A MULTIVARIABLE LAGUERRE-BASED INDIRECT ADAPTIVE PREDICTIVE CONTROLLER APPLIED TO A FUEL BLENDING PROCESS

M. Huzmezan and G.A. Dumont *
W.A. Gough and T. Janiewicz and S. Kovac and D. Meade **

* *University of British Columbia, Electrical and Computer Engineering*
{huzmezan, guyd}@ece.ubc.ca
** *Universal Dynamics Technologies Inc.*
{bgough, tjaniewicz, savak, dmeade}@BrainWave.com

Abstract. Process industries need a multivariable predictive controller that is low cost, easy to setup and maintains an adaptive behavior which accounts for plant non-linearities as well as potential mismodeling. In answer to this an indirect adaptive controller, now a commercial product implemented on a Windows-NT/2000/XP platform (BrainWave MultiMax), is proposed. To evaluate its performance the control of a fuel blending process is presented.

Keywords. Multivariable Control, Indirect Adaptive Control, Laguerre Identification, Model Based Predictive Control, Fuel Blending

1. INTRODUCTION

Process industries need a multivariable predictive controller that is low cost, easy to setup and maintains an adaptive behavior which accounts for plant non-linearities and mismodelling. 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.

In answer to these requirements an indirect adaptive controller is proposed. The particular structure of such a controller is described. In doing this we are showing how Laguerre orthonormal basis functions (Dumont and Zervos, 1986; Zervos, 1988; Zervos and Dumont, 1988) can be extended to multivariable systems and used to produce a valid linear process model. Further, we are presenting how this model can be used at each time step in a multivariable predictive controller to produce a plant input move that achieves good reference tracking in the presence of disturbances and actuator constraints. The architecture of BrainWave MultiMax, the resulting MIMO adaptive model based predictive controller, now a commercial product implemented on a Windows-NT /2000 /XP platform is also dicussed.

As mentioned for the identification part, a MIMO Laguerre orthonormal basis function identification was employed. Before making a decision with respect to this way of producing on-line an LTI plant model, a comparison with other established MIMO methods such as subspace identification (Larimore, 1990; VanOverschee and DeMoor, 1996) was pursued. Motivated by practical applicability we investigated the identification of multivariable marginally stable systems. The solution offered embeds this case. All these issues are addressed in Section 2.

Multivariable model-based predictive control (MBPC) methods have been widely and successfully used in certain sectors of the process industries for the last 20 years, particularly in the petrochemical sector (Morari, 1994). The main attraction of MBPC in the industrial world is the ability to handle constraints. In the case of input constraints this ability of the MBPC scheme can be achieved also via a MIMO anti-windup augmentation of the traditional integrator situated at the output of the controller. The plant dynamic model is used to predict the behavior of the process output variable within a limited time horizon. An online optimization procedure determines the manipulated variable. In the case of an on-line/real-time implementation, the computation time limits the controller bandwidth. To address this issue the indirect adaptive predictive algorithm has been implemented using sparse matrices. The implementation of the indirect adaptive predictive controller is explained in Section 3.

Section 4 discusses the benefits of implementing this controller to a fuel blending process that is difficult to control with conventional proportional integral derivative (PID) control due to the strong coupling between the process channels. Conclusions follow in Section 5.

2. THE MIMO LAGUERRE ORTHONORMAL BASIS FUNCTION IDENTIFICATION

Over the last decade a significant amount of work has been put into developing computationally reliable and less intensive identification schemes. Subspace methods are among the most powerful techniques to have emerged (Larimore, 1990; VanOverschee and DeMoor, 1996). Various forms of subspace identification methods, directed towards identifying a multivariable system using simple computations, are employed in an off-line fashion. There is a strong resemblance between subspace methods and the method proposed in this paper. The MIMO Laguerre orthonormal basis function identification is based on a projection of the plant model onto a linear space whose basis is formed by an orthonormal set of Laguerre functions. The difference is the possibility of an on-line implementation in the Laguerre network case.

There are a number of advantages resulting from the use of an orthonormal basis function for identification: i) the model structure is linear in the parameters subject to estimation - therefore known techniques like recursive least squares estimation can be used; ii) the orthonormality facilitates modelling with a fixed model structure hence avoiding problems generated by the convergence of the parameter estimate vector to a local minimum; iii) dead time dominant plants are easily dealt with; iv) if needed a reduced number of functions in the basis offers an efficient way to store the model parameters and filter the incoming plant data; v) the ability to include prior knowledge on the system poles vi) statistical properties of the estimate can be calculated; vii) the practical implementation is facilitated by the simple concept of the Laguerre basis function.

The Laplace domain representation of the Laguerre function, a complete orthonormal set in $\mathcal{L}_2$ is:

$$L_l(s) = \sqrt{2p}\frac{(s-p)^{l-1}}{(s+p)^l}\ , l = 1, \dots, N \qquad (1)$$

where l is the number of Laguerre filters ($l = 1, N$), $p > 0$ is the time scale, and $L_l(s)$ are the Laguerre polynomials. The SISO Laguerre ladder network can be expressed as a stable, observable and controllable state space form as:

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

where $l(k)^T = \left[l_1(k),\ \dots\ , l_N(k)\right]^T$ is the state of the ladder, and ${c_{ij}}^T(k) = \left[c_1(k), \dots, c_N(k)\right]$ are the Laguerre coefficients at time k. A_{ij} is a lower triangular square matrix with a dimension equal with the number of Laguerre filters in the network and b_{ij} is a column vector.

The corresponding discrete time state space representation of the Laguerre network (Zervos and Dumont, 1988) denoted for each ij^{th} SISO model as A_{ij}, B_{ij}, C_{ij}, D_{ij} is obtained for a fixed choice of the Laguerre pole location. We have a strong preference for a fixed real pole corresponding to each input of the plant since it improves the speed and accuracy of the estimation algorithm. In exchange this choice can lead to a slightly larger number of Laguerre filters required to model, for instance, underdamped second order dynamics. Methods used to search for the Laguerre network pole that provides the best model approximation have been tested but no major improvement over the conventional fixed pole choice backed by an appropriate decision over the sampling time has been observed in the case of a real time application. This approach, together with a fixed number of Laguerre filters per input channel, allows a common A_{ij} and b_{ij} for each input to all outputs SISO models in the MIMO case.

The MIMO model is achieved by assembling the SISO structure into the cells of a transfer matrix that linearly approximate the multivariable plant. The way the MIMO system identification using Laguerre orthonormal basis functions works is very similar with the SISO case (Dumont and Zervos, 1986; Zervos and Dumont, 1988). In the MIMO case the identification algorithm is aimed at estimating the parameters of the $C(k)$ Laguerre matrix of coefficients instead of the the row vector $c(k)$. A recursive estimator is used to identify the model, see (M.E. Salgado and Middleton, 1988). The variation of the RLS method used is characterized by parameters which reflect the forgetting factor as well as improved convergence characteristics. Before being employed in control the MIMO state space representation is reduced to a minimal realization based on an adequate tolerance.

Increased measurement noise or a large number of filters in the individual networks can lead to a reduced level of accuracy in the identified model. In (Ninness and Gomez, 1990) the reader can find a theoretical analysis that quantifies the under-modelling and measurement noise induced errors in the estimation. Hence, before employing the plant data for the recursive model estimation, it is mandatory to filter it. In particular if a dc offset or an integrator is present the data is filtered to remove this component.

As a result the identification mechanism presented above, generally suitable for stable systems, is modified to account for practical applications with an integrating characteristic in one or more input-output channels. Note that the same procedure of factoring the plant in a stable and a marginally stable part, considered known, can also be applied to a plant that contains known unstable dynamics. For both cases the robustness of the identification algorithm is conditioned by the exact knowledge of the marginally stable or unstable part of the plant.

3. INDIRECT ADAPTIVE PREDICTIVE CONTROLLER

The controller includes the following: i) an intuitive approach which can be understood without advanced mathematics; ii) tailoring of common elements of $MBPC$ schemes, such as models, objective functions, prediction horizons, to specific problems; iii) a constrained cost function accounting for both the tracking error and control moves; iv) ability to account for changes in the plant model at each time step; v) reference management employed for specific batch profiles.

The approach employed for the SISO commercial controller was extended in the MIMO case to include repeated optimization of a performance objective over a finite horizon extending from a future time up to a prediction horizon (Clarke and Mohtadi, 1989; Clarke, 1993). Given a set point, a reference is produced via filtering and used within the cost function. The algorithm drives the predicted output over the prediction horizon towards the reference via manipulating the control variable over the control horizon. Only the first move is implemented. Hence the future control movement is determined by minimizing the cost function:

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

The input constraints are addressed by a MIMO anti-windup mechanism. The horizons are N_u, N_1 and N_2 the control, initial and final prediction, respectively. The weights $Q(l)$ and $R(l)$ can be time dependent but constant over the future horizon. The norm $\|\|^2_Q$ within the cost function is defined as $\|\alpha\|^2_Q = \alpha^T Q \alpha$. It is assumed that $\Delta u(k+l) = 0$ for $l \geq N_u$. The optimization is carried out using a least squares solution produced using the same SVD algorithm which is part of the minimal realization reduction code.

The general structure of $MBPC$ schemes is respected: i) the optimizer contains the constrained cost function, its main task being to compute the present and future manipulated variable moves such that the predicted output follows the reference in a desirable manner; ii) the predictor employing the internal model and the measurement or estimate of the current state provides the optimizer with future predicted values of states and outputs; iii) the newly identified LTI models represent the plant; iv) the observer provides current state estimates used by the predictor.

Two important issues are raised during the model adaptation: i) under which conditions and how well the process estimate will converge to the real plant parameters; ii) 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 set-points and subjected to various loads. At this stage, we are working towards proving the convergence of the MIMO estimation procedure based on the following typical assumptions: i) persistent input excitation in all input channels; ii) bounded disturbances and iii) the model is considered to accurately describe the real plant. Note that some of these assumptions are necessary and in fact achievable in practice for good identification.

When estimation of the plant model is performed in closed loop, independent persistent excitation is a must, see (Goodwin and Sin, 1984). For instance, a step change in the reference can provide the identification algorithm with a significant amount of information during the initial samples that follow the change, but, as soon as the transient disappears into the plant noise the plant/model mismatch becomes unobservable. Hence, it is crucial for the controller to modify its settings to account for such changes. The alternative solution is a pseudo-random binary sequence with a frequency content extending to the plant bandwidth, added at the input of the plant. This alternative becomes mandatory in the case of a MIMO non-square system.

The adaptive control and identification algorithm have a number of free parameters. The controller design and implementation have minimized this number and we are currently looking at automating the setting of these parameters based on a given plant ideal model.

4. BENEFITS OF IMPLEMENTING THIS CONTROLLER TO A FUEL BLENDING PROCESS

The refinery where the fuel blending process [1] is located manufactures fuels, primarily gasoline, diesel fuel, and jet fuel. The refinery receives crude oil from Alaska via tanker and from Canada via pipeline. The refinery capacity is 108,000 barrels per day of crude feed. A by-product of the crude refining process is asphalt, which can be turned into a low cost fuel for ships and is also used for road construction. The process of transforming the asphalt into a low cost fuel requires blending the asphalt with cutting agents to meet both specific gravity and viscosity specifications that make the asphalt transportable. The cutting agents that are used can be either fuel products manufactured by the company or purchased from other companies. The fuel cutters are expensive and hence the need to minimize the cost of the cutters while maintaining the specific gravity and viscosity of the blended fuel is mandatory.

The utilization of the MIMO adaptive predictive controller 1 is illustrated in this brief study on the fuel blending process. For commercial reasons the

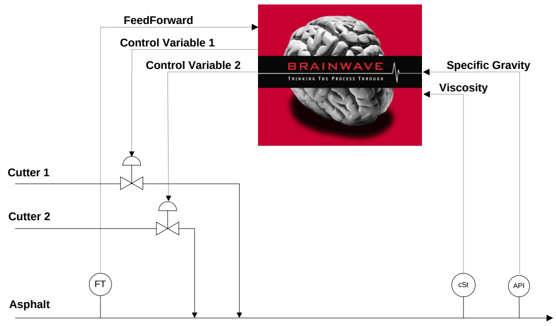

Fig. 1. The closed loop with the advanced adaptive MIMO controller

data presented reflects, up to a simulation model, the reality found in the refinery.

The MIMO plant has two inputs (two different cutter types) and two outputs (specific gravity and viscosity) and a measured disturbance (the flow of asphalt). The plant model presented large discrepancies between channels, different dynamics including different gains, time delay and strong cross-coupling. The fuel blending control loop had a time constant of 60 seconds and a dead time of 4 minutes. The blending of the cutter with the asphalt occurred when the asphalt temperature was 525F. The blended mixture then travels through a series of heat exchangers and the specific gravity is measured when the final mixture is 75F. The specific gravity must be maintained at 12.3 API (American Petroleum Institute specific gravity units) and the addition of the cutting medium must be minimized. The viscosity control loop presented similar dynamics with a negative gain.

These dynamics together with the cross-coupling between the main cutter input and the viscosity can be observed in Figure 2 which reflects the final result of learning the plant and measured disturbance models. BrainWave MultiMax, chosen as the advanced control software for online fuel blending of the cutters with the hot asphalt, was interfaced to a Siemens Moore Apacs System through a Modbus connection. An industrial computer was placed in the same cabinet as the Apacs system to run the BrainWave MultiMax controller. A derived function block was developed to interface the controller tag information to the tags corresponding to the Apacs system. Once the adaptive controller was integrated into the control strategy, bump tests were initiated to determine the models for the process response via its user interface. A multi-model approach was utilized to take into account the effect different cutters would have on the blended mixture. The process of bump

[1] We would like to acknowledge S. Kline from Tesoro Refining Company for allowing the field trials of the commercial BrainWave MultiMax Controller produced by the team from Universal Dynamics Ltd.

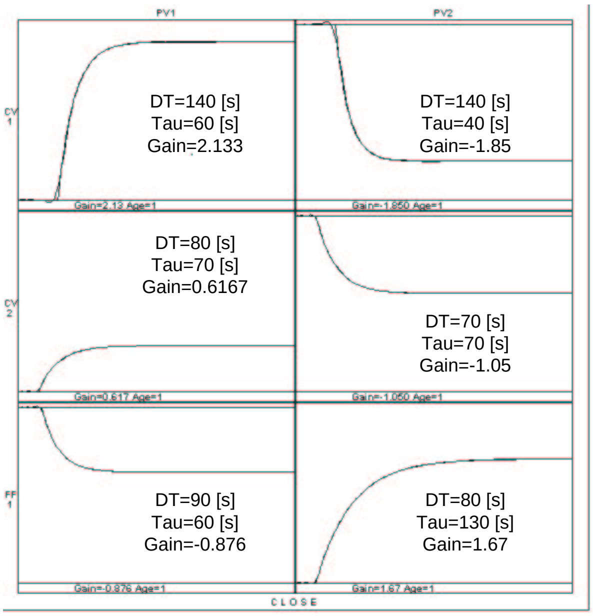

Fig. 2. The plant and feedforward models

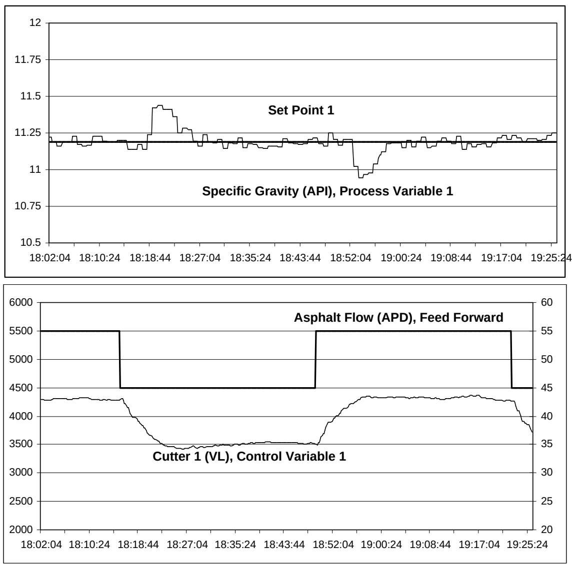

Fig. 3. The closed loop control of specific gravity

tests, model identification and control optimization took three days.

The results presented in Figures 3 and 4 exceeded the existing control performance by several orders of magnitude outperforming at the same time the manual control capabilities of the operators. These Figures the profile of the output disturbance and the command sequence generated by the controller to reject it, whilst providing excellent reference tracking within 0.5 API. At the same time the product viscosity is kept tight within

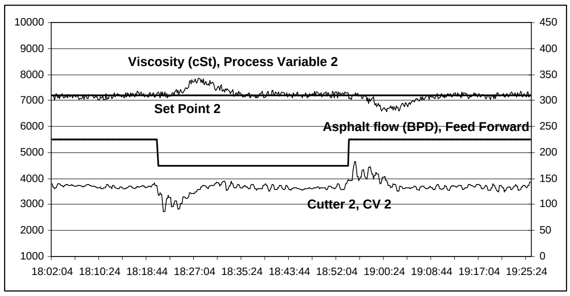

Fig. 4. The closed loop control of fuel viscosity

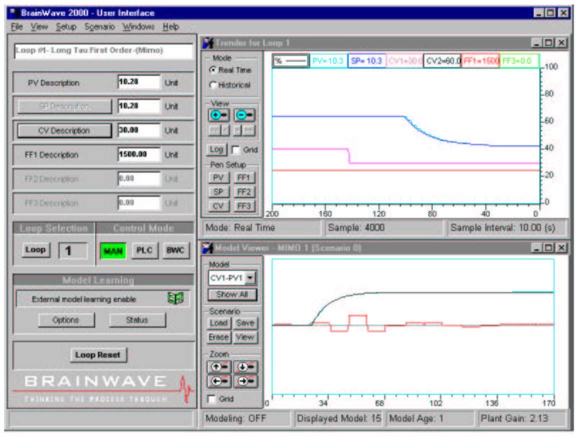

Fig. 5. A snapshot of the controller face plate reflecting the trender, model viewer and controller setup windows

acceptable bounds. As a result, reduced cutter addition is saving an estimated $ 150,000 dollars annually, with a return on investment of less than 2 months. In addition the possibility for the operators to redirect their attention to more critical loops is greatly appreciated. BrainWave MultiMax was implemented quickly and is easily modified by the company process engineers.

A snapshot from the controller face plate shown in Figure 5 is giving a flavor of the way the setup window blends in the trender for the process responses together with the model viewer which allows the user to supervise the accuracy of the online identification process.

5. CONCLUSIONS

The advanced model based predictive controller BrainWave MultiMax was developed in a modular structure for use on multi-input/multi-output MIMO processes with possible integrating responses, exhibiting long delays and time constants. The controller was developed and tested using a flexible Matlab Simulink test-bed, which enabled us to do most of the preliminary testing in this environment and subsequently implemented in C++. A thorough analysis of the parameters involved in the controller provided golden rules for a number of tuning parameters, dramatically reducing the commissioning time. Particular attention was paid to the development of the graphic user interface (GUI), the implementation in real time of the controller to achieve sample times as low as 0.1 [s] for a medium size MIMO system, together with a strict management of the controller features in order to make it user-friendly.

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. Prohibitive costs of predictive control and a low number of commercially available multivariable adaptive controllers prevent industries that operate on small profit margins to take advantage of such technology. This is exactly the niche market this controller is targeting.

In terms of applications the paper shows the benefits of the aforementioned controller to a fuel blending process, which is characterized by serious control challenges such as strong coupling between channels and significant delays in all channels. The controller performs well when the process is subject to large variations in the production rate with direct consequence upon the process dynamics.

Although, the proposed controller works well in a wide variety of situations it still lacks a theoretical analysis. For instance a proof making clear how the transition between the different internal models or settings in the controller affect the overall system stability, performance or the required robustness properties is necessary.

Current extensions of the controller are concentrated on automatic probing, automatic model validation and automatic horizons and weights adjustment based on model evolution.

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