ADAPTIVE INFERENTIAL CONTROL

K.A. Brodie, M. J. Willis, M. T. Tham.[1]

Abstract

Despite the successful application of advanced predictive control algorithms to many industrial chemical processes satisfactory system performance cannot always be guaranteed. This is often the case where the infrequent measurement of key process outputs is unavoidable due to sampling limitations. In such situations the ability to detect deviations from desired process behaviour is significantly impaired. Inferential estimation techniques employ more easily measured *secondary* variables to infer the desired *primary* variable. This facilitates the early detection of disturbances thus improved control performance is to be expected. An adaptive inferential measurement algorithm has been successfully applied to various industrial processes (Lant et al 1991; Mitchell et al 1995). This contribution discusses the development of a model based control strategy using the inferential estimation algorithm as a basis. The theoretical development of the adaptive inferential long range predictive control algorithm is outlined. The algorithm offers enhanced control performance when compared to existing model based design strategies.

Introduction

The measurement of key process variables at a rate suitable for on-line control is a problem common to many industrial processes. Either the instrumentation does not exist requiring the use of analysers with long cycle times or off-line laboratory assays. The penalty is that deviations from nominal operation may remain undetected for significant periods of time. Effort towards alleviating this problem has included the development of inferential estimators (Guilandoust et al 1987; Lant 1991) with considerable success when applied to industrial situations (Lant 1993; Mitchell et al 1995). Inferential estimators are reliant on the desired *primary* variable being related to other more easily measured *secondary* variables. The secondary outputs are used to *infer* a value of the primary variable at the more frequent sampling rate of the secondary variables. The inferential estimator is implemented in an adaptive framework with the parameters of the primary model updated whenever a value of the primary output becomes available. For further details see Lant (1991, 1993).

A natural progression of the work with the adaptive inferential estimator (AIE) is the development of an inferential controller. One method may be to employ the inferential estimator as an augmented measurement device providing the input for a conventional three term (PID) controller. However, inferential estimation is more justified in high performance applications. These are predominantly the domain of model based control algorithms such as Dynamic Matrix Control (DMC) developed by Cutler and Ramaker (1980) and Generalised Predictive Control (GPC) developed by Clarke et al (1987 a, b). Brunet-Manquat et al (1994) demonstrated how the inferential estimator can be synthesised into the Generalised Minimum Variance (GMV) control algorithm of Clarke and Gawthrop (1978). Initial results were encouraging. The adaptive inferential controller was shown to significantly out-perform the GMV controller and the combined AIE and GMV strategy. This paper demonstrates how the AIE can be incorporated into a long range predictive control strategy. A case study is presented demonstrating the effectiveness of the algorithm.

Adaptive inferential estimation

The adaptive inferential estimator used in this work was originally developed by Guilandoust (1988). The primary and secondary models are based on an observer canonical state space model and can be shown to take the following form:

$$v(t) = a_1 v(t-1) + \ldots + a_n v(t-n) + b_1 u(t-m-1) + \ldots + b_n u(t-m-n) + l_1 w(t-m-1) + \ldots + l_n w(t-m-n) + c_1 \varepsilon(t-1) + \ldots + c_n \varepsilon(t-n) \quad (1)$$

$$y(t) = \theta^T \phi(t-d) + e(t) \quad (2)$$

where $\theta^T = [\beta_1, \ldots, \beta_n, \tau_0, \ldots, \tau_n, \gamma_1, \ldots, \gamma_n, \delta_1, \ldots \delta_n]$

$\phi(t-d) = [u(t-m-d-1), \ldots, \hat{v}(t-d|t-d), \ldots, w(t-m-d-1), \ldots, \varepsilon(t-d), \ldots]$

$\varepsilon(t) = v(t) - \hat{v}(t)$

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[1] Department of Chemical and Process Engineering, University of Newcastle upon Tyne.

The estimates of the primary variable are calculated using,

$$\hat{y}(t+d) = \hat{\theta}^T \phi(t) \quad (3)$$

where u(t) is the manipulated input, y(t) and v(t) the measurements of the primary and secondary variable respectively, w(t) is deterministic disturbance, 'm' the smallest time delay in the state response to changes in u(t) and e(t) is the equation error.

The estimate is a function of the information available up to and including the current time, t. The implementation of the algorithm requires the following steps: update the parameters of the secondary model, use the 'new' model to calculate the filtered value of the secondary output, update the parameters of the primary model if a new value of y(t) becomes available, calculate the estimate of the primary output.

Adaptive inferential long range predictive controller

The use of a single model for both the controller and inferential estimator has a number of advantages including reduced computational overheads and a single adaptive model allows faster tracking of the process (Brunet-Manquat, 1994). Consider the inferential estimator presented previously:

$$\hat{y}(t) = \beta u(t-m-d) + \tau\hat{v}(t-d) + \gamma w(t-m-d) + \delta\varepsilon(t-d) \quad (4)$$

$$A\hat{v}(t) = Bu(t-m) + Lw(t-m) + C\varepsilon(t) \quad (5)$$

Substituting for $\hat{v}(t-d)$ in Eqn. (4) using Eqn. (5) gives:

$$A' y(t) = B' u(t) + L' w(t) + C' \varepsilon(t) \quad (6)$$

where,

$$A' = A, \; B' = z^{-m-d}[A\gamma + \tau L], \; L' = z^{-m-d}[A\gamma + \tau L], \; C' = z^{-d}[A\delta + \tau C]$$

This model has an ARMAX structure. However, it may be noted that the estimate of the primary variable is used as the autoregressive component of the model.

Long Range Predictive Controller

A long range predictive controller was developed based upon the GPC cost function and Eqn. (6). The use of the ARMAX process model, as opposed to the CARIMA process model used in the original version of GPC, yields the following control law:

$$\mathbf{u}_t = (\mathbf{G}^T\mathbf{G} + \lambda\mathbf{I})^{-1}[\mathbf{G}^T(\mathbf{y}_{sp} - \mathbf{f}) + \lambda\mathbf{I}\mathbf{u}_{t-1}] \quad (7)$$

where: $\mathbf{y}_{sp} = [y_{sp}(t+1), y_{sp}(t+2), \ldots, y_{sp}(t+N2)]^T$

$\mathbf{f} = [f(t+1), f(t+2), \ldots f(t+N2)]^T$

Here $\mathbf{u}_{t-1}$ is a vector of the previously calculated controls, **f** is the predictor equation known at time, t, and $\mathbf{y}_{sp}$ is a vector of the future set points. As future values of the deterministic disturbance, l(t), are unknown future values are therefore assumed equal to the current value. The same assumption is made for the future prediction error, e(t+j) which is used to remove offset that may be introduced via plant-model mismatch. The procedure adopted is identical to that used in DMC. **G** is as defined in the original version of GPC and λ a weighting factor to penalise changes in the manipulated input.

Case studies

Consider the following state space system:

$$\mathbf{x}(t+1) = \mathbf{A}\mathbf{x}(t) + \mathbf{B}u(t-m) + \mathbf{L}w(t-m), \; v(t) = \mathbf{H}\mathbf{x}(t), \; y(t) = \mathbf{D}\mathbf{x}(t-d)$$

where,

$$\mathbf{A} = \begin{bmatrix} 1.535 & 1 \\ -0.5866 & 0 \end{bmatrix}, \; \mathbf{B}^T = [0.028 \;\; 0.0234], \; \mathbf{D} = [1 \;\; 1], \; \mathbf{H} = [1 \;\; 0], \; \mathbf{L}^T = [0.6 \;\; 0.24], \; d = 4, \; m = 1$$

The performance of the inferential controller was evaluated against the CARIMA model based GPC. The primary output was controlled in both cases. The GPC was solely reliant upon the measured primary variable available once every four sample times.

A comparison of the servo and regulatory control characteristics of the controllers can be seen in Figure 1. A fourth order GPC was applied with a sample time = 4. The inferential controller was of second order. The setpoint for the system was a periodic step input of unit magnitude and a period of 800 samples. A periodic disturbance was introduced after 200 samples with a period of 800 samples and unit magnitude. For the first 120 samples the system was operated in open loop in order to identify model parameters before the controllers were commissioned. The manipulated input was clipped at ±5 units but not rate limited.

As is clearly illustrated in Figure 1, the inferential controller yields significantly better control performance when compared to the GPC. In the servo case, the GPC exhibits significant overshoot while the inferential controller gives an over damped response. In the regulatory case the difference between the GPC and inferential controller is again apparent. The inferential controller has faster disturbance rejection due to the faster detection of the initial disturbance via the secondary variable. The GPC has to wait up to 4 times longer than the inferential controller before the disturbance is detected. Both controllers reject the disturbance without offset.

Figure 2 shows the manipulated variable for both controllers. The AIC is far more active than the GPC. While in a practical implementation the activity of the AIC may not be realisable the purpose of this exercise is to demonstrate the potential of the algorithm. This is attributed to the sampling limitations placed on the GPC while the inferential controller can manipulate the process input at a rate much more suitable to the process characteristics.

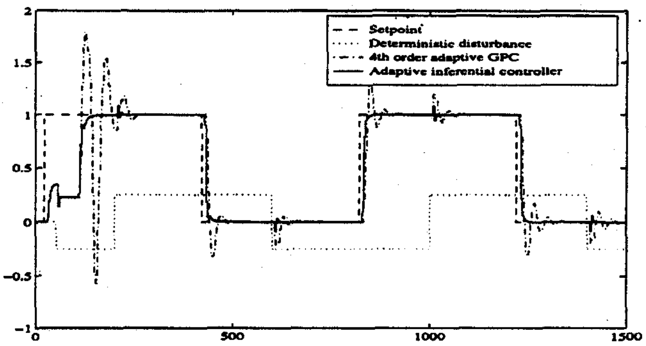

Figure 1. Comparison of process outputs for adaptive GPC and adaptive inferential control.

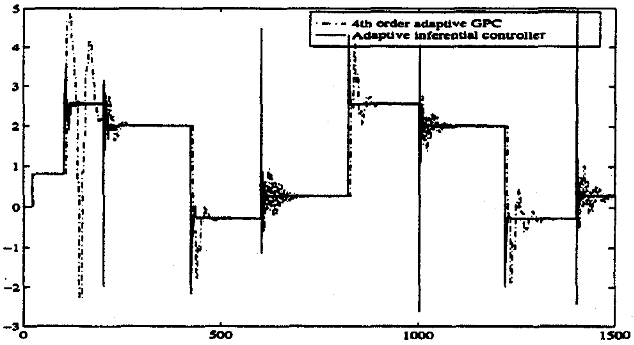

Figure 2. Comparison of manipulated inputs for adaptive GPC and adaptive inferential control.

Conclusions

An adaptive inferential controller has been developed in a long range predictive framework. Simulation has shown this controller to yield significant servo and regulatory performance improvements over a standard long range predictive controller (GPC) on a system with sampling limitations.

References

Clarke, D. W., Gawthrop, P. J. (1979). "Self-tuning control." Proceedings of the IEE, Volume 126, Number 6, pp. 633 -640.

Clarke, D. W., Mohtadi, C., Tuffs, P. S. (1987 a, b). "Generalised Predictive Control - Part 1: The basic algorithm" and "Generalised Predictive Control - Part 2: Extensions and interpretations", Automatica, 23, pp 137 - 160.

Cutler, C. R., Ramaker, B. L. (1979) "Dynamic Matrix Control - A Computer Control Algorithm" 86th AIChE National Meeting, April 4, 1979.

Guilandoust M. T., Morris A. J., Tham M. T. (1987) "Adaptive inferential control" IEE Proceedings, Volume 134, Part D, Number 3, pp., 171-179, May 1987.

Lant, P. A., Montague, G. A., Morris, A. J., Tham M. T. (1991). "Soft-sensors for process estimation and inferential control", J. Proc. Cont., Volume 1, pp. 3-14, January 1991.

Lant, P. A., Montague G. A., Tham M. T. (1993). "On the applicability of adaptive bioprocess state estimators", Biotechnology and Bioengineering, Volume 42, pp.1311-1321, 1993.

Mitchell A., Willis M. J., Tham M. T., Johnson N., Bitar S. S. (1995) "Data analysis and inferential estimation applied to a lubricant production plant." Proceedings of the American Control Conference, 1995.

Willis, M. J. (1990) "Control of a class of chemical reactors", Ph. D. Thesis, Department of Chemical and Process Engineering, University of Newcastle upon Tyne.

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