International Carpathian Control Conference ICCC' 2001
KRYNICA POLAND
May 22 25, 2001

MODIFIED SMITH-PREDICTOR MULTIRATE CONTROL UTILIZING SECONDARY PROCESS MEASUREMENTS

Rolf ERGON
Department of Process Automation,
Telemark University College,
Porsgrunn, Norway, rolf.ergon@hit.no

Abstract: The Smith-predictor is a well-known control structure for industrial time delay systems, where the basic idea is to estimate the nondelayed process output by use of a process model, and to use this estimate in an inner feedback control loop combined with an outer feedback loop based on the delayed estimation error. The model used may be either mechanistic or identified from recorded data. The paper discusses improvements of the Smith-predictor for systems where additional secondary process measurements without time delay are available as a basis for the estimation. The estimator may then be identified from recorded data also in the common case when the primary outputs are sampled at a lower rate than the secondary outputs. A simulation example demonstrates the feasibility and advantages of the suggested control structure.

Key words: Smith-predictor, secondary outputs, multirate control

1. Introduction

Time delay systems are frequently encountered in industrial control practice, and use of a Smith-predictor structure may be the best known strategy to follow [1]. The basic idea is then to use a process model to obtain an estimate of the nondelayed system output to be used in an inner feedback loop, combined with an outer feedback loop based on the delayed estimation error. The model used may be either mechanistic or identified from recorded data.

In many industrial cases the process under control has one primary output measurement $y_1(k)$ and several secondary measurements $y_2(k)$. As indicated in Fig. 1, the measurements $y_2(k)$ may together with the controller output $u(k)$ be used as inputs to an estimator for the primary property $z(k)$ without time-delay. The estimator thus replaces the traditional Smith-predictor model. Since the secondary measurements may carry valuable information about the process disturbance $v(k)$, the estimate of $z(k)$ may be considerably improved by use of the additional $y_2(k)$ information. The estimator may be designed on the basis of a mechanistic process model, including known noise covariances. It may, however, be more conveniently identified from experimental process data. Feedback or feedforward of $y_2(k)$ may also be incorporated in the control structure.

In Fig. 1 the noise sources $v(k)$, $w_1(k)$ and $w_2(k)$ are assumed to be white. This is often a reasonable assumption for the measurement noise, while the process noise $v(k)$ may have to be modeled as filtered white noise, with the filter included in the process model.

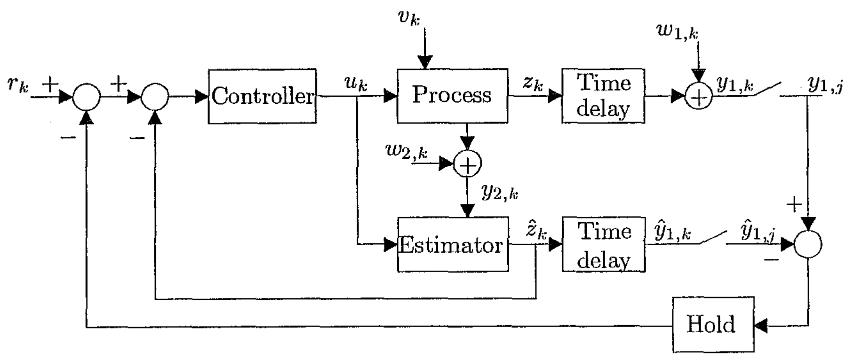

Fig. 1. Modified Smith-predictor multirate control utilizing secondary process measurements

As also indicated in Fig. 1 the primary output will in many cases be sampled at a low rate, i.e. $y_1(j)$ may be just some of the high sampling rate $y_1(k)$ values. This is typically the case for product quality measurements, where physical sampling and e.g. chemical analysis are necessary. A low primary output sampling rate makes it necessary with a hold function in the outer feedback loop. Alternatively, the $y_1(j)$ measurements may be compared with the corresponding $r(j)$ reference values in an outer feedback loop with integral action.

2. Estimator identification

Identification of the estimator from experimental data with both $y_2(k)$ and $u(k)$ as inputs may be performed by use of a prediction error method based on an underlying Kalman filter [2]. The time delay is then simply removed by appropriate data shifting. In order to obtain a theoretically optimal solution an output error (OE) structure must be specified [3], although also an ARMAX structure or a subspace identification method may give good enough results for practical use. The argument for an OE structure is that neither past nor present nondelayed $y_1(k)$ values will be available during normal operation, and in order to obtain correct Kalman gains they should thus not be used in the identification stage. The identification is straightforward when $y_1(k)$ values are available at the same high rate as $y_2(k)$ and $u(k)$, and the prediction error method can also be modified to handle the low and even irregular primary output sampling rate case [4]. We then minimize the criterion function

$$V_N(\theta) = \frac{1}{N}\sum_{j=1}^{N}[y_1(j) - \hat{y}_1(j)]^2, \tag{1}$$

where N is the number of $y_1(j)$ samples in the modeling set.

In the low primary output sampling rate case it is still required that $y_2(k)$ and $u(k)$ are sampled often enough in order to capture the dynamics of the process, and we thus have a multirate sampling identification problem. The standard initial value procedure based on a least squares identification of an ARX model cannot then be used, and we have to resort to some *ad hoc* initial value method [5]. It is also required that the $y_1(j)$ data are representative, with the same statistical distribution as $y_1(k)$. Further note that minimization of (1) in the multirate case is possible only for the OE structure, i.e. theoretical optimality coincides with practical feasibility.

3. Simulated system

Fig. 2 shows a two-stage stirred-tank mixing process where the feed flow rate q_F=2 m^3/min is constant, while the feed concentration $c_F(t)$ [kg/m^3] varies around 50 kg/m^3. The flow rate $q_A(t)$=$u(t)$ [m^3/min] is the manipulated input from the controller, while c_A=800 kg/m^3 is constant. The volumes are V_1=4 m^3 and V_2=3 m^3, and $x_1(t)$ and $x_2(t)$ are the concentrations in the tanks. The primary output concentration $x_1(t)$ is measured by a high quality analytical instrument, causing a time delay D=10 min, while $x_2(t)$ is measured by an instrument without time delay, but with more measurement noise. The transportation time between the tanks is considered negligible.

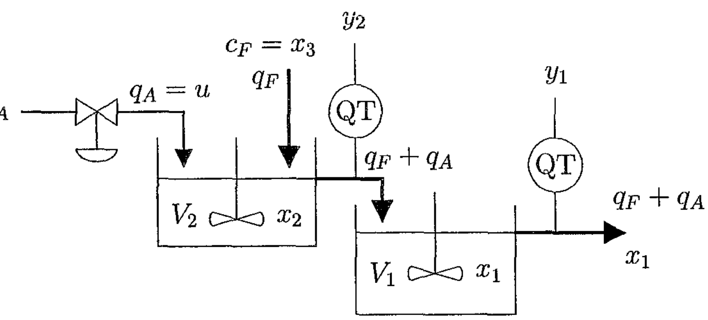

Fig. 2. Two-stage stirred-tank mixing process in simulation example

The time varying feed concentration is modeled as

$$\dot{x}_3(t) = -a[x_3(t) - 50] + v(t), \tag{2}$$

where a=0.05 min^{-1} and $v(t)$ is white noise. After an Euler discretization with sampling interval T, the discrete-time nonlinear process model is

$$x_1(k+1) = [1 - \frac{Tq_F}{V_1}]x_1(k) + \frac{Tq_F}{V_1}x_2(k) + \frac{T}{V_1}u(k)[x_2(k) - x_1(k)]$$
$$x_2(k+1) = [1 - \frac{Tq_F}{V_2}]x_2(k) + \frac{Tq_F}{V_2}x_3(k) - \frac{T}{V_2}u(k)x_2(k) + \frac{Tc_A}{V_2}u(k)$$
$$x_3(k+1) = [1 - Ta][x_3(k) - 50] + v(k) \quad (3)$$
$$y_1(k) = x_1(k) + w_1(k)$$
$$y_2(k) = x_2(k) + w_2(k),$$

where the sample rate is chosen to T=0.5 min, and where $v(k)$, $w_1(k)$ and $w_2(k)$ are white and independent noise sequences with variances chosen to r_v=0.02, r_1=0.0001 and r_2=0.01.

The process was controlled as shown in Fig. 1, using a proportional-integral controller given by

$$e(k) = r(k) - y_1(k) + \hat{y}_1(k) - \hat{z}(k)$$
$$u(k) = u_0 + K_p[e(k) + \frac{T}{T_i}\sum_{i=1}^{k} e(i)], \quad (4)$$

where u_0=0.1429, and where the controller parameters were chosen as K_p=0.004 and T_i=34 min, based on some trial and error starting with the Ziegler-Nichols continuous cycling method [1]. For simplicity of notation, (4) assumes high rate sampling of the primary output, and must thus be appropriately altered in the multirate case.

4. Identification of estimator

The process in Fig. 2 was simulated according to (3), and the estimator in Fig. 1 was then identified from input-output data. An ordinary second-order Smith-predictor using only $u(k)$ as input and $y_1(k)$ as output was identified by use of the *armax* function in the System Identification Toolbox (SITB) for use with Matlab [2], and the deterministic part of the model was subsequently used as estimator. The number of samples in the modeling set was N=400. A modified second-order Smith-predictor using both $u(k)$ and $y_2(k)$ as inputs and $y_1(k)$ as output was identified by use of the SITB function *pem*, with an OE model specified, and with N=400. Finally, a modified second-order Smith-predictor using low sampling rate data $y_1(j)$ as output was identified by a modified *pem* function minimizing (1). The $y_1(j)$ sampling interval was in this case T_1=20T=10 min, i.e. the same as the time delay D=10. The number of $u(k)$ and $y_2(k)$ samples was N_2=8000, i.e. the number of $y_1(k)$ samples was N=400. In all cases the input was a filtered pseudo-random binary sequence (PRBS) with autocovariance $r_u(p)$=0.0016$(0.8)^{|p|}$. The initial value problem in the multirate sampling case was solved by first identifying an ARMAX model with $u(k)$ as input and $y_2(k)$ as output, and then finding the static relation between the model state $x(j)$ and the primary output $y_1(j)$ by an ordinary least squares (LS) method. After an appropriate similarity transformation, this gives an initial model for the OE estimator to be identified. Typical validation responses for this procedure are shown in Fig. 3.

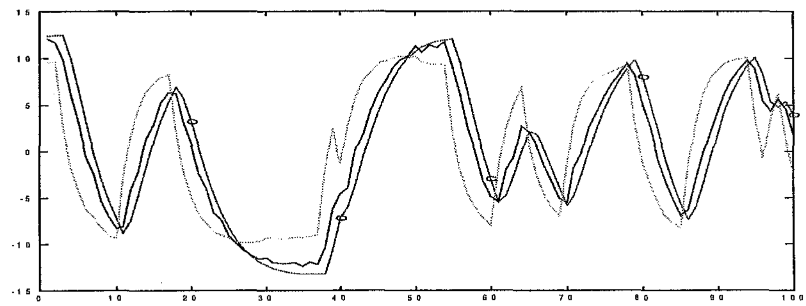

Fig. 3. Segment of $y_1(k)$ validation responses (centered data) for initial ARMAX+LS estimator (dotted weak line) and final OE estimator (solid line). The ideal response is shown by dotted line with o-markings at the j sampling instants.

5. Simulation results

Simulation results for the control structure in Fig. 1 with the process in Fig. 2 and the identified estimators are shown in Fig. 4. Each typical RMSE value is based on 100 Monte Carlo runs, and computed according to (5). Note that in the simulation $y_1(k)$ is known also in the low sampling rate case.

$$RMSE = \sqrt{0.001\sum_{501}^{1500}\left[r(k) - y_1(k)\right]^2} \qquad (5)$$

For the specific process in Fig. 2, the control can also be based on feeding back the $y_2(k)$ signal instead of the $z(k)$ estimate, and holding only $y_1(j)$. The best result is in fact achieved by feedback of both $y_2(k)$ and the $z(k)$ estimate. These control structures using feedback of $y_2(k)$ requires $2r(k)$ as set point.

6. Conclusions

The modified Smith-predictor using also the secondary measurement information results in a considerably improved control performance, as compared with an ordinary Smith-predictor control structure. The primary output estimator may be identified from recorded data also in the multirate case with low primary output sampling rate. The modified Smith-predictor control structure in the simulation example essentially keeps its good performance also when the primary output sampling interval is twenty times the ordinary sampling interval, and much longer than what is apparently necessary in order to capture the dynamics in the system. In the specific simulation example, additional improvement was achieved by also feeding back the secondary measurement.

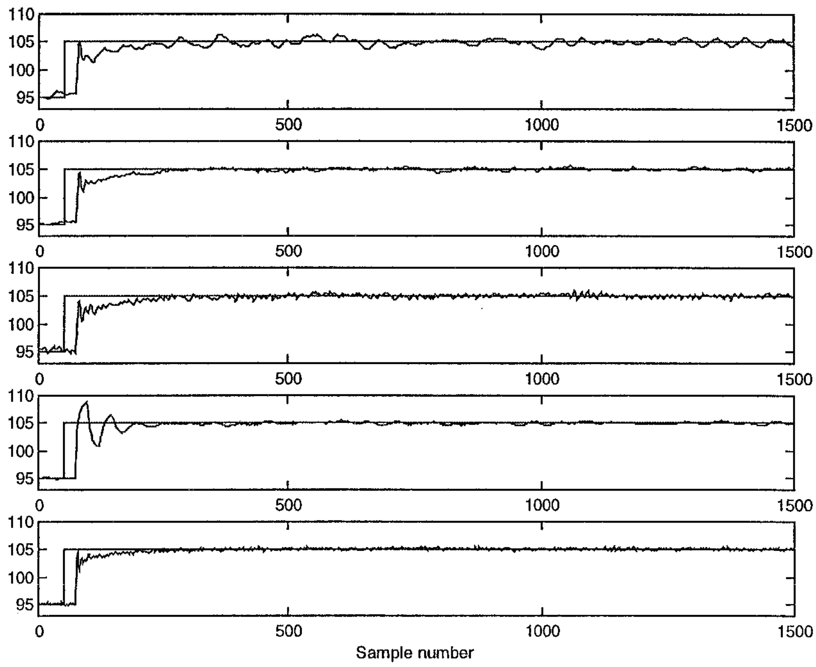

Fig. 4. Step responses for (with typical RMSE values based on 100 Monte Carlo runs):
a) ordinary Smith-predictor control (0.52),
b) modified Smith-predictor control (0.23),
c) modified Smith-predictor control with low primary output sampling rate (0.25),
d) same as c) but feedback of $y_2(k)$ instead of the $z(k)$ estimate and holding only $y_1(k)$ (0.19), and
e) modified Smith-predictor control with low primary output sampling rate plus feedback of $y_2(k)$ (0.14).

References

[1] Seborg D.E., T.F. Edgar and D.A. Mellichamp: *Process Dynamics and Control.* Wiley, 1989, ISBN 0-471-85933-8

[2] Ljung L.: *System Identification Toolbox for Matlab.* The MathWorks Inc., Mass., 1995

[3] Ergon R.: *On primary output estimation by use of secondary measurements as input signals in system identification.* IEEE Trans. Autom. Control, Vol. 44, 821-825, 1999

[4] Ergon R.: *Dynamic system calibration: The low primary output sampling rate case.* Modeling, Identification and Control, Vol. 19, 99-107, 1998

[5] Ergon R.: *Dynamic System Multivariate Calibration for Optimal Primary Output Estimation.* PhD thesis, the Norwegian University of Science and Technology/Telemark University College, Trondheim/Porsgrunn, Norway, 1999