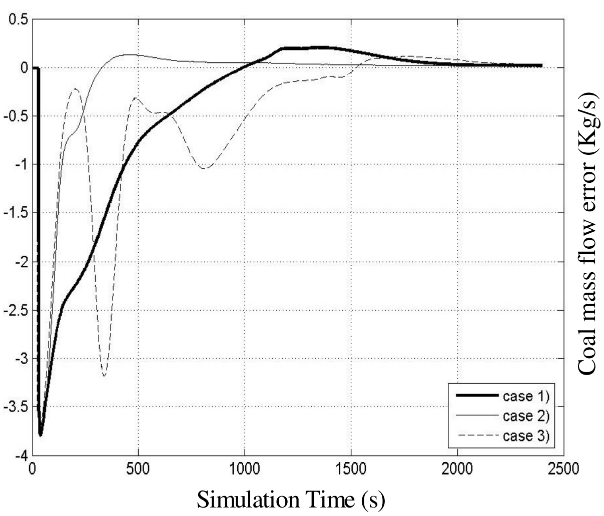


Fig. 2. Comparison of the coal mass flow error obtained in response to a step variation of electrical power from 550 to 590 MW. Cases 1), 2) and 3) are defined in the third paragraph.

coal flow regulation scheme and parameters, whereas in case 2) the coal flow estimation has been substituted with the actual measure and the master PI regulator parameters has been re-tuned (Kp=9; Ti=700s) obtaining a much faster time response. Finally in case 3) the usual coal flow estimation has been used with PI enhanced parameters (Kp=3; Ti=700s)

TABLE I
ESTIMATION ERROR VARIANCE

Model Order	550-590 MW PRBS variations	460-500 MW PRBS variations	600-640 MW PRBS variations
2	0.8715	1.7264	1.0737
4	0.2785	0.6307	0.6114
6	0.1520	0.4461	0.6628
8	0.0970	0.2965	0.5686
10	0.1559	0.6248	0.5595

Estimation error variance of different black box model order obtained in response to PRBS variations of the electrical power request.

leading to wide oscillations. In conclusion the simulations demonstrate that with the actual coal flow estimation it is not possible to improve the response of the coal flow control loop, whereas having a better estimation, good improvements can be achieved. In the following sections two different approaches to obtain a better coal flow estimation using Kalman filtering are presented.

IV. BLACK BOX MODEL ESTIMATION

In this section a black box model of the mill-boiler-turbine system is used for the estimation of the coal mass flow with a Kalman filter [9]. After a careful analysis of the process behavior using the plant simulator, a structure with 2 inputs and 2 outputs has been chosen for the black box model. The input variables are:

1) The electrical power request (u_l) (that is the only variable controllable by the plant operators);
2) The coal flow (w_c).

The output variables are:

1) The water temperature at the furnace first pass walls outlet (which is measurable and has demonstrated to be strictly influenced by fuel flow variations);
2) The generated electrical power.

The state-space model

$$\begin{cases} x(k+1) = Ax(k) + B_l u_l(k) + B_c w_c(k) \\ y(k+1) = Cx(k+1) \end{cases} \tag{1}$$

where x is the state vector and y the output vector, has been identified using data obtained from the simulator imposing 40 MW amplitude Pseudo Random Binary Sequence (PRBS) variations to the requested electrical power (550-590 MW). In Table I the estimation error variances are presented. These variances have been obtained validating different order black box models responses imposing PRBS variations of the same amplitude to the requested electrical power at different plant loads. The best results have been obtained with the eighth order system characterized by the following matrices:

$$A=\begin{bmatrix} 0 & 0 & 0 & 0.0045 & 0 & 0 & 0 & 0 \\ 0.5000 & 0 & 0 & 0.2279 & 0 & 0 & 0 & 0 \\ 0 & 1.0000 & 0 & -0.7120 & 0 & 0 & 0 & 0 \\ 0 & 0 & 4.0000 & 2.9276 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.3107 \\ 0 & 0 & 0 & 0 & 0.5000 & 0 & 0 & -0.0645 \\ 0 & 0 & 0 & 0 & 0 & 1.0000 & 0 & -0.7982 \\ 0 & 0 & 0 & 0 & 0 & 0 & 2.0000 & 2.4137 \end{bmatrix}$$

$$B_l=\begin{bmatrix} -0.0147 \\ 0.0233 \\ -0.0246 \\ 0.0344 \\ 0.0799 \\ -0.0968 \\ 0.0708 \\ -0.0275 \end{bmatrix} \quad B_c=\begin{bmatrix} 0.4878 \\ -0.7316 \\ 0.7313 \\ -0.9748 \\ -0.1823 \\ 0.3323 \\ -0.3945 \\ 0.3068 \end{bmatrix} \quad D=\begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}$$

$$C=\begin{bmatrix} 0 & 0 & 0 & 4 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 2 \end{bmatrix}$$

Subsequently the resulting system (1) has been enlarged including the coal flow (that is the quantity to be estimated) among the system states as shown in (2), hence having as unique input the electrical power request.

$$\begin{cases} \xi(k+1)=\begin{bmatrix} A & B_c \\ 0 & I \end{bmatrix}\xi(k)+\begin{bmatrix} B_l \\ 0 \end{bmatrix}u_l(k) \\ y(k+1)=[C \quad 0]\xi(k+1) \\ \xi=\begin{bmatrix} x \\ w_c \end{bmatrix} \end{cases} \tag{2}$$

The obtained enlarged system has been used to estimate the coal flow by means of a Kalman filter obtaining good results as shown in Fig. 8. In this figure the fuel flow measure and estimation time responses are compared in step transients of the electrical power request. The same figure also includes the fuel flow *previous estimation* and the extended Kalman filter estimation that will be described in the following paragraph.

The resulting Kalman filter has been tested also in noising conditions without appreciably affecting the performances of the estimator as shown in Fig. 3.

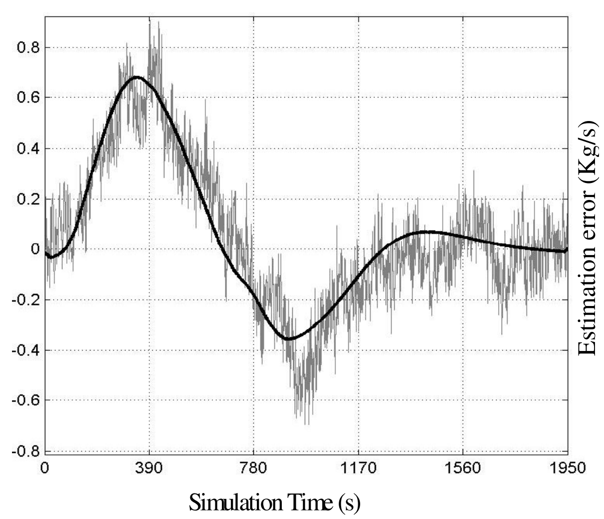


Fig. 3. Comparison of the estimation error obtained in response to a step variation of electrical power from 550 to 590 MW with (gray line) and without (black line) adding white gaussian noise to the input measures.

V. Nonlinear Physical Model Based Estimation

In order to introduce the process typical nonlinearities hence enlarging the domain of validity of the model and to approach the problem preserving the congruence among the system state variables, a non linear model, based on the first principles equations, has been developed. This causes the disadvantage of a more difficult model and estimation approach than the previous one leaving to the final user the choice of the preferred solution having in mind the respective pros and cons. In particular a physical-mathematical model of the furnace first pass walls has been developed, as in a power plant this zone is the first influenced by a fuel flow variation due to its proximity to the burners.

Analyzing the furnace system, under the assumption of having fast dynamics, the steady state mass and energy conservation equations of the air/gas side can be written:

$$w_c h_c + w_a c_{p\_a} T_a + w_{ric} h_{ric} - w_f c_{p\_f} T_f - \varepsilon_1 T_f^4 = 0$$

$$w_f = w_c + w_a + w_{ric}$$

in which w_c is the coal mass flow, h_c is the coal calorific value, w_a is the comburent air mass flow, c_{p_a} is the air calorific capacity, T_a is the comburent air temperature, w_{ric} is the exhaust gas recirculation mass flow, h_{ric} is the specific hentalpy of exhaust gas, w_f is the furnace outlet gas mass

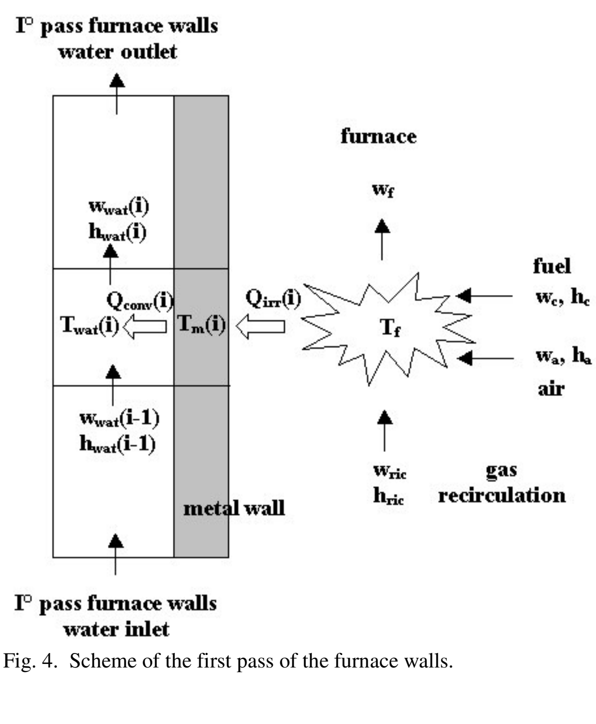


Fig. 4. Scheme of the first pass of the furnace walls.

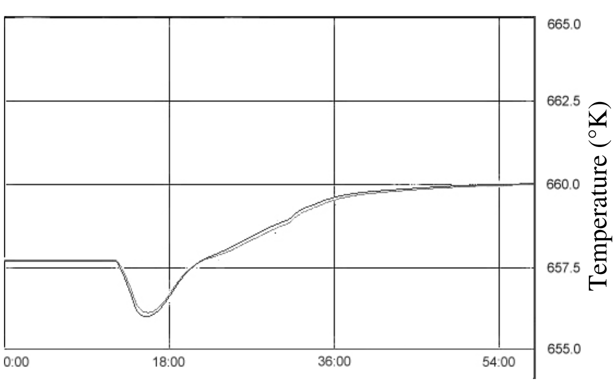
flow, c_{p_f} is the furnace outlet gas calorific capacity, T_f the furnace outlet gas temperature and ε_1 is the emissivity of the furnace multiplied by the walls exchange surface.

Subsequently the physical model for the water-side of the furnace first pass walls has been developed with a lumped approach (see Fig. 4). For the *i-th* lump at the time t the energy conservation equations for the water and for the metal of the walls and the exchanged convective and radiation heat can be written in the discrete time form:

$$\begin{cases} Q_{conv} = \gamma_{wat}\left[T_m(i,t-\Delta t) - T_{wat}(i,t-\Delta t)\right] \\ Q_{irr} = \varepsilon_2 T_f^4 \\ T_m(i,t) = T_m(i,t-\Delta t) + \dfrac{\Delta t\left[Q_{irr} - Q_{conv}\right]}{c_m} \\ h_{wat}(i,t) = h_{wat}(i,t-\Delta t) + \\ \qquad + \dfrac{\Delta t\{w_{wat}(t)\left[h_{wat}(i-1,t-\Delta t) - h_{wat}(i,t-\Delta t)\right] + Q_{conv}\}}{V\rho_{wat}} \end{cases}$$

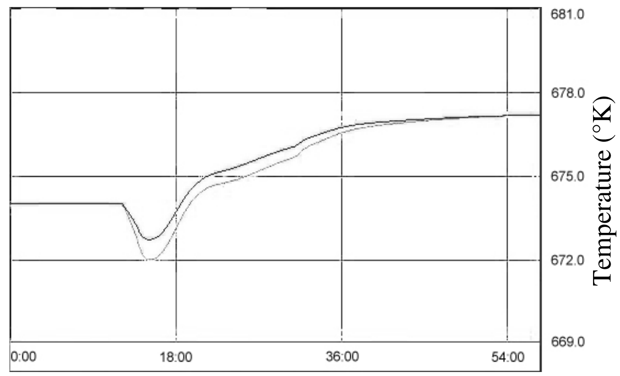
in which Q_{conv} is the convective heat exchanged between metal and water, γ_{wat} is the convective exchange coefficient, T_m is the metal temperature, T_{wat} is the water temperature, Δt is the sampling time, Q_{irr} is the heat exchanged by radiation, ε_2 is the emissivity of the furnace multiplied by the first pass walls exchange surface, c_m is the metal thermal capacity, h_{wat} is the specific hentalpy of water, V is the volume of the *i-th* lump and ρ_{wat} is the water density.

The number of states of the resulting model is hence twice the number of the implemented lumps. This model requires more input variables than the previous one (w_c, T_a, w_{ric}, h_{ric}, w_{wat}, h_{wat} and the inlet water pressure) and computes the outlet water temperature and the average metal temperature of the last lump which are the measured plant variables.



Simulation Time (min)

Fig. 5. Comparison of the reference (*black line*) and the model (*gray line*) water temperature in response to a step variation of electrical power request from 550 to 590 MW.



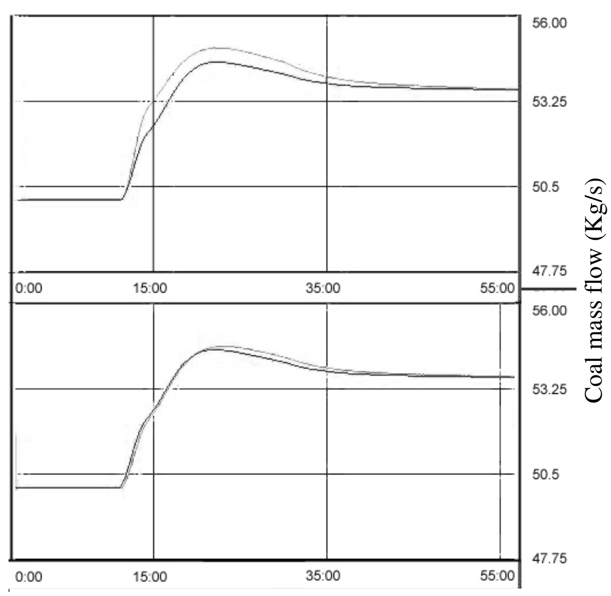
Simulation Time (min)

Fig. 6. Comparison of the reference (*black line*) and the model (*gray line*) metal temperature in response to a step variation of electrical power request from 550 to 590 MW.

For what concerns the identification of the model parameters, the problem has been approached as a multi-variable function minimum research that has been solved using a conjugate gradient method with plant data obtained by means of the simulator.

The resulting system responses to a 40 MW amplitude step variation of the electrical power request are depicted in Fig. 5 and Fig. 6. As one can see, the steady state model approximation is good for both the output variables, whereas in transient conditions the error of the average metal temperature of the last lump is greater than that of the outlet water temperature (that is indeed acceptable).

As for the previous model, the resulting system has been widened including the coal mass flow among its states. However, unlike the previous case, for this newly added state a first order transfer function, having the electrical power



Simulation Time (min)

Fig. 7. Comparison of the coal mass flow (*black line*) and of the extended Kalman filter estimation (*gray line*) in response to a step variation of electrical power request from 550 to 590 MW.

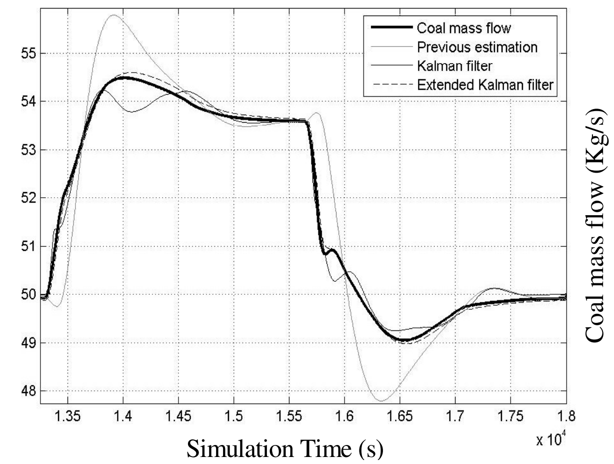


Fig. 8. Comparison of the coal mass flow, the previous estimation, the Kalman filter estimation and the extended Kalman filter estimation in response to step variations of electrical power request in the range 550-590 MW.

request as input, has been used. In order to improve the robustness of the resulting estimator with respect to the parameters modifications at different plant loads, the state vector has been further widened to include part of them.

Afterwards the extended Kalman filter has been used to obtain the estimation of the coal mass flow. Since the model shows a better estimation of the water temperature with respect to the metal one, a greater variance of the metal temperature measure has been chosen. This has led to a better estimation of the coal mass flow, as shown in the lower graphic of Fig. 7, with respect to the upper one in which the same variance has been given to both the measures of water and metal.

In Fig. 8 the effective coal mass flow, the previous estimation, the Kalman filter estimation and the extended Kalman filter estimation are depicted in response to step variations of electrical power request in the range 550 to 590 MW. As shown in this figure, the smaller estimation error is obtained using the extended Kalman filter.

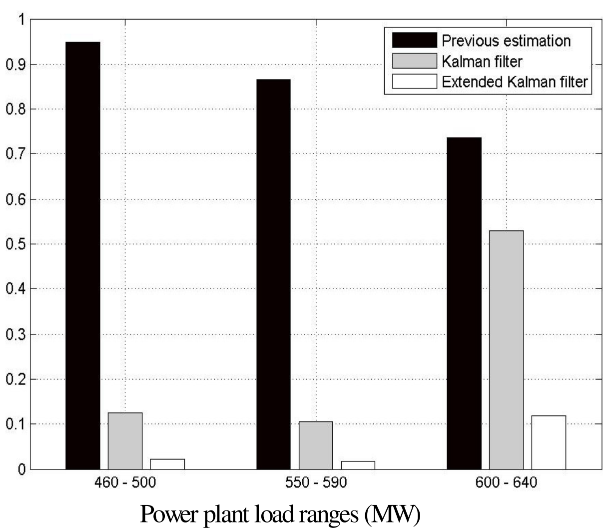


Fig. 9. Coal flow estimation error variance in response to a PRBS variation of electrical power request at different plant loads.

In order to compare the three estimation methods, PRBS variations of the electrical power request at different plant loads have been simulated. The obtained estimation error variances, depicted in Fig. 9, confirm the goodness of the two Kalman estimations with particular emphasis with the extended one.

VI. Closed Loop Control With Kalman Estimation Feedback

Once established the correct behavior of the extended Kalman estimation, this variable has been used as feedback for the closed loop control of the coal mass flow, thus replacing the empirical estimation previously adopted on the actual plant.

Such substitution has led to a sharp improvement of the dynamic performances of the control system because allows a tighten tuning of the regulator (*Kp*=5.2*; Ti*=600s) thus obtaining a higher cut-off frequency preserving a very good damping factor too. Indeed the new regulation scheme has a settling time three times smaller than the original one.

The advantages originated from the use of Kalman filtering influence also the dynamic of two important plant variables, namely the main steam temperature and pressure, in which the amplitude of the deviations from their respective set-points, induced from changes on the requested electrical power, has been reduced of about an half.

Fig. 10 and 11 represent the variances of the main steam temperature and pressure respectively, in which three cases are compared:

case a) The feedback variable is the *previous estimation* and the original regulation tuning is preserved,

case b) The feedback variable is the extended Kalman filter estimation and the original regulation tuning is preserved,

case c) The feedback variable is the extended Kalman filter

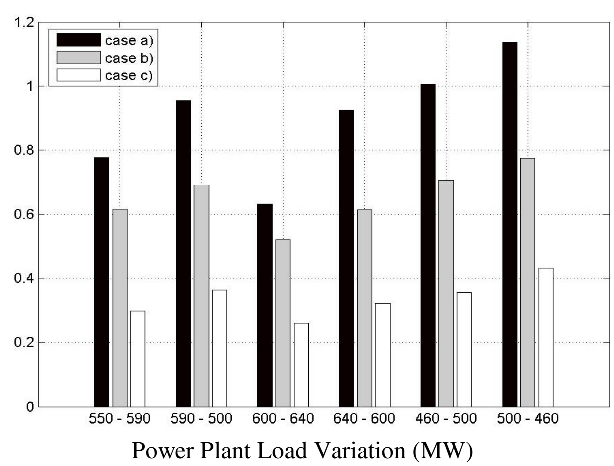


Fig. 10. Main steam temperature variance obtained in response of several step variations of the electrical power request. Cases a), b) and c) are defined in the sixth paragraph.

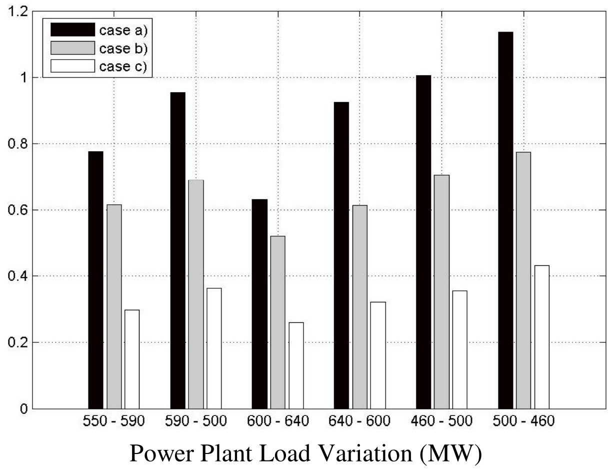


Fig. 11. Main steam pressure variance obtained in response of several step variations of the electrical power request. Cases a), b) and c) are defined in the sixth paragraph.

estimation and the new regulation tuning is adopted.

Moreover the improvement of the coal mass flow control system and the smaller disturbances induced in the boiler have led to a better controlled dynamic of the generated electrical power with a reduced settling time.

Of particular interest is the property of both the presented Kalman estimations of being a good indicator of the heat flux entering the furnace even in presence of modifications of the calorific value of the coal. Such property is due to the choice to not estimate the effective fuel mass flow, but the equivalent fuel mass flow conjecturing constant calorific value, hence obtaining a linear relation between the coal mass flow and the heat entering the furnace. In order to evaluate the robustness of the resulting control system to this kind of disturbances, step variations of the calorific value have been simulated. The response of the main plant controlled variables obtained closing the coal flow control loop both with the previous estimation and with the extended

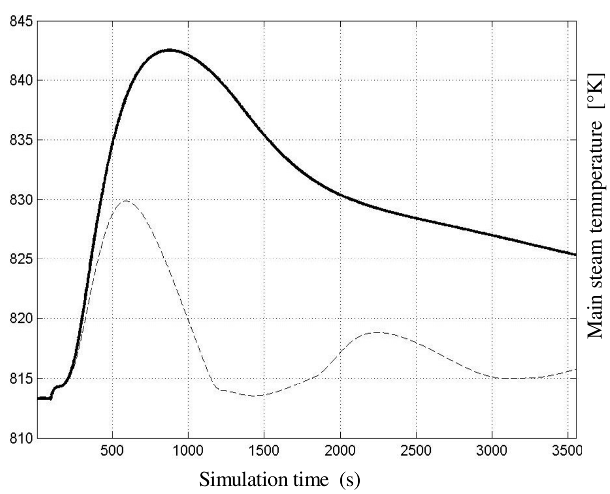


Fig. 12. Main steam temperature response to a step variation of the coal calorific value, (*hatched line*) for the extended Kalman filter estimation, (*black line*) for the *previous estimation*

Kalman filter estimation have been compared. In the last case smaller deviation and settling time have been obtained: see for instance the steam temperature response in Fig. 12.

VII. Conclusion

In this paper two different approaches for the estimation of the coal mass flow using Kalman filtering have been discussed. The former is based on a mill-boiler-turbine system black box model and the latter is based on a nonlinear furnace physical model. In both cases the Kalman estimation has obtained a good correspondence with the effective coal mass flow, both in steady state condition and in transients. If compared with the empirical estimation previously adopted on the plant the estimation error variance has been reduced of an order of magnitude.

Closing the coal flow control loop with the Kalman estimation in substitution of the missing measure has allowed a more tighten tuning of the control system, leading to a sharp improvement of its dynamic performances without compromising the system stability. Even the amplitude of the disturbances on the main steam temperature and pressure, induced by electrical power request variations, have been significantly reduced.

All these factors, combined with the resulting control system robustness to modifications of the coal calorific value, concur in making the Kalman filter a good solution to the coal mass flow control problem in power plants.

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