Multivariable Laguerre-Based Indirect Adaptive Predictive Control A Reliable Practical Solution for Process Control

M. Huzmezan *and G. A. Dumont†
University of British Columbia
Pulp and Paper Centre
2385 East Mall
Vancouver, Canada, V6T 1Z4

W.A. Gough ‡and S. Kovac §
Universal Dynamics Technologies Inc.
100 - 13700 International Place
Richmond, Canada, V6V 2X8

Abstract

The classic way to control a system, in a model based framework, is to obtain a model of the system and then to use it for the design of a controller, process that can be executed online by an indirect adaptive controller. This work is devoted to describe the particular structure of such a controller. Therefore in this paper we show how Laguerre orthonormal basis functions can be extended to multivariate systems and used to produce a valid linear process model. Further this model can be used in a constrained multivariable predictive controller, at each time step, to produce a control move that accounts for a good reference tracking in the presence of disturbances and a reduced actuator movement within given constraints. A simulation model is used to evaluate the controller performance.

Keywords: MIMO Indirect Adaptive Control, Constrained Model Based Predictive Control (MBPC), MIMO Laguerre Identification.

1. Introduction

Process industries need a multivariable predictive controller that is low cost, easy to setup and maintains an adaptive behaviour which accounts for plant nonlinearities as well as potential mismodeling.

Therefore, to answer this request, we present in this paper the architecture of a system, i.e a multi-input/multi-output (MIMO) adaptive model based predictive controller (MBPC), which has attributes like: low-cost, reliable and easy-to-use. This controller is now a real time prototype implemented on a Windows-NT platform to be used in plant trials.

The classic way to control a system, in a model based framework, is to obtain a model of the system and then to use it for the design of a controller. This is the choice we have made for the architecture of our controller which as result became indirect and adaptive.

*e-mails: huzmezan@ppc.ubc.ca
†guyd@ppc.ubc.ca
‡bgough@udtech.com
§skovac@udtech.com

For the identification part of the procedure Laguerre orthonormal basis function identification was employed. Since our aim was to deal with MIMO systems the SISO algorithm [3] was extended to include multivariate features. Before making a decision with respect to this particular way of producing on-line a linear plant model a comparison with other established MIMO methods like subspace identification was pursued. Further the identification of marginally stable system was investigated and a solution provided. More on these issues in Section 2.

The beginning of multivariable model based predictive control methods can be tracked back in late 70s. It has become very widely and successfully used in certain sectors of the process industries, particularly the petro-chemical sector. The main attraction for this method in the industrial world was the ability to use a dynamic model of the process in order to predict the behaviour of the controlled variable within a limited time horizon. In fact the idea behind this controller is to use the predicted process variable in an on-line optimization procedure such as to determine the manipulated variable. This procedure is explained further in Section 3. Predictive control method deals naturally with constraints and multivariable systems. The problem associated with the on-line/real time implementation is the computation time which limits the controller bandwidth. As we continuously improve the algorithm and the computer speeds continue to increase this problem will disappear. Moreover in process industries, where the update time is of the order of several minutes, the computation time represents less of an issue.

One of the reasons of taking the indirect adaptive approach is the previous practical experience which Universal Dynamics Ltd. build over 10 years in the area of developing and applying a SISO Laguerre based indirect adaptive predictive controller, U.S.Patent # 5335164. This reason together with the theoretical support outlined in Sections 2-4. forms the foundation of the controller employed on simulation model in Section 5. Sections 6. and 7. will reveal to the reader the benefits of a commercial implementation and conclusions, respectively.

2. The MIMO Laguerre orthonormal basis function identification

Recently a significant amount of work in the academic community was put into developing cheap and reliable identification schemes from the computational and numerical point of view, respectively. Subspace methods [7, 11] have constituted for the past couple of years "the solution" for identification of MIMO stable systems. There are various forms of subspace methods, all of them are directed towards the same goal of identifying a multivariable system using only simple computations.

The resemblance between subspace methods and the MIMO Laguerre orthonormal basis function identification is that the Laguerre coefficients represent a projection of the plant model onto a linear space whose basis is formed by an orthonormal set of Laguerre functions.

There are a number of appealing advantages of using an orthonormal basis function for identification:

- The structure is linear in the model parameters subject to estimation, therefore known techniques like recursive least squares estimation can be used, see [3].
- Since we deal with a fixed structure of the model, in spite of the iterative procedure, we can avoid problems generated usually by the convergence of the parameter estimate vector to a local minimum [3]
- The concept proved its simplicity when dealing with unknown dead time processes, closely resembling Pade type of approximation. Moreover, the orthonormality facilitates the modeling of dead time dominant plants.
- A reduced number of functions in the basis is possible giving in exchange an efficient way to store the model parameters and filter the incoming plant data.
- The distinguishing feature of this method is the ability to include prior knowledge on the system poles.
- As described in [12] statistical properties of the estimate can be calculated.
- The scheme practical implementation is facilitated by the simple concept of the Laguerre basis function, the reason why we have chosen this particular orthonormal basis.

The way the MIMO system identification using Laguerre orthonormal basis functions works is very similar with the SISO case [8]. The plant model transfer matrix is represented as a series expansion in the basis and then approximated with a finite number of terms. The difference between the MIMO and SISO case is that a the model structure is not unique. Therefore our MIMO model is achieved by "copying" the SISO structure to the cells of a transfer matrix that will linearly approximate the multivariable plant.

The SISO construction is detailed in [3, 13]. Briefly we show here the Laplace domain representation of the Laguerre function, a complete orthonormal set in $\mathcal{L}_2$:

$$L_i(s) = \sqrt{2p}\frac{(s-p)^{i-1}}{(s+p)^i} \quad , \quad i = 1, \ldots, N \qquad (1)$$

where i is the number of Laguerre filters ($i = 1, N$), $p > 0$ is the time scale, and $L_i(s)$ are the Laguerre polynomials. The reason for using the Laplace domain description is its simplicity in representing the Laguerre ladder network.

Specifying prior information about the system is achieved in our case via a choice for the pole location for each individual cell of the global transfer matrix used to model the process, leading to a matrix of poles. This choice is made automatically based on an series of independent off line optimizations corresponding for each channel. This method is searching for the optimal Laguerre network pole such as to provide the best approximation of a given individual transfer function. Such a feature enables the system to recognize the wide distribution of time constants in the different channels of the MIMO model. We have a strong preference for real poles since the speed and accuracy of the estimation algorithm is greatly improved. This choice will lead to a slightly larger number of Laguerre filters required to model second order dynamics.

Each SISO Laguerre ladder network can be expressed as a stable, observable and controllable state space form as:

$$\begin{aligned} l(k+1) &= A_{ij} l(k) + b_{ij} u(k) \qquad (2) \\ y(k) &= c_{ij}^T l(k) \qquad (3) \end{aligned}$$

with $l(k)^T = \begin{bmatrix} l_1(k), & \ldots & , l_N(k) \end{bmatrix}^T$ is the state of the ladder, and $c_{ij}{}_k^T(k) = \begin{bmatrix} c_1(k), \ldots, c_N(k) \end{bmatrix}$ are the Laguerre coefficients at time k. A_{ij} is a lower triangular square (N x N) matrix.

Once all the individual transfer functions of the plant model were defined we pack them into a global state space representation for which a minimal realization is considered. This represents our basis during the identification algorithm.

Before employing the plant data for the recursive model estimation is desirable to filter it, in particular if a dc offset or an integrator is present we want to the data filter to remove this component. Hence, we will always deal with filtered versions of the IO data.

The recursive estimator used to produce the model, see [9], is characterised by the following parameters which reflect the forgetting factor as well as improved convergence characteristics. Nominal values for its parameters are: $\alpha = 0.5$, $\beta = 0.005$, $\delta = 0.005$, $\lambda = 0.98$, $P = 10\dot{I}$, $K = [0...0]^T$.

Increased measurement noise or a large number of filters in the individual networks will lead to a reduced level of accuracy in the identified model. In [10] the reader can find a theoretical analysis performed to quantify the undermodelling and measurement noise induced errors in the estimation.

The form of the identification mechanism presented above is suitable for stable systems. Sometimes in practical applications we are challenged by systems with an integrating characteristic of one or more channels. In such conditions our approach is to factor the plant in its stable and marginally stable part, considered known. Note that the same procedure can be applied to a plant that contains a well known unstable dynamics. Of course in this case the robustness of the identification algorithm is conditioned by the exact knowledge of the marginally stable or unstable part of it.

3. Constrained multivariable MBPC

Consistent effort spend in the last couple of years in the development and analysis of MBPC made the algorithm to exhibit features like:

- A fairly intuitive approach which can be understood without advanced mathematics.
- The common elements of $MBPC$ schemes, such as models, objective functions, prediction horizons, etc, can be tailored to specific problems.
- A cost function accounting for both the tracking error and control moves.
- The ability to account for changes in the plant model at each time step.
- The usual combination of linear dynamics and inequality constraints allows realistic nonlinearities to be handled.
- An implementation based on a QP algorithm in the constrained case or for a fast solution a simple least squares solver option.
- Reference management which can be employed for specific batch profiles.

The defining feature of $MBPC$ is the repeated optimisation of a performance objective over a finite horizon extending from a future time (N_1) up to a prediction horizon (N_2) [2, 1]. Figure 1 characterises the way prediction is used within the $MBPC$ control strategy. Given a setpoint, a reference $r(k+l)$ is produced and used within the optimisation of the cost function (4). Manipulating the control variable $u(k+l)$, over the control horizon (N_u), the algorithm drives the predicted output $\tilde{y}(k+l)$, over the prediction horizon, towards the reference.

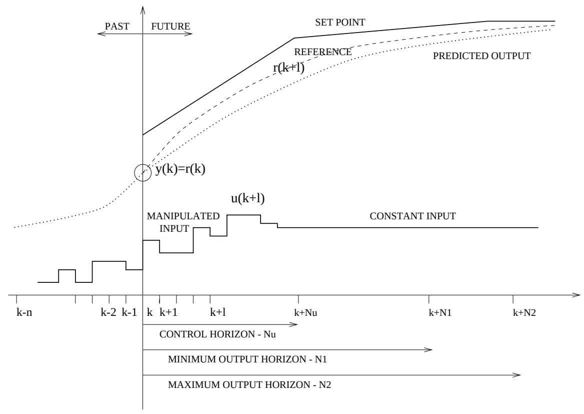

Figure 1: Prediction strategy

The future control movement is determined by minimising the cost function:

$$J(k) = \sum_{l=N_1}^{N_2} \|(\tilde{y}(k+l) - r(k+l)\|^2_{Q(l)} + \sum_{l=0}^{N_u} \|\Delta u(k+l)\|^2_{R(l)} \tag{4}$$

subject to constraints on:

- the inputs levels $u_l(l) \leq u(l) \leq u_u(l)$ where $k \leq l \leq k+N_u-1$
- the input rates of change $\Delta u_l(l) \leq \Delta u(l) \leq \Delta u_u(l)$ where $k \leq l \leq k+N_u-1$
- the output (and state) levels $y_l(l) \leq \tilde{y}(l) \leq y_u(l)$ where $k+N_1 \leq l \leq k+N_2$

$Q(l)$ and $R(l)$ are weights independent of time k and the norm $\|.\|^2_Q$ within the cost function is defined as $\|\alpha\|^2_Q = \alpha^T Q \alpha$. It is assumed that $\Delta u(l) = 0$ for $l \geq k+N_u$. As in [6] the optimisation is carried out using a quadratic program (QP).

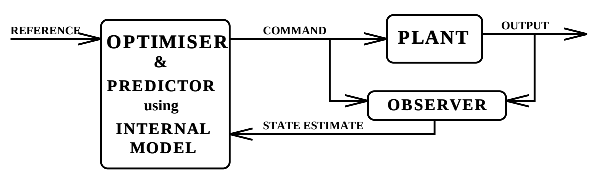

Figure 2: The structure of $MBPC$ schemes

The general structure, Figure 2, of $MBPC$ schemes is the following:

Optimiser contains the constrained cost function. The main task of the optimiser is to compute the present and future manipulated variable moves such that the predicted output follows the reference in a desirable manner.

Predictor employing the internal model and the measurement or estimate of the current state provides the optimiser with future predicted values of states and outputs.

Internal model represents the plant. In this paper we use a state-space linear time invariant model for the plant.

Observer provides current state estimates, which can be used in the predictor.

If we have knowledge of the existence of marginally stable plant then, as described in [6], the control movement is computed based on the prediction of the augmented model. This approach respects the internal model principle. Ramping references or disturbances are treated in a similar manner to ensure a zero steady state error.

4. Indirect adaptive control method

The indirect adaptive control scheme suggested uses a modified recursive least square algorithm, see [9], to estimate the parameters of the models involved in the control equation.

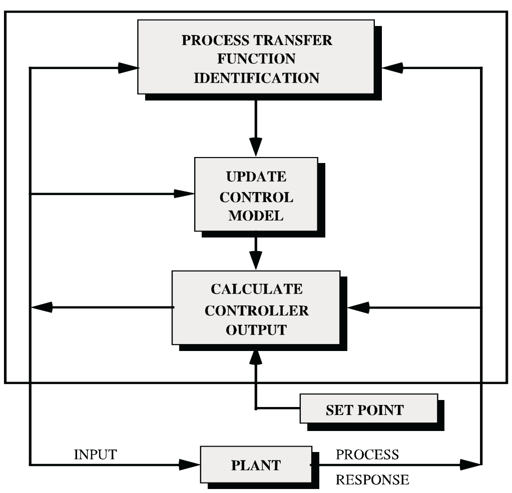

Figure 3: The closed loop of the advanced control system applied to the batch reactor

The adaptive control identification algorithm has a number of free parameters. A designer has to minimize this number since the scheme is implemented in real time. For instance the choice of the Laguerre filter pole p can be restricted to a fixed value once an initial guess for the system model is available. For a given plant there is an optimal pole that will minimize the number of filters required to obtain a required accuracy for the model. A frequent situation encountered in process industries involves multirate systems. At present our approach is to unify the sampling rate and manipulate the matrix of poles in exchange. Since for a given model of the plant the crossover frequency region is very important from the perspective of the closed loop system transient response a good choice for the Laguerre pole will be in that area.

In a similar fashion the dead time of the process is well modeled by a Laguerre network, depending on its number of filters. A tradeoff has been observed between the deadtime modeling and the model settling time. Too many filters will result in a long process model settling time.

The closed loop system is depicted in Figure 3. The advanced controller was implemented in C++ and runs on the Windows-NT^{TM} operating system. An OLE for process control (called OPC server) is used to communicate, for instance, to the existent Distributed Control System (DCS). Logic was programed in the DCS device to allow operation from the existing operator console. The operator can select between manual, PID (DCS) or advanced control modes.

Two important issues are raised during the adaptation:

1. under which conditions and how well the process estimate will converge to the real plant parameters.
2. what can we say about the stability of these scheme when we are in fact switching between controllers designed based on plants identified at different setpoints and subjected to various loads.

It is possible and we are working at this stage to prove the convergence of the MIMO estimation procedure based on the following typical assumptions: persistent input excitation in all input channels, bounded disturbances and a model considered to describe accurately the real plant. Note that some of these assumptions are necessary and achievable in practice for a good identification.

When the estimation of the plant model is done in a recursive least squares manner the persistent excitation is a requirement, see [4]. This condition translates into special characteristics of the shape of the manipulated variable which are external to the adaptive loop. Unfortunately in practice the external signals may not fulfill the requirements due to the set-point profile or to the fact that in the MIMO case the number of input variables can be larger than that of outputs/references.

For instance, say for a square MIMO system, a step change in the reference can provide the identification algorithm with a significant amount of information in the moments that follow the change but as soon as the transient disappears into the plant noise the plant/model mismatches become unobservable.

It is crucial therefore for the controller to modify its settings to account for such kind of changes or as an alternative a PRBS signal has to be added at the plant input. The second alternative is compulsory in the case of a non square system (more inputs than outputs).

Since the control law is computed at each time instant issues of stability and the convergence of the method become paramount. In [14] these issues are partially addressed. Further in [5] the stability of switching systems with average dwell time is analyzed and we believe that this work, under certain assumptions, can be applied to our indirect adaptive controller scheme.

Although, the proposed controller works well in a wide variety of situations it still lacks a theoretical analysis. For instance it is not yet clear how the transition between the different internal models or settings in the controller might affect the overall system stability and performance or what are in this cases its robustness properties. Another important issue is the on-line model validation. In other words we are still searching an answer to the question "Which model is best for control, the one employed at the present or the one just identified?".

5. The controller performance

The utility of the MIMO adaptive predictive controller is illustrated in this paper with a brief simulation study. The choice for the plant includes a MIMO case with large discrepancies between channels such as: different dynamics (including different gains), time delay, inverse response and strong cross-coupling. The plant $G(z)$ has four inputs and three outputs:

$$G_{11}(z) = 20\frac{(z-0.8)(z-0.1)z^{-4}}{(z-0.5)(z-0.4)} \qquad G_{12}(z) = 20\frac{(z-0.5)(z-1.2)z^{-2}}{(z-0.1)(z-0.2)}$$

$$G_{13}(z) = 0.2\frac{z^{-3}}{(z-0.4)} \qquad G_{14}(z) = 0.4\frac{(z-0.4)z^{-6}}{(z-0.7)}$$

$$G_{21}(z) = 0.2\frac{(z-0.1)}{(z-0.8)(z-0.2)} \qquad G_{22}(z) = 0.2\frac{z^{-3}}{(z-0.4)}$$

$$G_{23}(z) = 5\frac{(z-1.2)}{(z-0.5)} \qquad G_{24}(z) = 0.1\frac{z^{-2}}{(z-0.9)}$$

$$G_{31}(z) = 3\frac{(z-0.9)z^{-1}}{(z-0.2)(z-0.3)} \qquad G_{32}(z) = 0.2\frac{z^{-2}}{(z-0.8)}$$

$$G_{33}(z) = 0.2\frac{z^{-2}}{(z-0.8)} \qquad G_{34}(z) = 20\frac{(z-1.2)z^{-4}}{(z-0.3)(z-0.5)}$$

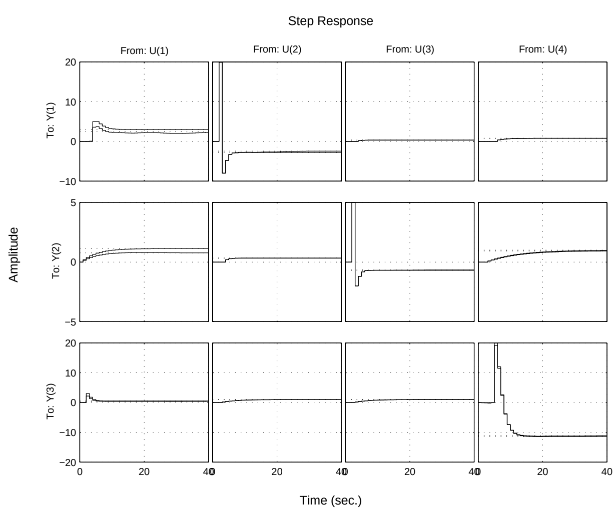

Figure 4: A snapshot of the controller face plate reflecting the quality of the identification algorithm

The development, see Figure 4, allows us to look at step responses of the identified model. In this case to show the ability of the identification algorithm these step responses are overlaid on the real plant responses (unknown in practical situations). Hence, we are able to view how the algorithm accounts for the large discrepancies between the individual entries of the system transfer matrix. This snapshot from the controller face plate is useful to compare how well the identification algorithm performed and it reflects the evolution of the model during the identification and control procedure.

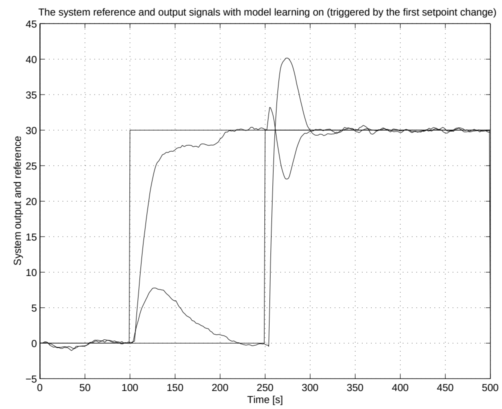

Figure 5: Time responses for a sequence of steps in the reference signals subject to random walk type of disturbances

The hypothesis presented in the previous section was satisfied in the sense that a persistent excitation in all channels was employed as square waves with different fundamental frequencies of 0.1 and 0.3 Hz, respectively. The amplitude of the excitation signals was small compared to the reference signals, not affecting the closed loop behaviour. For more realism in our simulation we have also considered the output data being corrupted with a stationary white Gaussian measurement noise.

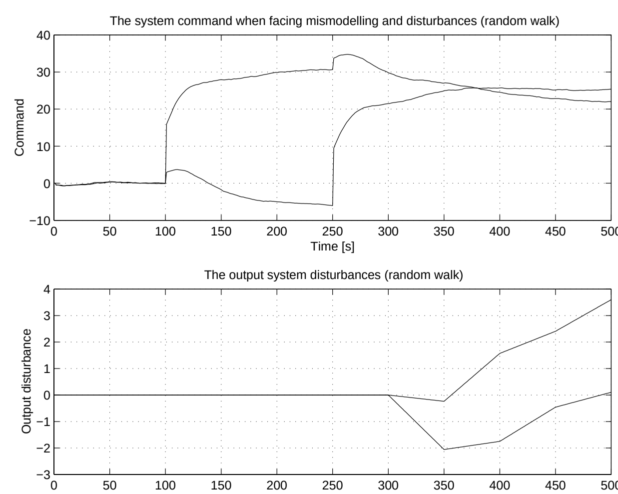

Figure 6: The disturbance profile across the batch together with the command moves

In Figure 5 we show a typical time response plot used to help the user understand how the controller performs on the process. In this case for clarity of the plots we have used a 2×2 system. A random walk type of disturbance was applied simultaneously with steps in the reference signals. In this paper we do not focus on showing the benefit of having a constrained algorithm mainly because of lack of space but as well because this issue was addressed extensively in the literature, see [6]. Instead we concentrate on how the internal model principle was applied such as to reject ramping disturbances.

Observe in Figure 6 the profile of the output disturbance and the command sequence generated by the controller to reject it, all this while providing a good tracking of the reference.

6. Conclusions

An advanced model based predictive controller was developed for use on MIMO processes with a possible integrating response, exibiting long dead time and time constants. The controller was developed in a modular structure. A flexible test-bed like the Matlab Simulink development space [6] was enahanced with the identification module. This enables us to go towards the implementation of hardware in the loop directly.

Since the R&D was pursued in Matlab-Simulink we were able to do most of the preliminary testing in this environment. Mapping the Matlab code into C++ represented now an easier task. A thorough analysis of the parameters involved in the controller provided some golden values for a number of tuning parameters, hence reducing commissioning time.

Bringing this product to the market involves a consistent financial effort and further developments at the level of the graphic user interface (GUI) such as to take advantage of the company's previous experience in terms of blending the controller features with a proper way to manage the overwhelming quantity of information for the industrial user. Laboratory tests with the beta version are currently being conducted to evaluate the real time capability of the controller.

The applicability of this controller ranges from pulp and paper to biomedical engineering. The main benefits of this control strategy are: a systematic tuning procedure, reduced cross couplings between channels and minimized closed loop overshoot and settling time, all which lead to good integral performance indexes.

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