MODEL BASED PREDICTIVE CONTROL OF A DRUM-TYPE BOILER

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ABSTRACT

High fuel costs, stringent safety and pollution standards and the need to increase plant life-time have all driven the search for better boiler control. Traditional PID control cannot achieve the best possible results as it does not account for the strong interactions between the controlled variables. Much work has been done in the area of optimal control, but the improvements gained in performance have been lost to some extent by the difficulties involved in tuning such controllers. A linear predictive controller is presented in this paper, which is both fully multivariable and computationally efficient. It is also easy to tune as the controller tuning parameters are physically meaningful.

1. Introduction

Boilers consume large amounts of fuel and produce considerable amounts of carbon dioxide and other environmentally damaging gases. Improving boiler control pays large dividends, in terms of reduced fuel costs, reduced pollution, improved safety and an extended plant life-time.

The boiler control problem is characterised by certain features - the boiler process is highly nonlinear, it's dynamics vary with load and it is strongly multivariable. It is also inherently unstable due to the integrator affect of the drum. In addition, boilers are commonly used in a situation where the load can change suddenly and without prior warning. Despite this the process must operate within tight constraints. Finally, it is a relatively slow process, and the time available for controller computation is not overly restrictive.

Traditionally boilers have been controlled by PID control. The typical PID controller configuration makes good use of prior knowledge of the boiler process, and is well understood. However it does not account for interactions among the controlled variables with the result that the individual control loops must compete with each other in an attempt to achieve their individual objectives.

A number of more sophisticated control schemes have been proposed to tackle those problems. Multivariable optimal control schemes which compensates for interactions between the controlled variables, have been suggested by McDonald and Kwatny [1] and Tysso.[2]

More recently, predictive control has been suggested by Hogg [3] as another very powerful and versatile method of boiler control. In this paper a linear predictive controller, based on Richalet's method [4], is proposed. The controller is fully multivariable, but is computationally efficient and is very easy to tune.

2. Description of Process

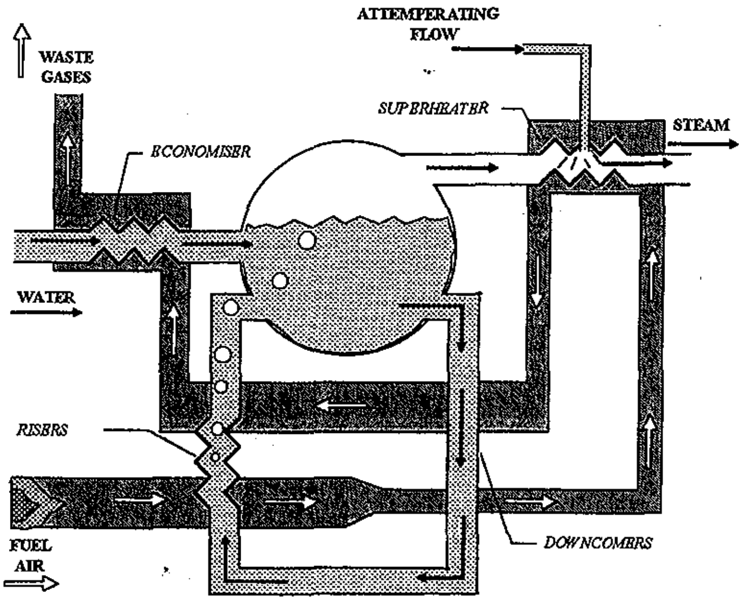

Fig. 1. Schematic of Boiler

The boiler process is represented by a 20th order nonlinear first principles model. This model was derived using the laws of continuity of mass, energy and momentum, heat transfer equations, and combustion reaction equations. It has been validated successfully against actual plant data [5].

3. Overview of Control Strategy

Table 1. lists the manipulated variables and the controlled variables for the boiler.

Manipulated Variables	Controlled Variables
Fuel flow	Steam pressure
Feedwater flow	Drum level
Attemperating flow	Steam temperature

Table 1 Controller Input and Output Variables

In conventional boiler control, three SISO PID controllers are used to control the three controlled variables. Steam pressure, drum level and steam temperature are controlled by fuel flow, feedwater flow and attemperating flow respectively.

In this paper a combined MIMO and SISO approach has been adopted. There are significant interactions between the three controlled variables and initially it seemed likely that a full multivariable approach could be of benefit here. In practice this approach was not practical as the superheater steam temperature dynamics are considerably faster than the superheater steam pressure and drum level dynamics. Consequently steam temperature was controlled by a fast predictive controller using attemperation as the manipulating variable. Steam pressure and drum level were controlled by a slower multivariable controller using fuel flow and feedwater flow as the manipulating variables.

4. Predictive Control Strategy

A predictive controller attempts to achieve it's objective by finding the controller action which minimises an appropriate cost function. The cost function must consider the error between the predicted plant output and a reference trajectory over a finite or even infinite time span, known as the prediction horizon. The solution to the minimisation problem specifies the controller output for each sampling period in the prediction horizon. However, only the first set of controller outputs is actually applied. At the next sampling period, a new controller solution is calculated, which takes into account any changes, such as variations in the process output or setpoint.

The predictive controller includes the following three fundamental components:

- Cost Function
- Model
- Controller Solution

4.1 Cost Function

In this case, the cost function has been chosen as the error between the increase in the desired reference trajectory and the increase in the predicted model output at specified points in the future called coincidence points. By stating the cost function incrementally, the affect of steady state modelling errors on the controller action are automatically eliminated. The desired reference trajectory is an exponential curve between the current process output and the set-point. This cost function is simple but still allows great freedom in controller tuning. The system response can be changed in two different ways. Firstly the rate of increase of the desired reference trajectory may be varied. Secondly the set of coincidence points may be changed - choosing coincidence points in the near future results in a more active control action. Unlike typical weighting functions, both of these tuning parameters are physically meaningful. Fig. 2 shows the desired reference trajectory from the current process output to the setpoint. .

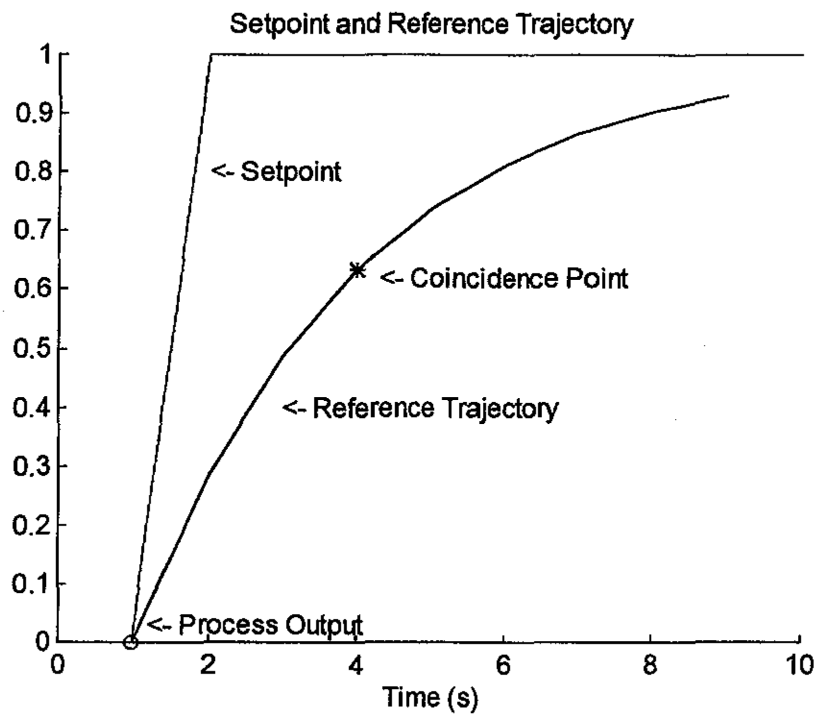

Fig.2 Predictive Reference Trajectory with a Single Coincidence Point

4.2 Model

The internal model used by the predictive controller may be of any type - transfer function, state space, ARMA, neural network etc. However, if a linear model is used, an analytical controller solution can be obtained,.

A linear model of the complete plant was obtained by perturbing the nonlinear model about a steady state operating point. The state-space linear model was then reduced to a ten state continuous state-space linear model. Fig. 3. shows the simulated value of steam pressure calculated by the nonlinear plant and by the reduced linear model when random square wave type signals are applied to the three manipulated variables.

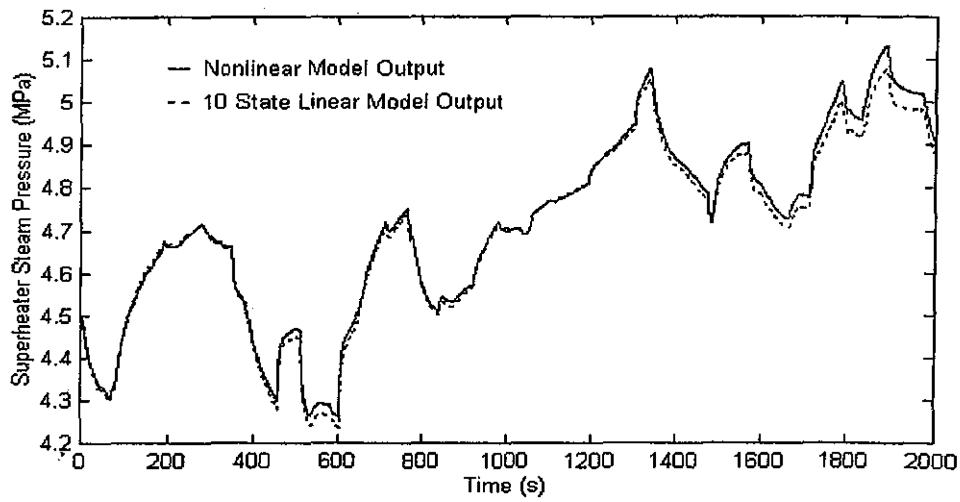

Fig. 3 Comparison of nonlinear and linear model output

A linear model of the superheater is also obtained for use in the steam temperature controller.

4.3 Derivation of Control Law

The error between the increase in the desired reference trajectory and the predicted increase in a model output, at some coincidence point H_j, can be expressed mathematically as:

$$E_{i,j} = (y_{m_i}(n+H_j) - y_{m_i}(n)) - (R_i(n+H_j) - R_i(n))$$

where

$$E_{i,j} = \text{error at } j^{th} \text{ coincidence point for } i^{th} \text{ output}$$

$$y_{m_i} = i^{th} \text{ model output} \qquad (1)$$

$$H_j = j^{th} \text{ coincidence point}$$

$$R_i = \text{reference trajectory for } i^{th} \text{ output}$$

The desired reference trajectory rises exponentially from the process output to the setpoint. In other words, the desired *error* trajectory between the process output and the setpoint decreases exponentially.

$$\varepsilon(n+H_j) = \lambda_i^{H_j} \varepsilon_i(n)$$

where

$$\begin{aligned} &\varepsilon_i(n) = S_i - y_{p_i}(n) \\ &S_i \;=\; \textit{Setpoint for } i^{th} \textit{ process output} \\ &y_{p_i} \;=\; i^{th} \textit{ process output (controlled variable)} \\ &0 \le \lambda_i \le 1 \end{aligned} \tag{2}$$

The physical relevance of λ_i can be seen by writing it in terms of the 66% rise-time of the desired exponential curve.

$$\lambda_i = exp(-\frac{T_s}{\tau_i})$$

where (3)

$$\begin{aligned} &T_s \;=\; \textit{sampling period} \\ &\tau_i \;=\; \textit{66\% rise-time} \end{aligned}$$

The desired change in reference trajectory can be rewritten as:

$$R_i(n+H_j) - R_i(n) = \varepsilon_i(n) - \varepsilon_i(n+H_j) = \varepsilon_i(n)(1-\lambda_i^{H_j})] \tag{4}$$

The error can now be expressed as:

$$E_{i,j} = (y_{m_i}(n+H_j) - y_{m_i}(n) - \varepsilon_i(n)(1-\lambda_i^{H^j}) \tag{5}$$

The model output $y_{m_i}(n)$ is obtained using the linear state-space model of the boiler:

$$\begin{aligned} &x(n+1) = Ax(n) + Bu(n) \\ &y_{m_i}(n) = C_i x(n) \end{aligned}$$

where (6)

$$\begin{aligned} &x(n) \;=\; \textit{vector of state variables of model} \\ &u(n) \;=\; \textit{vector of manipulated variables} \\ &C_i \;=\; i^{th} \textit{ row of } C \end{aligned}$$

The predicted model output $y_{m_i}(n+H_j)$ requires the future controller outputs for H_j sampling periods. This is not available as the controller output is recalculated as each sampling period. Instead, it is assumed that the future control output remains constant. Adopting this assumption, the predicted model output is:

$$y_{m_i}(n+H_j) = C_i A^{H_j} x(n) + C_i B \sum_{p=1}^{H_j} A^{p-1} u(n) \tag{7}$$

The error can now be rewritten as:

$$E_{i,j} = C_i(A^{H_j} - 1)x(n) + C_i B \sum_{p=1}^{H_j} A^{p-1} u(n) - (1-\lambda_i^{H_j})\varepsilon_i(n) \tag{8}$$

For simplicity the error can be rewritten as:

$$E_{i,j} = L_{i,j}x(n) + M_{i,j}u(n) + N_{i,j}\varepsilon_i(n)$$

where

$$L_{i,j} = C_i(A^{H_j} - 1)$$

$$M_{i,j} = C_i B \sum_{i=1}^{k} A^{i-1} \tag{9}$$

$$N_{i,j} = -(1 - \lambda_i^{H_j})$$

The complete set of equations can be rewritten in matrix format as

$$E = Lx(n) + Mu(n) + N * \varepsilon(n) \tag{10}$$

(* denotes vector multiplication)

The control solution is found using the method of least squares. The sum of the squared errors is J where:

$$\begin{aligned} J &= E^t E \\ &= (Lx(n) + Mu(n) + N.\varepsilon(n))^t (Lx(n) + Mu(n) + N * \varepsilon(n)) \end{aligned} \tag{11}$$

The partial derivative of J with respect to $u(n)$ is minimised to yield the controller solution.

$$\begin{aligned} &\frac{\delta E}{\delta u} = 2u(n)^T M^T M + 2x(n)^T L^T M + 2\varepsilon^T N^T M = 0 \\ &\Rightarrow u(n) = -(M^T M)^{-1} M^T (Lx(n) + N * \varepsilon(n)) \end{aligned} \tag{12}$$

5. Control Over Full Plant Operating Range

The previous section describes the development of a linear predictive controller which is based upon a linear model of the plant. The linear model represents the plant very well around a particular operating point. However, it does not represent the plant well at other operating points. Likewise the controller tuning parameters have been chosen to give the best possible results at a particular operating point and may give poor results at other operating points. In effect, it is not possible to achieve good controller performance over the full operating range of a nonlinear plant using a single linear controller. This problem is generally overcome using either adaptive or gain scheduling techniques. An alternative control strategy which uses fuzzy logic was developed for this work. Three linear controllers, based on linearised models of the boiler at the 10%, 50% and 90% operating points are left to run concurrently. The actual controller output is equal to a weighted sum of the output of each of the three controllers. The weights are dependent on the current operating point of the boiler and on prespecified fuzzy sets, shown below in Fig. 4.

These fuzzy sets allow the control to move in a smooth way between the three different linear controllers as necessary. They also take into account that good models are available at the 10%, 50% and 90% operating points and are valid over the region around those operating points. Using this strategy it is not neccessary to assume that the parameters of a linear model change smoothly with operating point. Likewise this strategy does not require interpolation which would

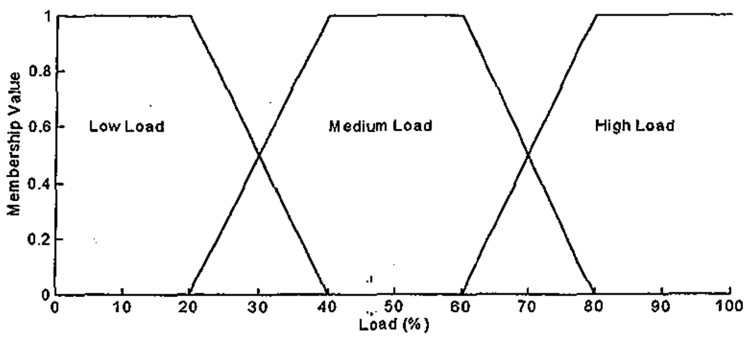

Fig. 4 Fuzzy Sets

be computationally costly for this model which has a large number of parameters. Finally the stability of each controller can be verified.

6. Results

Fig. 5 shows the plant response to a 5% step increase in load around 50% load and the corresponding controller outputs. The response of a plant under analog PID control is also shown (dotted line).

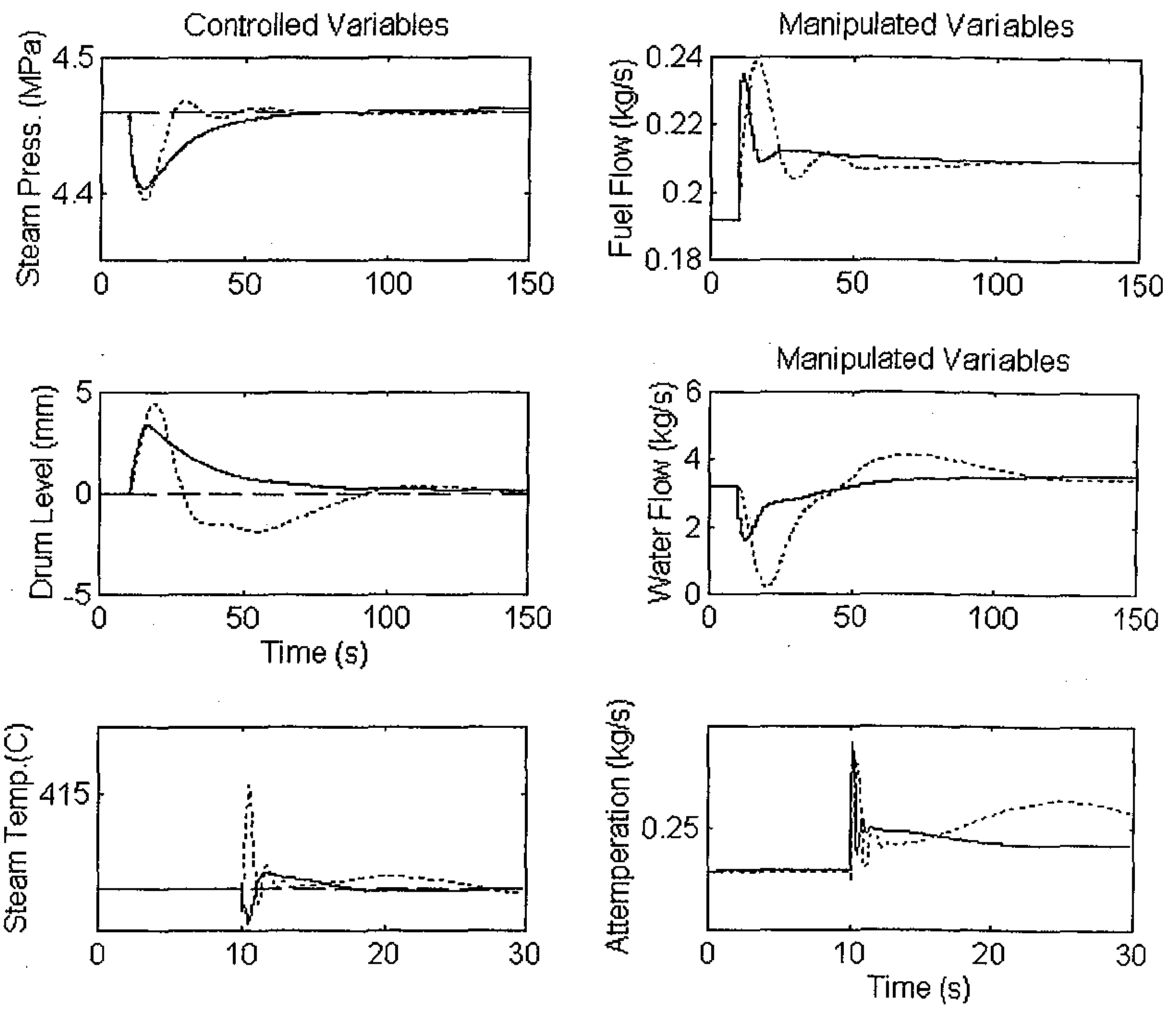

Fig. 5. Response to a Load Change

It can be seen that the digital predictive controllers provide much better response than the analog PID controller. The controlled variables remain closer to the setpoint and following the disturbance return to their setpoint along a smooth exponential reference trajectory. In addition to this controller action is smoother and less vigorous than the PID controller output as the controller takes advantage of knowledge about the predicted plant behaviour. Feedwater flow provides a good example of the benefits of predictive control. The PID drum level controller continues to decrease feedwater flow until drum level starts to decrease. Drum level then drops below the setpoint. The predictive controller can predict that drum level will start to decrease (as steam flow increases) and starts to increase feedwater flow before drum level starts to fall. Such action is only possible with a model-based predictive control strategy which has explicit knowledge of the nonminimum phase effects of the system.

7. Conclusions

Simulation results show that predictive control is considerably better than conventional PID control. This improvement has been achieved in several ways. The predictive controller can exploit knowledge about the expected response to the plant. The multivariable drum level and steam pressure controller also exploits knowledge about the interactions between these two variables. The controller is well tuned as the tuning parameters are physically meaningful. Finally, the controller has been fuzzified to operate well over the full operating range of the plant.

Predictive controller is a strong control strategy. It is clear that considerably better boiler control can be achieved using predictive control than conventional PID control. This improvement was obtained at the cost of some design effort. However a very large payback can be expected in terms of fuel costs, plant life-time and steam quality.

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