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Advanced control system of the steam pressure in a fire-tube boiler

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Abstract: The urgent requirement to optimize the consumption of energetic resources justifies the application of advanced control strategies to automate equipment that consumes higher amounts of fossil fuels, among them the fire-tube boilers. From a control engineering point of view, these systems are characterized by a difficult dynamic behavior, multiple inputs and outputs, time delay and several uncertainties. In this work an advanced control system with an Adaptive-GPC algorithm of the steam pressure inside a fire-tube boiler is presented. System identification techniques were employed to obtain a mathematical model that characterizes the dynamic behavior of the process under study. Simulation results evidenced that this model describes with high exactitude the process of steam pressure variation inside the boiler. The model obtained was subsequently used to design the advanced control system. The system was implemented in a utility fire-tube boiler and the results showed its efficiency to deal with variations of the dynamic parameters of the process arisen at different operating conditions. It also showed its superiority against a control system using a PID algorithm.

1. INTRODUCTION

Currently fossil fuels are used as a main source of energy worldwide. Their impending depletion and the serious environmental problems that their combustion originates, urge to take measures to make possible an efficient and intelligent use of this kind of fuels (Lindsley, 2000). In developed as well as in developing countries industrial energy consumption can account for as much as 50% of the total energy consumption. Therefore, a slight improvement in consumption efficiency can provide a considerably large saving of energy, besides reduction in NO_X and CO_2 emissions (Rajan, 2006). Fire-tube boilers are among the main fossil fuels consumers (Dukelow, 1999; Rivas Perez et al., 2000). In this kind of equipment, combustion control is achieved by regulating the steam pressure variation process inside the boiler (Lindsley, 1991). This is the reason why this process presents a considerable importance in boiler performance. Previous efforts have been made to address this problem (Sheng 2006, Hogg, 1991). However they are either performed on water-tube boilers, which has different dynamical properties or are based in a theoretical model.

To obtain a high efficiency of fire-tube boilers, effective control systems of steam pressure variation are required (Rodriguez Vasquez, Rivas Perez and Sotomayor Moriano, 2007). Application of conventional control systems (PID) to the process under study does not allow to obtain the desired efficiency, due to the difficult dynamic behavior of the this process, which is characterized by variations in its dynamic parameters along with time delay (Rivas Perez, Feliu Batlle and Sotomayor Moriano, 2005).

Model-based Predictive Control is considered among the advanced control techniques that have achieved great success in practical applications (Martín Sánchez and Rodellar, 2005; Tatjewski, 2007). Self-regulated Generalized Predictive Control (adaptive-GPC) constitutes a variant of the MBPC algorithm that in the last years has reported significant results in industrial process control with difficult dynamic behavior (Tatjewski, 2007). However, it is necessary to state that the design of this class of control systems, in comparison with the design of conventional ones like PID is far more complicated (Martín Sánchez and Rodellar, 2005).

The objective of this work is to design an adaptive-GPC control system for the steam pressure variation process inside a fire-tube boiler that allows an effective performance of this kind of equipment facing variations in its dynamic parameters. To achieve this goal it is required to have a mathematical model that describes adequately the dynamic behavior of the process to control (Feliu Batlle et al., 2005).

The paper is organized as follow. In Section 2 a mathematical model that describes the dynamic behavior of the steam pressure inside a fire-tube boiler is offered. The adaptive generalized predictive control strategy (adaptive-GPC) is presented in Section 3. Section 4 is devoted to show the simulation results of designed advanced control system. The implementation results on an industrial utility fire-tube boiler are presented in Section 5. The comparison of designed advanced control system with a PI predictive (PPI) controller performance is developed in Section 6. Discussion and conclusions are presented in the last section.

2. SYSTEM IDENTIFICATION OF STEAM PRESSURE VARIATION PROCESS INSIDE A FIRE-TUBE BOILER.

Experimental set-up used to carry out data acquisition of input and output variables required to obtain the mathematical model of the steam pressure variation process inside the fire-tube boiler using system identification techniques (Ljung, 1999) is shown in Fig.1.

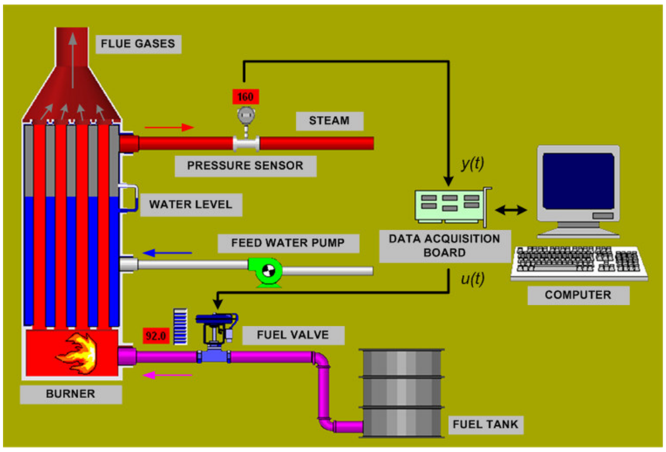

Fig. 1. Experimental set-up used to collect data of the steam pressure variation process inside the boiler.

This experimental set-up consisted of the following devices: pressure sensor (0-700 kPa absolute pressure), servo valve that regulates fuel flow entering into the burner, data acquisition card and a personal computer (PC).

Non-parametric identification procedure began with a static gain experiment to determine the operative region in which the process behaves linearly. Next, a step input signal experiment was carried out, in which the step signal applied to the process $u(t)$ was a change in the fuel valve opening between 12,5 % and 22,5 %. Steam pressure inside the boiler was recorded as the process response $y(t)$. The evolution of both $u(t)$ and $y(t)$ in time was finally plotted in Fig. 2. It is shown from Fig. 2 that the dynamic behavior of the process studied can be described as a second order system with time delay of $\approx 30s$ and a settling time of $\approx 120s$.

A second experiment was developed by exciting the process with a pseudo-random binary sequence (PRBS). This experiment was carried out using a sampling time of $T = 5\,s$, designed as $\approx 1/20$ of the settling time of the process response (Aström and Wittenmark, 1997).

In order to validate the results obtained in the step-input signal experiment, spectral and correlation analysis were performed using the data acquired in the PRBS-input signal experiment. Results from these analyses corroborate that the dynamic behavior of the process studied is described by means of a second order system with time delay (τ) of $\approx 32\,s$ and settling time of $\approx 120\,s$.

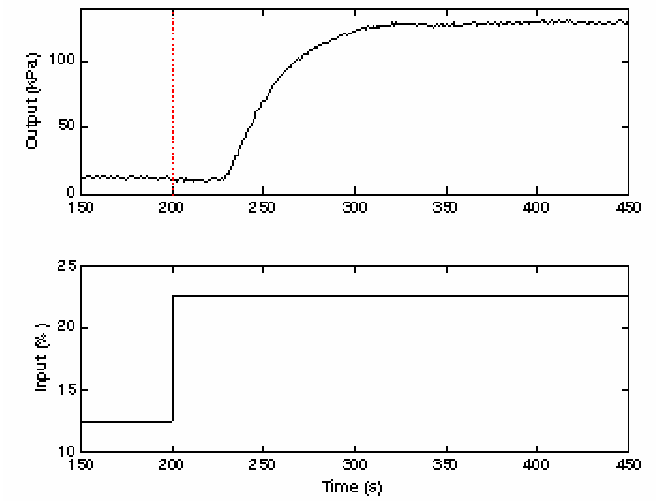

Fig. 2. Step signal input experiment results.

In the course of parametric identification, one of the most significant steps taken was the selection of model structure. To ensure a correct choice, several different structures were evaluated, among them: ARMAX, ARX and Box-Jenkins. Of particular interest is the ARMAX (Auto-Regressive Moving Average with External Input), since it allows to model the process behavior considering control and disturbance inputs. This constitutes the basic structure of the GPC control systems (Camacho and Bordons, 2004). That is the reason why this structure was chosen as a candidate structure to model the process of this study. As an alternative structure for comparison purposes an ARX (Auto-Regressive with External Input) structure was selected.

Table 1 shows the different structure orders and time delay values chosen to better estimate the parameters of the candidate models. These candidate models parameters were estimated by minimizing the prediction error with square criterion.

Table 1. Defining parameters of the selected model candidate structures.

Structure	na	nb	nc	d
ARX	2	2	0	7
ARX	3	3	0	7
ARMAX	1	1	1	7
ARMAX	1	2	2	7
ARMAX	2	2	2	7
ARMAX	3	3	3	7
ARMAX	4	4	4	7

Next step was validation of the candidate models using several methods, among them Final Prediction Error (FPE) criterion, analysis of pole-zero cancellation and finally cross-validation with experimental data obtained for validation purposes. This last method is considered to be the best to validate models (Ljung, 1999).

By using these methods candidate models that do not describe adequately the dynamic behavior of the process under study were discarded. Finally a mathematical model with second order ARMAX - [2 2 2 7] structure was selected. Results of cross validation are shown in Fig. 3.

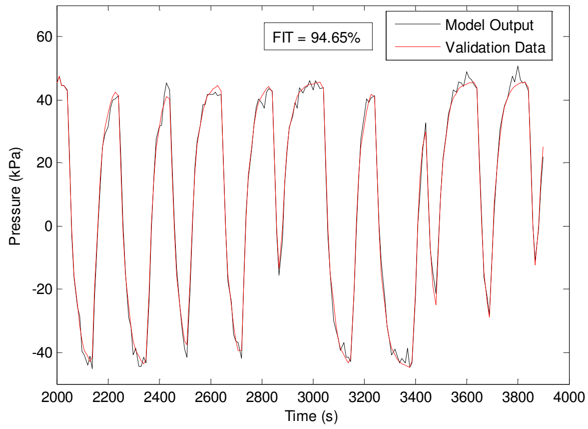

Fig. 3. Cross validation results of the ARMAX - [2 2 2 7] model using experimental data.

The estimated parameters of the ARMAX - [2 2 2 7] model chosen are shown in Table 2. These values parameterize the structure described by the following expression:

Table 2. Estimated values of model parameters with ARMAX - [2227] structure

Structure	a_1	a_2	b_1	b_2	c_1	c_2
ARMAX [2227]	-1.197	0.289	0.108	0.720	-0.689	0.238

$$y(t) = a_1 y(t-1) - a_2 y(t-2) + b_1 u(t-8) + \dots \\ \dots + b_2 u(t-9) + e(t) + c_1 e(t-1) + c_2 y(t-2). \quad (1)$$

3. ADAPTIVE GENERALIZED PREDICTIVE CONTROL STRATEGY (ADAPTIVE-GPC)

In several industrial applications where disturbances are non-stationary is more convenient to use an integrated ARMAX model (Clarke, 1994; Maciejowski, 2002), which is known as ARIMAX. This model can be described by means of the following equation:

$$A(q^{-1})y(t) = B(q^{-1})q^{-d}u(t) + C(q^{-1})\frac{e(t)}{\Delta}, \quad (2)$$

where: $\Delta = 1 - q^{-1}$; $A(q^{-1}), B(q^{-1}), C(q^{-1})$ - polynomials that characterize the dynamic behavior of the process studied; $u(t), y(t)$ - process input and output signals; $e(t)$ - random sequence of zero mean value; d - process time delay.

From the model (2), GPC predicts future process outputs using past values of the input and output signals $u(t+j), y(t+j), j \le 0$, along with present and future values of the control signal variation $\Delta u(t+j), j \ge 0$ within a time range known as prediction horizon $[t+N_1, t+N_2]$. It is important to define the concept of control horizon N_u, which constitutes a time interval from which the control signal variation is regarded as zero $\Delta u(t+j) = 0,\ j \le N_u$. Defining the vectors:

$$\hat{y} = [\hat{y}(t+N_1) \ \cdots \ \hat{y}(t+N_2)]^T;$$

$$f = [f(t+N_1) \ \cdots \ f(t+N_2)]^T;$$

$$\hat{u} = [\Delta u(t) \ \cdots \ \Delta u(t+N_u)]^T,$$

the prediction of the process output is described by the following expression:

$$\hat{y} = G\hat{u} + f, \quad (3)$$

where: G - matrix of size $n \times N_u$; f - vector that represents the free response of the process under control.

The elements of G and f are obtained recursively by using the process model (2). A cost function is employed to make the future process output within the established prediction horizon follow a determined internal reference signal $w(t+j), j \ge 0$, while penalizing the control effort required to achieve this goal. The general expression of such a cost function is represented by the expression:

$$J(N_1, N_2, N_u) = \sum_{j=N_1}^{N_2} [\hat{y}(t+j \mid t) - w(t+j)]^2 + \dots \\ \dots \sum_{j=1}^{N_u} \lambda(j)[\Delta u(t+j-1)]^2, \quad (4)$$

where: $\lambda(j)$ - weight sequence that penalizes the future control signals; n - number of values of the prediction horizon considered (N_1, N_2); $w(t+j), j \ge 0$ - internal reference trajectory.

To obtain the control law, the cost function (4) is represented considering (3) by the expression:

$$J = (G\hat{u} + f - w)^T (G\hat{u} + f - w) + \lambda \hat{u}^T \hat{u} \\ = \frac{1}{2}\hat{u}^T H \hat{u} + b\hat{u} + f_0, \quad (5)$$

where: $H = 2(G^T G + \lambda I)$; $b = 2(f-w)^T$;

$f_0 = 2(f-w)^T (f-w)$.

A minimum of (5), if there is no constrains applied to the control signal, can be calculated analytically by means of the expression:

$$\hat{u} = -H^{-1}b^T = -2H^{-1}G^T(f-w). \quad (6)$$

Because a receding strategy is used, only the first element of the vector $\hat{u}$ is applied, which is $\Delta u(t)$, repeating the whole procedure in the next sampling instant. Therefore:

$$u(t) = u(t-1) + \Delta u(t)\,. \tag{7}$$

Variation of the dynamic parameters of the process constitutes one of the difficulties that arise when using a GPC controller (Morari. and Lee, 1999). A self-tuning regulator (STR) would help to minimize this problem since it is based on the addition of an adjustment stage of the controller parameters from a new estimate of the process parameters. (Allgöwer et al., 1999).

An identification algorithm widely used in GPC systems is maximum likelihood (ML) which is a variant of the recursive prediction error method (RPEM) (Hogg and El-Rabaie, 1991). Using concepts of matrix algebra, model (1) can be described by the following expression:

$$y(t) = \varphi^T(t,\theta)\hat{\theta}(t-1) + e(t)\,, \tag{8}$$

where: $\varphi(t) = [-y(t-1) \quad -y(t-2) \quad -u(t-1-7) \quad \cdots \quad -u(t-2-7) \quad e(t-1) \quad e(t-2)]$ - regression vector;

$\theta = [a_1 \quad a_2 \quad b_1 \quad b_2 \quad c_1 \quad c_2]^T$ - model parameters vector.

To estimate the parameters vector θ of the model using the maximum likelihood algorithm, the following recursive system of equations must be solved:

$$\hat{\theta} = \hat{\theta}(t-1) + L(t)\left[y(t) - \varphi^T(t)\theta(t-1)\right], \tag{9}$$

where:

$$L(t) = \frac{P(t-1)\psi(t)}{\gamma(t) + \psi^T(t)P(t-1)\psi(t)}\,; \tag{10}$$

$$P(t) = \frac{1}{\gamma(t)}\left[P(t-1) - \frac{P(t-1)\psi(t)\psi^T(t)P(t-1)}{\gamma(t) + \psi^T(t)P(t-1)\psi(t)}\right]; \tag{11}$$

$$\psi(t) = \frac{1}{C(q^{-1})}\varphi(t)\,; \tag{12}$$

$\gamma(t)$ - weight sequence known as "forget factor", usually constant (Ljung, 1999).

As an initial value of $P(t)$ a large number is considered, in this case 1,0056. The initial value of $\hat{\theta}(t-1)$ is obtained from the identified model (Table 2). In this way, the parameters of the process model are estimated in each sampling instant and if variations arise, the GPC controller parameters can be adjusted.

4. SIMULATION RESULTS

To simulate the adaptive-GPC control system designed several parameters are to be determined in order to obtain an effective performance of the system. Since the process under study has a time delay of 7 sampling instants, N_1 was assigned a value of 8. Prediction horizon size was determined intuitively (Camacho and Bordons, 2004), in this case the assigned value was 10 to allow the GPC system predict the process output in a time interval similar to the settling time. Control horizon size is also determined intuitively (Camacho and Bordons, 2004) and in this case a value of $N_u = 3$ was assigned. The penalizing sequence of the control signal was regarded as constant (λ) and its value was determined empirically [15] by means of a trial and error procedure. An adequate value for λ was found at $\lambda = 100$. The value of α was found in a similar fashion. The value determined empirically was $\alpha = 0.76$. The performance of the GPC control system designed for the process under study using these parameters is shown in Fig. 4. in which the output of the control system follows adequately the reference signal.

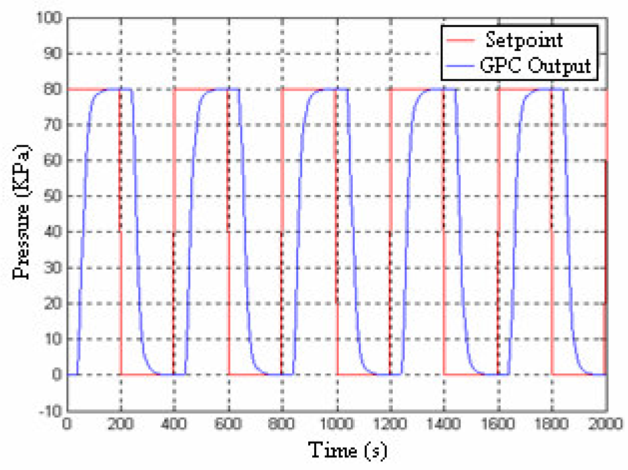

Fig.4. GPC control system performance using $N_1 = 10, N_2 = 18, \lambda = 100, \alpha = 0.76$.

A second experiment was performed when the process object of study changes its dynamical parameters. The polynomial that has the most amount of information about the dynamic behavior of the system is $A(q^{-1})$, since it contains the process poles (Ogata, 1996). Therefore, a variation in one parameter of this polynomial can account for a variation of the dynamic behavior of the process. In this experiment process parameter $a_1 = -1.197$ was changed to $a_1 = -1.30$, which represents an approximate variation of 10% of its original value. Results from this experiment are shown in Fig. 5 within the time interval from 0 s to 1000 s. It can be observed from Fig. 5 that the performance of the control system is considerably deteriorated. Plant response exhibits a great overshoot and oscillations.

Finally, a last test was performed using an adaptive-GPC control system design to control the plant with the same parametric variation. Forget factor $\gamma(t)$ was regarded as constant (γ) and again it was determined intuitively (Camacho and Bordons, 2004). In this case a value of $\gamma = 0.985$ was assigned. Results of this simulation test are shown in Fig. 5 in a time interval from 1000 s to 2000 s. It is clearly observed that shortly after the update of the controller parameters begins ($t = 1000\,s$), the controller restores its desired performance.

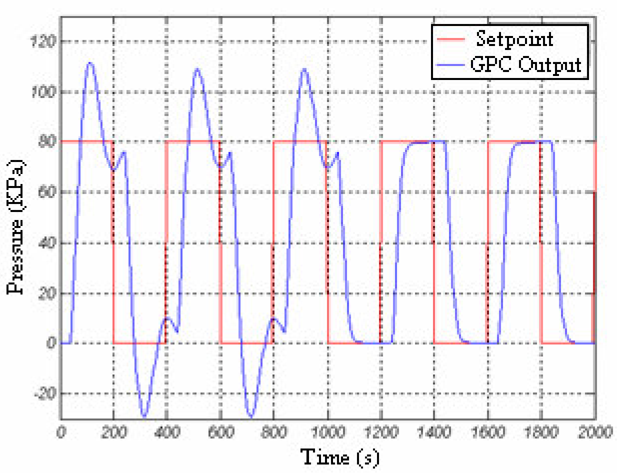

Fig. 5. Control system performance with parameter variation from $a_1 = -1.197$ to $a_1 = -1.30$. From $t = 0$ to $t = 1000$ only GPC control system is used. From $t = 1000$ the adaptive-GPC control system is used.

5. IMPLEMENTATION IN A 100BHP FIRE-TUBE BOILER

The control strategy designed and simulated so far was then used to implement a control system for a 100BHP utility fire-tube boiler. Some characteristics of the system is a nominal capacity of 3450 steam pounds / hour and operating range between 500 and 700 kPa. This boiler is used for several purposes and its load can vary greatly during its operating cycle. That is why the performance offered by a PID controller is not enough. Since this is a piece of equipment already installed, we have to deal with some constraints, as for example the number of control and manipulated variables that in this case are reduced to the SISO system. As we stated previously, the boiler is a complex system with several interacting loops. The constraints imposed in this case can allow us to test the performance of the control system designed using only one of the loops.

The system identification procedure was pretty straightforward and validated the previous study. The performance of the control system designed is shown in Fig. 6, where different operating conditions have been tested. It can be seen that the performance of the control strategy is good regardless the variations in load and the SISO constraint. At time t=4000s a load disturbance was introduced. At time t=5200s the performance of the control system was satisfactory again. Although performance is altered when load variations are introduced, it is recovered soon after.

It is important to mention that an auxiliary anti-wind up algorithm was used. This strategy allows the parameters to be updated only when a significant deviation of the output from the set point is detected. One problem that can arouse in this case is a lack of excitation of the plant that can lead to a poorly defined model. Since this boiler operates in a cycle, excitation to the plant is expected every 4 hours. However, if another longer cycle is used, a PRBS with amplitude of 3kPa is applied every 4 hours to ensure adaptability. This short amplitude does not interfere with the boiler normal operation.

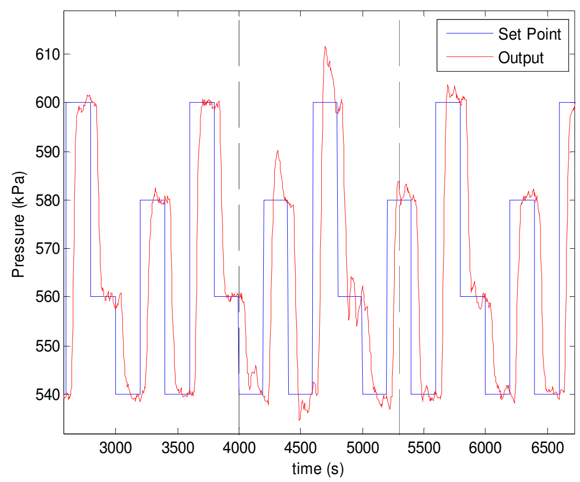

Fig. 6. Adaptive-GPC implemented in a 100BHP utility fire-tube boiler.

Implementation of an advanced control strategy traditionally has been a difficult task because of the complexity of the algorithms. However, with new developer's tools available for editing and compiling software, this task can be implemented with little effort. Moreover, MPC tuning is very intuitive in operation. (Camacho, 2004)

6. COMPARISON WITH A PI PREDICTIVE (PPI) CONTROLLER PERFORMANCE

PID controllers are by far the control systems most currently used in industrial applications, in which more than 95% of the control loops use a PID algorithm (Martín Sánchez and Rodellar 2005). One variant of the classic PID algorithm is called PPI (Predictive PI) and has better capabilities to deal with time delay (Aström and Wittenmark 1997). This algorithm is based on a first order with time delay of the process to control, which is the model obtained from the acquired data using the step-input signal experiment.

The control signal calculated using the PPI algorithm, unlike the traditional PID algorithms, considers explicitly the process time delay. The method used to tune the PPI controller is known as "λ-Tuning", in which the dynamic behavior of the closed-loop system is adjusted by using a desired transfer function (Aström, 1994). This algorithm was previously implemented in the boiler object of study. This control strategy performed well under its design conditions. However, its performance decayed under different conditions and heavy load variations as shown in Fig. 7. Under changes in operating conditions there is little room to tune the controller over again. Even more, these abrupt variations can account for a loss in energy consumption efficiency.

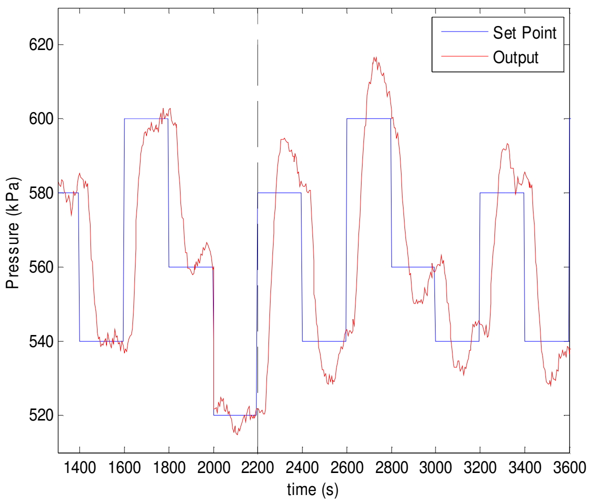

Fig. 7. Performance of the former PPI controller when load variations leaded to changes in process parameters.

7. DISCUSSION AND CONCLUSIONS

The design of an adaptive-GPC control system of the steam pressure variation process inside a fire-tube boiler was presented.

In order to determine the mathematical model that best describes the dynamic behavior of the process, a complete system identification procedure was carried out. As a result, a second order ARMAX mathematical model with time delay of 35 s was obtained. Simulation results evidenced that this model describes with high exactitude the process of steam pressure variation inside the boiler. This model was subsequently used to design the advanced control system.

The generalized predictive control strategy used was presented. The criteria adopted in the controller design and in the determination of its adjustment parameters were explained.

Simulation results of the adaptive-GPC control system designed were presented showing its good performance. The maximum likelihood identification algorithm was used to estimate the parameters vector θ of the process model.

The control strategy was implemented in a 100BHP fire-tube boiler, showing efficiency to deal with variations of the process dynamic parameters due to changes in operating conditions as well as with reference variations.

A comparison between the performances of the adaptive-GPC controller designed and of a predictive PI (PPI) control system revealed a considerable improvement in the performance of the closed loop system when using the first one, especially in the case of process parameters variation due to change in operating conditions.

8. REFERENCES

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