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# Simplified Predictive Control Employing Kalman Filter

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Abstract

Kalman Filter application to model predictive control is discussed. Most of refinery and petrochemical processes contain uncertainties in their output. Simplified state estimation algorithm is merged to model predictive control to improve overall control accuracy.

## 1. Introduction

In recent years, model predictive control has been expanding its application areas even in oil refining and petrochemical industries. Benefits of model predictive control are manifested by its conprehensive properties as depicted as below.

1) Applicable to processes with large dead-time and non-minimum phase.
2) Good responsiveness to setpoint change.
3) Non-interference control for multivariable processes.
4) Plant model is described by a step response characteristics that is familiar to operators.

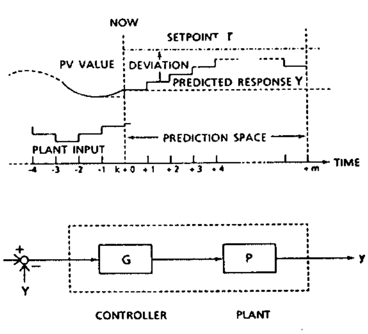


Fig.1 Concept of Model Predictive Control

However, in the periphery of such an advanced control algorithm, there still remains practical problems when it is applied to the actual plant. Preprocessing of plant output with uncertainties would be an example.
Due to the deterministic nature of present model predictive control, system is vulnerable to noise contamination as well as to unexpected external disturbances. Further more, in refining and petrochemical process, special sensing characteristics peculiar to chemical analyser causes control performance deterioration. To resolve such problems, some sort of state estimation technique should be taken into consideration.

## 2. Kalman Filter as state observer

From the viewpoint of process control, chemical analyser has several unfavorable features ; i.e. long processing time, lower sensing resolution, ……. Convetional low pass filter is not always valid for the case. Kalman Filter will become an alternative solution.
Consider the plant model described by the state equation as below.

$$\hat{X}^{*} = A\hat{X} + B_{\Delta}\tilde{u} \qquad 2\text{-}1)$$
$$\hat{y}^{*} = C\hat{X}^{*} \qquad 2\text{-}2)$$
$$\hat{X} = \hat{X}^{*} + K(\tilde{y} - \hat{y}^{*}) \qquad 2\text{-}3)$$

where

$X = [x_0, x_1, \cdots x_n]^T$ : state vector

$\Delta U = \begin{bmatrix} \Delta u_1 \\ \Delta u_2 \end{bmatrix}$ : plant input

$y$ : plant output

where

$$A = \begin{bmatrix} 1 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & \vdots \\ \vdots & & \ddots & 1 & \vdots \\ \vdots & & & \ddots & 1 \\ 0 & \cdots & \cdot & 0 & 0 \end{bmatrix}$$ : state transition matrix

$$B = \begin{bmatrix} b_{1-1} & b_{2-1} \\ b_{1-1} & b_{2-1} \\ b_{1-2} & b_{2-2} \\ \vdots & \vdots \\ b_{1-n} & b_{2-n} \end{bmatrix}$$ : gain matrix

$$C = \begin{bmatrix} 1, 0, \cdots 0 \end{bmatrix}$$ : observation vector

$$K = \begin{bmatrix} k_0, k_1, \cdots k_n \end{bmatrix}^T$$ : Kalman Filter gain

$\hat{}$, $\hat{}^{\circ}$, $\sim$ denote estimates, provisional estimates and measured vatnes respectively. Kalman Filter is merged into state equation and plant dynamics is represented by the array of impulse response gains B. Dead time included in process can be defined by putting $b_{1-i}=0$, $b_{2-i}=0$, for $i \leq L$.

Kalman filter Gain K is derived by means of incremental calculation

$$\begin{cases} K = MC^T(CMC^T + w)^{-1} & \text{2-4)} \\ M = A(I - KC)A^T + BVB^T & \text{2-5)} \end{cases}$$

where

M : estimates error covariance

$$V = \begin{bmatrix} V_1 & 0 \\ 0 & V_2 \end{bmatrix}$$

$v_1$ : error variance of plant input
$v_2$ : error variance of distrubance
$v_3$ : error variance of measured value

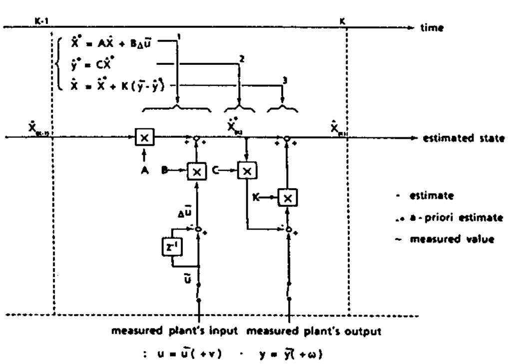


Fig. 2 State Estimator(Single Input/Single Output)

3. Control Strategy

From the estimated state vector, series of system response will successively be projected using the following conversion matrix.

$$y_p = C_p\hat{X} \qquad \text{3-1)}$$

$$C_p = \begin{bmatrix} 1 & 0 & 1 & & & 0 \\ 1 & 0 & 1 & 1 & & \\ \vdots & \vdots & \vdots & & \ddots & \\ \vdots & \vdots & \vdots & & & \\ 1 & 0 & 1 & \cdots & \cdots & 1 \end{bmatrix}$$

The element $x_0$ of state X is the present value of state and the remainder $x_1, x_2, \cdots x_n$ are projected values of state variable increment. Using the latest measured information, plant response gain array $B_i$ is derived by the response matrix as defined as follows.

$$P = [C_1B_i, C_2B_i \cdots C_{n-1}B_i] \qquad \text{3-2)}$$

where

$$C_1 = \begin{bmatrix} 1 & 0 & 0 & & 0 \\ 1 & 1 & 0 & & \\ 1 & 1 & 1 & & \\ \vdots & \vdots & \vdots & & \\ 1 & 1 & 1 & \cdots & 1 \end{bmatrix} \qquad C_2 = \begin{bmatrix} 0 & 0 & & & 0 \\ 1 & 0 & & & \\ 1 & 1 & & & \\ \vdots & \vdots & & & \\ 1 & 1 & \cdots & 1 & 0 \end{bmatrix}$$

$$\cdots C_{n-1} = \begin{bmatrix} 0 & 0 & & 0 \\ 0 & 0 & & \\ 0 & 0 & & \\ \vdots & \vdots & & \\ 1 & 0 & 0 \cdots & 0 \end{bmatrix}$$

$$B_i = [b_{1-1}, b_{1-2}, \cdots b_{1-(n-1)}]^T$$

$C_i$, $B_i$ means projected plant response after the time k+m with respect to plant input step at the time k+(m-1).

In order to define how well the projected process output tracks the target trajectory, a criterion function is introduced as follows.

$$J = E^TQE + U^TU \qquad \text{3-3)}$$

where

$E = r - Y_p$ : control error

r : target trajectory

$Q = \text{diag}[q_1, q_2 \cdots \cdots q_{n-1}]$ : weight matrix

Control gain vector to minmimize the criterion function 3-3) is represented by

$$G = \frac{E}{\Delta U} = (P^TQP + I)^{-1}P^TQ \qquad 3\text{-}4)$$

## 4. Experimental Results

As was mentioned in 1, some types of on-line chemical analyser have sensing resolution as rough as 2% of full scale. Notwithstanding such sensing cheracteristics, regorous control accuracy is required in refinery and petrochemical process. As a preliminary study simulation was performed, applying the above mentioned predictive control to the process model with coarse sensing device. Fig.5 shows the control performance in comparison with that of conventional model predictive control.

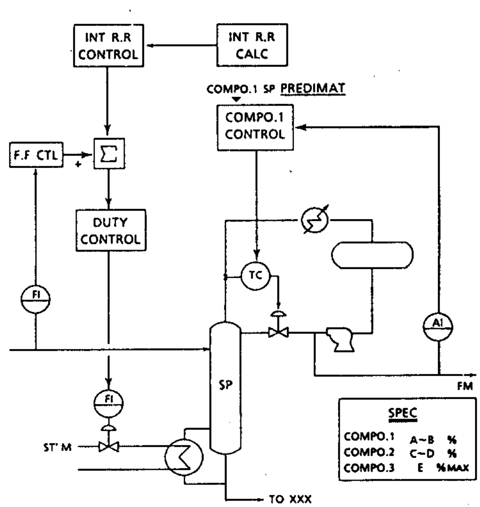


Fig.3 Overhead Composition Control Diagram

Then experiment was made on the real distillation process. Overhead composition of destillation column is governed by the column top temperature, which is usually controlled to the predetermined setpoint using analyser data as control input. Overhead composition indicates inverse response with respect to temperature change and processing time of analyser exceeds 20 minutes. Fig.6 shows the control results of overhead composition performance with and without predictive control algorithm described above.

## 5. Conclusion

Simplified model predictive control with state estimator has been applied to temperature stabilization for distillation column and successfully attained an improved performance.
One-line implementation has been made on 32 bit microprocessor in the distributed control system environment, in which interactive man-machine facility and simulation software are furnished. To facilitate the users, the complete software has been packaged for off-the-shelf usage.


Referance
(1) R.M.C. Dekeyser et al : "A comparative study of self-adaptive long-range predictive control method", Automatica, Vol.24 No.2 pp.149-163, 1988
(2) D.W. Clarke et al : "Generalized predictive control-parts I & II", Automatica, Vol.23, No.2 pp.137-160, 1987


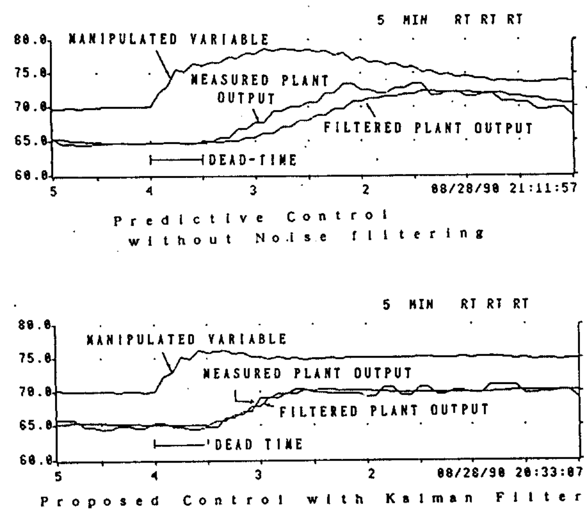


Fig.4 Comparison of Control Performance

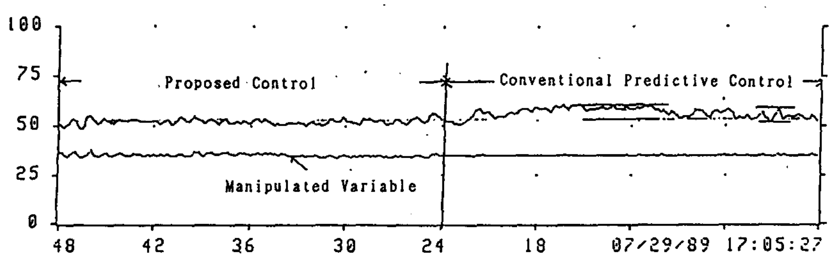


Fig. 5 Performance Comparison of Column Top Temperature Control

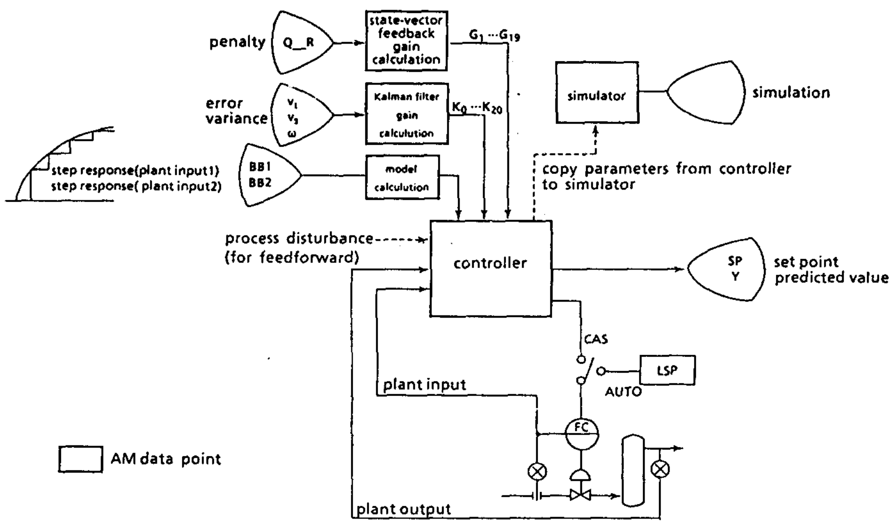


Fig. 6 Overall System Diagram