INNOVATION IN INDUSTRIAL MODEL PREDICTIVE CONTROL

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Synopsis

The industrial application of Model Predictive Control (MPC) has been largely confined to the petrochemical arena. Crossover into the general process industries has been limited. Among the reasons that may be proposed for this can be highlighted:

- a lack of precedent applications
- large engineering costs
- inappropriate control technologies.

This paper describes initiatives to address such barriers so that the benefits of MPC can be more widely available :

- demonstration projects on mainstream process applications
- software tools to minimise engineering costs
- embedding MPC within the plant regulatory control system
- a flexible approach to control technology so that solutions match the problem encountered rather than the other way round.

INTRODUCTION

In February 1997, Predictive Control Ltd(PCL), a small Model Predictive Control Company that had evolved from the University of Manchester, was acquired by Siebe PLC. This has brought about a close association with sister Siebe companies such as Foxboro, more lately Simulation Sciences(SimSci) and most lately Eurotherm International. In the last two years, considerable effort has been directed to advance both the software and control engineering capabilities of PCL's MPC product Connoisseur[3,9] and to extend its industrial application base. These activities have been carried out under joint programmes, mainly involving PCL, Foxboro, SimSci and the Engineering School at the University(Control Technology Centre Ltd).

This paper is concerned with aspects of these technological developments, in particular;

i) Widening the scope of exploitation of MPC in industry. MPC has become a commodity technology for hydro-carbon processing. The potential for exploitation in wider industry is vast. To give indication of this potential, three recent, and successful application projects that have been carried out by Foxboro are reviewed.

ii) Software Engineering. An application of MPC can be complex, dominated not by control engineering but by issues of integration with plant data and with plant operators and engineers; by issues of integrity within a Distributed Control System(DCS) infrastructure and issues of reliability and maintainability. Software has been developed to cut through these issues so the commissioning engineer can focus on controller development rather than being distracted by the needs of application architecture. Such stream-lining allows time-scales for project execution to be cut dramatically.

iii) More progressive control technology. The control engineering capability of Connoisseur is under continuous enhancement in line with state of art. One recent project is to extend the MPC to be able to manage processes for which the dynamics are modelled with non-linear Radial Basis Function (RBF) neural networks. This offers potential for better dealing with processes that have difficult non-linear relationships[4,5], which for example are more prevalent in the arena of batch processing than in the continuous processing that has been the traditional arena for MPC exploitation. The capability of a prototype non-linear controller is reviewed.

COPPER ORE GRINDING APPLICATION

This application was commissioned at ASARCO's Mission Mine in Arizona on the North Mill Grinding Operation. A 'proof of concept' study was carried out during April and May of 1998 with the majority of final commissioning completed during the latter part of the same year. The Mission Mine North Mill processes copper ore to produce copper concentrate. The operation includes a total of eight grinding circuits together with associated upstream ore handling and downstream flotation operations. Of these grinding circuits six lines consist of a single rod mill operating in series with two ball mill and cyclone combinations. The two ball mills are operated in parallel. A further two circuits consist of a single rod mill and ball mill connected in series.
For this application, successful control encompasses two major issues;

- Driving the line to its optimum operating point, and
- Maintaining control through variations in ore characteristics.

Both of these capabilities have been demonstrated successfully by the MPC application.

During operation the MPC scheme has demonstrated the ability to increase feed rate to each grinding circuit without violating operating limits on the mill such as maximum particle size, cyclone overflow density, cyclone pump current, etc. It has also demonstrated the ability to minimise particle sizes when the feed was limited by increasing recycle mass flow.. This has the dual benefits of increasing recovery and minimising wear on the ball mills.

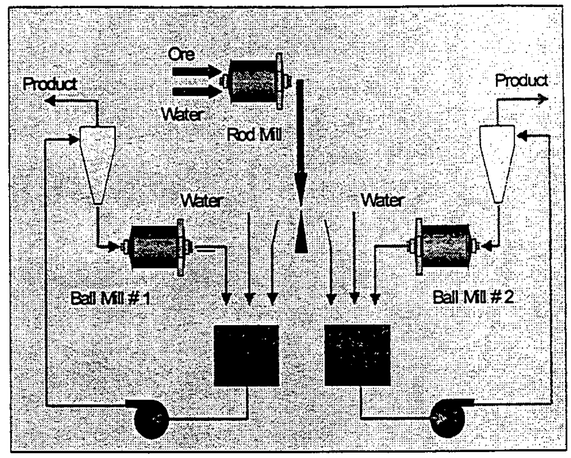

Fig 1 Simplified Grinding Circuit

Some of the operational problems that were overcome in the commissioning of the MPC application include:

- Mill overloads
- Varying ore characteristics
- Variable process gains
- Variable and complex process dynamics, including inverse response.
- Multiple process constraints / multiple lines
- Changing equipment capacity
- Changing feed availability
- Difficult process measurements
- Abrupt upsets

The complete MPC solution for the Mission Mine operation consists of a number of distinct components, each of these are described briefly below:

Multivariable Control:

A separate multivariable controller is used to control each of the eight grinding circuits. Columns in Figure 2 represent Manipulated Variables(MVs) within the control scheme, rows depict Controlled Variables(CVs) which represent both operating objectives and process equipment constraints.

Rather than use a single dynamic process model to cover all aspects of process operation, including variable ore hardness, each controller has access to a number of process models which each represent the process dynamics under a different operating regime. The controller will select automatically the appropriate control model by determining which one provides the best fit to the prevailing conditions. The controllers also make use of on-line adaptation facilities to modify control models in line with longer term drifts in operation such as mill wear.

	Mill feed rate	Feed splitter	Mill #1 water	Mill #2 water
#1 particle size	X	X	X	
#2 particle size	X	X		X
#1 cyclone feed mass flow	X	X	X	
#2 cyclone feed mass flow	X	X		X
#1 cyclone overflow density	X	X	X	
#2 cyclone overflow density	X	X		X
#1 cyclone feed density	X	X	X	
#2 cyclone feed density	X	X		X
#1 pump amps	X	X	X	
#2 pump amps	X	X		X
#1 cyclone feed flow	X	X	X	
#2 cyclone feed flow	X	X		X

Figure 2: Cause and Effect Matrix for Single Grinding Circuit

Steady State Optimisation:

In addition to the dynamic multivariable controller, each grinding circuit has a Linear Programme optimisation scheme that optimises the operation of each line. When feed is available the optimiser will maximise feed rate subject to equipment constraints. When feed availability is limited the optimiser is configured to minimise product particle size.

Plant Wide Feed Allocation:

Based on information about the availability of fresh feed and the current operation of each grinding circuit the plant wide feed allocation scheme will distribute the available feed across all operational lines in order to optimise overall equipment utilisation. The feed allocation application uses a constrained optimisation scheme based on Quadratic Programming technology.

Coarse Ore Storage Bin Level Management:

This is a rule-based scheme using fuzzy logic technology which monitors the levels of the ore storage bins that are fed from the upstream ore handling facility. The bin management scheme will determine the total available ore for the feed allocation scheme.

Mill Overload Control:

Mill overload is the 'recurring obstacle' to process optimisation. Any increases in ore hardness and size will cause an accumulation of ore in the grinding circuit and may ultimately overload the mill. This condition is detected by monitoring key process measurements including derivatives of mill current and recycle pulp mass flow. On detection of an incipient overload condition the controller must act promptly to reduce mill feedrate, or shift load between the ball mill circuits. The overload controller acts as a supervisory mechanism to the control and optimisation schemes on each grinding circuit.

Benefits

The basic regulatory system for the grinding circuit, which was in use before the MPC system, manipulates feed rate to control particle size. This design maximises feed rate subject to particle size specifications, which are input by the operator based on management directives or downstream flotation recovery requirements. At other times, the operator may disable particle size controls and fix the feed rate to the grinding sections. The scheme does not explicitly address equipment loading constraints or variations in ore characteristics. Each line operates independently of the others.

By contrast, the MPC scheme provides optimum operation of the grinding section of the plant under all feed conditions. When availability of feed is not the production bottleneck, the individual controllers maintain constraint control for each grinding line, maximising production rate to equipment capacity and operator entered product size constraints.

When feed is limited by upstream conditions, the system optimises performance of all the grinding lines by limiting overall production to operator set limits, while allocating feed to equalise particle size at the smallest possible value. The feed allocation scheme oversees the co-ordinated operations of all grinding lines, allocating feed for maximum downstream recovery during these periods. Under all conditions, process constraints arising from mill loading, ore hardness, water supply limitations, etc. are respected.

UTILITY BOILER OPTIMISATION APPLICATION

This project was conducted on Unit 3 of The Lower Colorado River Authority's, Sim Gideon Power Plant, located 5 miles east of Bastrop, Texas. The unit is a 340 MW, natural gas, tangentially fired, single furnace, Combustion Engineering boiler. The objective of the project was to use an advanced control software tool interfacing to the existing Foxboro I/A control system to improve the unit efficiency (heat rate - Btu/kWh) without detrimental effect to greenhouse gas emissions from the boiler. A secondary objective of the project was to reduce emissions of oxides of nitrogen (NO_x). Reducing unit heat rate would naturally achieve reducted in carbon dioxide (CO_2) emissions per MW of generation.

The control solution was designed to reduce overall unit heat rate which is principally achieved by reducing air flows (excess oxygen) within the boiler and by maintaining superheat and reheat temperatures at their required operating target. In order to avoid compromising existing control of the boiler the MPC scheme was designed to manipulate bias parameters to existing regulatory schemes. Figure 3 below shows the cause and effect matrix. The application was commissioned over a 7 week period which consisted of 3 weeks of plant step tests, 2 weeks spent on data analysis and controller design and a further two weeks at site installing the controller and training the unit operators.

	O_2 Bias	Aux. Air Bias	Fuel Air Bias	A Level Bias	B Level Bias
RH Temp	X	X	X	X	X
S. SH Desup Spray Valve	X	X	X	X	X
N. SH Desup Spray Valve	X	X	X	X	X
Auxiliary Air Demand	X	X	X	X	X
FD Fan Demand	X	X	X		
Fuel Air Demand			X		
Stack Nox	X	X	X	X	X
Stack CO	X	X	X	X	X
Unit Heat Rate	X	X	X	X	X

Figure 3: Cause and Effect Matrix for Utility Boiler

Benefits

To verify the effect that the optimiser had on the process a separate verification test plan was produced. This plan simulated the normal unit load profile for a typical day. The same test of 10 hour duration was conducted twice on consecutive days; once with the new optimiser in service and once without the optimiser in service. The results of this evaluation showed a .35% reduction in unit heat-rate over all load conditions and transitions and a .55% improvement during steady load. The test results also showed an improvement in NOx emissions.

LIME KILN OPTIMISATION APPLICATION

A lime kiln is an important unit operation in the production of pulp for paper manufacture, supplying reburned lime to the recausticising operation. The lime kiln is the largest single energy consumer in the mill. The main objective of lime kiln operation is to produce uniform quality lime. Additional operating objectives include minimising fuel consumption and complying with environmental regulations. Given the long process delays and interaction inherent to the lime kiln, these objectives can be extremely difficult to achieve under traditional kiln operation.

The kiln is operated over a wide range of production rates. In addition to production rate changes the lime mud feed is cut off for approximately 5 minutes in every 4-8 hours in order to clean the mud filters. These process disturbances can result in a significant variation in lime quality as well as increasing the risk of damage to the kiln refractory due to overheating.

Figure 5 shows a block diagram of the overall control scheme. The lime kiln controller maintains the required kiln temperature profile by manipulating the kiln firing rate and air flows. Excess oxygen and kiln emissions provide additional constraints to the operation.

Lime quality is determined by the amount of residual carbonate in the re-burned lime product and is measured by the process operator every 2-4 hours. In order to enable closed loop control of this variable an inferential model of lime quality was developed using a neural network. Lime quality is a strong function of the temperature profile of the kiln, in order to maintain closed loop control of this non-linear variable a simple fuzzy rule based control scheme is utilised. The fuzzy control scheme sets the required kiln operating temperature based on inferred lime quality and current lime discharge temperature.

The lime kiln optimisation scheme was commissioned over a 4 week period which included 1 week of plant step tests, 1 week

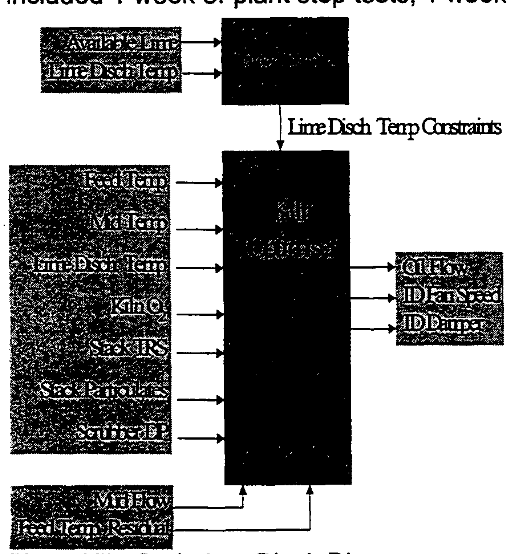

Fig. 5 Kiln Optimiser Block Diagram

of data analysis and controller design and a further two weeks at site installing the controller and training the unit operators[1,2].

Benefits

The following benefits are obtained from the lime kiln optimisation scheme.

- Reduced variability of lime quality.
- Reduced fuel consumption.
- Reduced risk of kiln damage due to high temperatures (kiln refractory and feed equipment damage).
- Overall improvement in kiln stability (rejection of disturbances due to mud filter rewash).
- Potential for increased production where equipment capacity is limited.
- Reduced airflow reduces emissions due to dust losses and improves overall efficiency through reduced exit gas temperatures.

SOFTWARE ENGINEERING

Historically MPC evolved in the petrochemical industry where large scale control problems had led to complex PID control structures. The amount of computation involved in MPC directed most implementations towards a high-end workstation integrated into the process Distributed Control System (DCS) through a local network. However MPC products are now in their second and third generation and, as the control algorithms become more efficient and computing power is soaring, it is now common to see MPC solutions installed on a cheap PC clone.

Unfortunately by locating the MPC software on a separate computer, connected to the process over a network, the fault tolerance of the system as a whole is degraded. Mature MPC products have the ability to deal with lost sensors and actuators, but problems with the network or computer can take the controller unpredictably off-line. There is also an issue of operator retraining, a costly but necessary task when a new system is introduced. The use of an MPC product brings new information and user interfaces to the operator's console.

Integration

MPC has become an essential technology to enable companies in the process industry to attain ever higher performance objectives. MPC products generally provide a number of tools that help to achieve this objective. However it is not the cost of equipment and software that generally dictate the cost of commissioning advanced control on a process, it is the engineering time. It is therefore important that an engineer spend as much time on the process as possible doing actual control engineering, rather than system configuration and maintenance.

Configuration of both hardware and software is a time consuming but necessary task that exists in every new application. The DCS must be interrogated to extract a list of available sensors and measurements, these are then used to co-ordinate a process response test in order to collect data for modelling. Once a control scheme has been developed, the DCS user interface must be configured to give the operators access to the key parameters and information necessary to operate the new control scheme. These are both examples of configuration tasks that are essential, but detract from the job of engineering an effective control strategy for the process.

A set of tools has been developed which closely integrates the Foxboro I/A System(the DCS) and the Connoisseur product suite(the Parent product). Known as the Integration Product this consists of the Parent Product software, an extended set of DCS Application Objects, the API server, and a set of configuration utilities(see Figure 6). The net result is a hardware and software control system which is easier to use, wastes less engineering time, and outperforms traditional control strategies.

The Integration Product supports the automatic configuration of the MPC signal database. The DCS is scanned for all relevant process signals for a defined process area, as this avoids the possibility of missing important information during data collection. The MPC is then automatically configured with the appropriate MVs in order to generate plant test sequences(for example, PRBS).

After data collection the control engineer is then free to develop the appropriate models and controllers from the test run on the process. The resultant control scheme can be validated using the relevant MPC simulation facilities before deployment.

The DCS utilises an object-oriented database to which external applications can write information via the API server. The MPC package is thus able to write information into and read information back out of the DCS. The DCS control system uses data within the object database to control the process. The Integration product utilities support the automatic configuration of the object database, the operator displays, and all the signal information required to support the application, including sensor validation status, MV read-back, wind-up status, etc.

The Integration product uses the standard DCS control features that allow secure supervisory control of the DCS control blocks. This allows access to features such as back-calculated setpoint values to allow bumpless initialisation together with explicit wind-up indication. The automatic time-out detection and fallback actions that are available are used to provide safe and secure control in all situations.

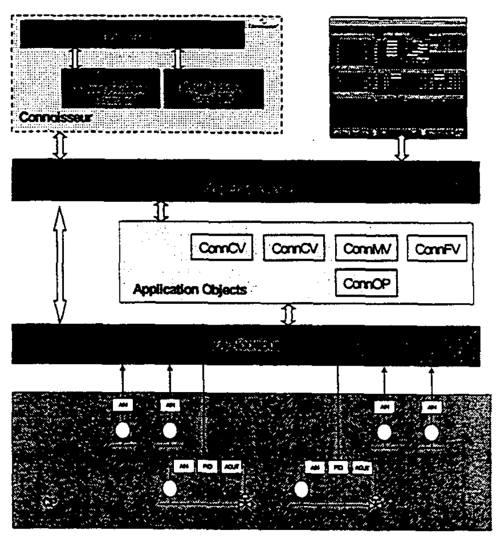

Figure 6 – Integrated I/A Architecture

The utilities can also generate a standard DCS display(see Figure 7) for use on the operator consoles on the process. This provides a seamless integration between the operator and the MPC software. All the information required for execution of MPC is displayed in an environment that is familiar to the operator, reducing the need for training with the new technology. The MPC design system is still available, so that a control engineer can tweak the controller at source.

The Integration product reduces the engineering time required to commission a new application through the reduction of configuration time of both the hardware and software, and allows the control engineers to concentrate on the control problem. It also allows for a standard implementation to be reproduced on subsequent applications with minimal configuration effort.

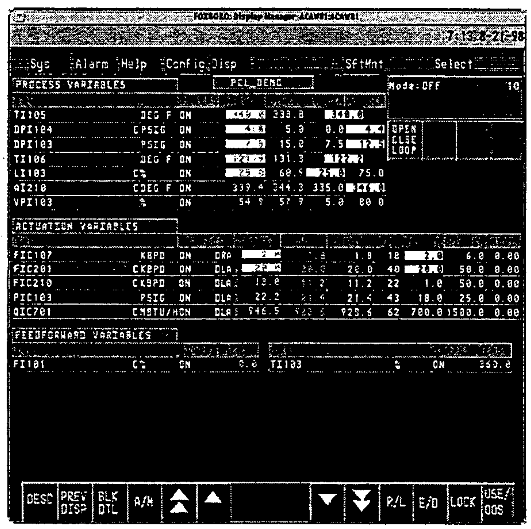

Figure 7– Auto-generated I/A Display

Embedded MPC

An embedded MPC product has been developed which enables the deployment of MPC within a Control Processor (CP) on the Foxboro I/A System. This product is foremost a deployment option for MPC, and the parent MPC product is still required to test the process for data collection, identify model structures and coefficients and design an appropriate controller. The resulting controller can then be downloaded into the CP on the process. (see Figure 8). The MPC product can then be detached from the plant, and MPC executed from the CP.

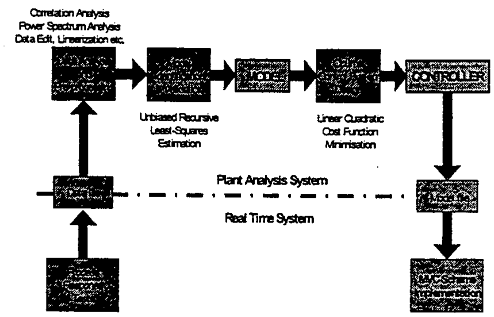

Figure 8 - Embedded MPC Workflow

In this workflow construct, the "heavy lifting" of analysis and identification is performed outside the DCS to generate the application "configuration, with the run-time entity in the most secure level of the DCS hierarchy.

The MPC application is downloaded into two new block types in the CP, retaining the standard block operation, displays and alarms of the CP. This is considered an evolution of the block processing capabilities of the DCS, and will ease transition and training of operators(Figure 9). The MPC application is treated as a supervisory control entity and utilises the DCS's Secure Supervisory Control (SSC) to ease integration into existing CP based control schemes. The MPC application is run as a low priority task in the CP, so that any issues with the application will not affect the regulatory control system integrity.

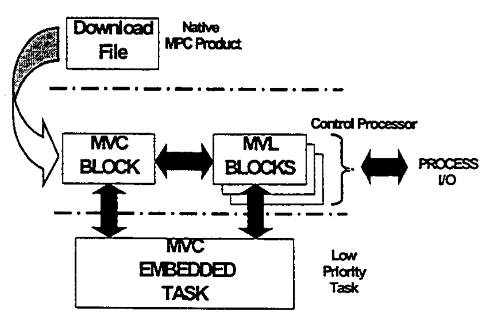

Figure 9 - Embedded MPC Concept

A significant concern from a product maintenance perspective was creating a means of keeping the Embedded MPC product current. This issue was solved by creating a common code stream for the parent and the Embedded MPC products. The respective products literally share a common code base, ensuring identical control behaviour, and bringing advances in the control engineering of the parent product over to the Embedded MPC product. The particular MPC algorithm has brought excellent unmeasured load rejection performance to the DCS.

The Embedded MPC product addresses a number of key issues associated with MPC, and in doing so widens the potential applications base for users. The product is offered on a true fault tolerant platform, offering DCS levels of availability, and removing the need for a separate workstation and network.

The Embedded MPC product has been integrated into the CP block family with considerable attention being paid to the look and feel. The intention is to provide an advanced control capability whilst retaining the user friendly look and feel of the DCS. This should result in the expanded use of the technology but without the attendant high training and maintenance costs.

A PROTOTYPE FOR INDUSTRIAL NON-LINEAR MPC.

This section describes work in progress to develop algorithms to employ the complete multivariable and constraint management concepts of MPC in a non-linear context.

Linear MPC

Within Connoisseur[3,9], one approach to linear MPC is to employ Quadratic Programming(QP) to minimise a cost function compounded from predicted MV absolute and incremental moves and CV errors[3]. This QP is configured to deal only with hard constraints(i.e. those associated with MVs). CV constraint violations(soft constraints) are dealt with by using closed loop simulation to estimate process behaviour over a defined prediction horizon. If violations are predicted, the control objectives are altered, subject to defined priorities that permit sensible management of degrees of freedom, to prevent the anticipated violations from arising. In comparison with solving the soft constraints within the full QP address, this approach is computationally more efficient, avoids issues of unfeasibility and provides better control engineering balance between the management of setpoints and of soft constraints.

Implementation of Non-linear MPC

The approach chosen for Non-linear MPC is to maintain the philosophy described above for the linear case. However, in place of the linear ARX model typically used for model prediction, the system is instead modelled using a Radial Basis Function (RBF) neural network[10,11]. The resulting MPC cost function thus incorporates a general non-linear component from the predictions of the CV errors. Two options have been considered for the minimisation of this function –
Successive Quadratic Programming[5,6] (SQP) and a Genetic Algorithm[7,8] (GA) approach.

This approach to non-linear control involves the minimisation of the non-linear cost function and repetitive evaluations of the non-linear model as the solution progresses[4]. An alternative approach has been proposed [5] based on a mechanistic process model in which the model and the MPC cost function minimisation are solved simultaneously, giving a potential saving in computational effort for large systems. However, this method requires the development of a specific mechanistic model for each process to be controlled which is a huge overhead in comparison to the relative simplicity of modelling a non-linear process with an RBF neural network. The proposed methodology is thus justified as offering a flexible method of implementing non-linear control for a wide range of processes with little more effort than for the linear case.

In MPC, constraint management is of primary importance in ensuring a valid solution. Whereas SQP is an inherently constrained optimisation technique, allowing the constraints to be dealt with directly, GAs require the constraints to be included as part of the coding of the genetic strings, and in addition to the standard MPC cost function.

Although both SQP and, through manipulation of the cost function, the GA approach, are capable of handling non-linear soft constraints, there is no need to do so within the MPC methodology described above. Therefore, because only traditional linear(i.e. hard) constraints are considered within the non-linear MPC prototype, this significantly simplifies the coding of both the SQP and GA approaches, and eliminates the errors of linear constraint approximation within the SQP.

Successive Quadratic Programming

Successive (or Sequential) Quadratic Programming (SQP) [6] is a constrained non-linear optimisation technique which, as such, is ideal for use in non-linear Model Predictive Control applications. SQP relies upon gradient information, including a Hessian matrix that may be known in advance or updated on-line from an initial estimate.

SQP is an iterative process, with two distinct stages at each iteration. Firstly a Quadratic Programming (QP) problem is solved to yield the direction in which the solution should move. As the use of a quadratic solution is only approximate for a general non-linear function, a step length must then be computed such that the combined move guarantees to reduce the objective function in some optimal way.

As mentioned above, only constraints on the MVs are explicitly considered within the SQP routine, in order to ensure a robust solution procedure. Both absolute and incremental constraints are included, although the majority are redundant at any particular solution point. Again, this approach has been adopted to ensure a rapid, robust solution of the QP problem.

The starting point of the solution is initialised to the current values of the MVs at initialisation (i.e. a "do nothing" strategy) and the solution found in terms of the absolute MV values. The Hessian matrix is initially set to an identity matrix and updated on-line using the BFGS Algorithm[6]. This approach ensures a positive-definite Hessian matrix at every iteration and thus the continuing solution of the QP problem, plus quadratic convergence as the final solution is approached. In practice, the updating approach is necessary for non-linear control as the Hessian matrix cannot be estimated from the RBF model as it can from a linear ARX model. However, the guarantee of positive definiteness makes it arguable that the updated Hessian approach is optimal even in situations for which the Hessian matrix may be evaluated exactly.

At each iteration, the QP problem is formed in terms of the constraints, constraint gradients and the gradients of the cost function, to yield a direction of movement. In the second stage, a one-dimensional minimisation approach is employed to find the distance that the solution should move to optimally reduce the cost function. For this 1D problem, an additional merit function is defined from the MPC cost function and the constraints, and this is minimised in order to guarantee a valid solution for the MVs.

Case Studies in Non-linear MPC

In order to demonstrate the functionality of the prototype SQP controller, two simulation cases studies are presented. In the first, a comparison is given of the use of SQP and the traditional linear QP for the control of a linearly approximated model of an Oil Fractionation Distillation Column[9](the Fractionator), modelled using a linear ARX model. Clearly, the use of SQP in these circumstances is unnecessary and highly inefficient as much of the available information from the linear model is not utilised. However, the SQP solution should reduce to an approximation of the QP solution for a linear model and, as a result, this comparison should provide confidence in the operation of the SQP algorithm. In the second case study, the SQP approach is used to control a non-linear system, modelled by an RBF, for which traditional linear MPC is shown to be unsatisfactory.

The Fractionator plant is modelled using 7 CVs , 3 MVs and 2 Feedforward Variables(

FVs). The MPC is configured to present a problem of challenge to the SQP and involves multiple hard and soft constraints[9]. Figure 10 shows the responses of some of the Variables of the system to a number of step setpoint changes, when under the control of the linear QP controller. The top two traces show CVs responding to these changes and the bottom three traces are the three MVs moving to effect the changes. Very similar performance is seen in Figure 11 for which the system responds to similar step setpoint changes under the control of the SQP-based controller. The faster responses associated with the SQP application are because of different scaling associated with cost function weightings. At the time of writing of this paper, exactly equivalent interpretation of cost function weightings between the two methods had not been fully resolved. The time ranges of the two figures are identical at 12minutes. The SQP has been exposed to a host of constraint control issues with this simulated example and performance in general matches that of the linear QP.

This comparison proves the capability of the SQP to match the control performance of straightforward QP for which the Hessian is computed directly from the linear model. However, time to solution for the SQP(at 10 seconds), is a factor of 10 greater than for the QP. As mentioned above, the use of the SQP to solve linear problems is highly

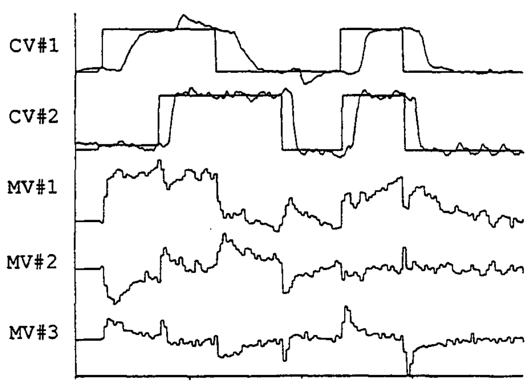

Figure 10. Linear MPC with QP

inefficient because of the generality of the algorithm which does not require any prior knowledge of the model structure. In practice, the SQP solution may take a significant number of iterations to converge even for a quadratic problem, due to the

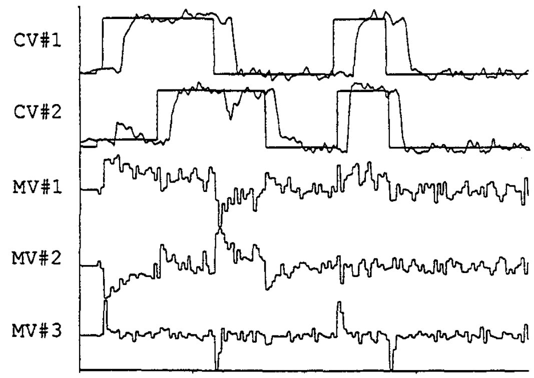

Figure 11. Linear MPC with SQP

updating of the Hessian matrix(about 20 such iterations are required for the example illustrated above). This inefficiency may be overcome to some extent by the use of a warm-start capability (i.e. storing the Hessian matrix between runs of the SQP algorithm) to provide a better, if not exact, starting estimate of the Hessian.

The second case study is based on a non-linear model of a plant in which the pH level of the product is to be controlled via manipulation of the reagent flow. Two FVs are included in the problem statement corresponding to effluent flow and effluent pH respectively. The non-linear relationship between the pH level and the reagent flow is such that the pH responds readily to changes in the reagent flow around the middle of its range but is relatively unresponsive to changes in flow as the upper and lower limits of the pH range are reached. The cause to effect relationships of this system have been modelled with an RBF network and this non-linear relationship has been processed by the SQP to effect control.

Figure 12 shows the response of the process with the Non-linear controller in operation. The top trace is the CV(i.e. pH) which varies between 0 and 9. The second trace is the MV(i.e. reagent flow) varying across its full scale range. The total span of data is 27 minutes with the controller updating every second. The bottom two traces are the FVs. It can be seen that the response of the process to setpoint and FV changes is consistent across the operating regime, due to the use of a realistic non-linear model within the MPC formulation. However close inspection of Figure 12 shows that the CV and setpoint part company from time to time. Most of these occurrences correspond to high saturation of the MV. The remainder correspond to situations where the process gain essentially drops to zero because of the influence of the non-linearity. It is interesting to note that under such a situation the MV is not subject to integral wind up, which would arise for classical regulatory control.

If linear MPC is employed, based on an approximate linear ARX model, the

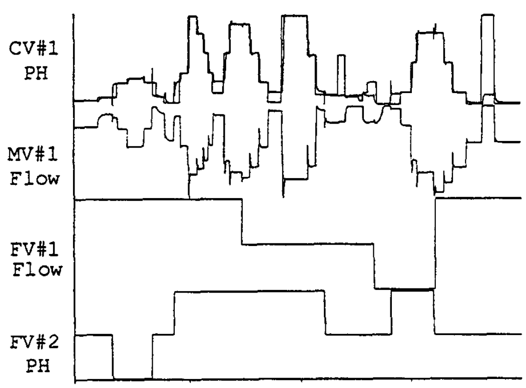

Figure 12. Non-linear pH control

response to changes in the pH setpoint is strongly dependent upon the operating regime of the process. The response is over-damped in some regions and highly oscillatory elsewhere.

Confidence has thus been gained in the correct implementation of the SQP algorithm through comparison to a well understood linear control problem. Furthermore, it has been demonstrated that the SQP-based non-linear controller prototype is capable of controlling non-linear systems for which current linear MPC methods are inadequate.

Genetic Algorithm Approach

An alternative approach to the non-linear minimisation problem at the centre of non-linear MPC is also under study using a Genetic Algorithm(GA) approach[7,8].

GAs are a class of global non-linear optimisation techniques which use a directed random search strategy. Originally designed to mimic the theory of Darwinian evolution, a body of statistical analysis now exists which backs up the theory of GAs.

For the optimisation of a non-linear function using a GA, it is only required to be able to evaluate the function for any possible solution point – no explicit mathematical model or gradient information is required. For many problems, this facet of GAs offers a significant advantage over traditional optimisation techniques. In addition, although no non-linear optimisation technique (other than, of course, exhaustive search) can ever guarantee to find the minimum or maximum of an arbitrary non-linear function, Genetic Algorithms have been used successfully in many applications where traditional non-linear optimisation techniques have failed. The advantage of GAs over more traditional gradient descent-type algorithms in these cases is that, at each iteration, a GA maintains a set of potential solutions to the non-linear problem from across the search space. As a result, a Genetic Algorithm is far less likely to become trapped in a sub-optimal local minimum than one of the methods which progresses towards a solution iteratively from a single initial position. Clearly, there is a computational overhead associated with the use of such techniques. However, it is now possible to consider the use of Genetic Algorithms for certain real-time applications.

Currently the GA-based non-linear controller is in development. Results of this novel approach, and comparisons with the results of the SQP algorithm are expected soon.

CONCLUSIONS

This paper has touched upon a broad range of issues that relate to the industrial exploitation of MPC.

The three application studies emphasise the need for flexibility in approach. None of these solutions was attainable by the exploitation of MPC alone. It proves necessary to have to augment the standard technology with various enhanced features(e.g. adaptive modelling with the grinding circuits, purpose calculations with the boiler optimisation, fuzzy logic rule based control with the Lime Kiln) in order to achieve final acceptable and successful outcome.

The momentum of computing technology means that the described software engineering programme is a continuously ongoing affair and there is much yet to be achieved. It is a constant battle to maintain pace with operating systems such as Windows NT and development systems such as Java(both of which figure strongly in the various products referred to above). The embedded MPC module is currently of restricted scope because of limitations in the power of the DCS hardware. The DCS will be progressively transformed in coming months which will enable the CP to support more comprehensive solutions, perhaps even to the point of being able to absorb the latest non-linear aspects!

It is early days for the non-linear technology. It is one thing to establish and prove an engineering prototype. It is quite another to consolidate that prototype to the point where it can contribute to the day to day exploitation of MPC. Most MPC applications do not require a non-linear approach. A key issue is to determine process situations that require a non-linear solution so that such solutions do not propagate in applications that can be dealt with quite adequately by the more straightforward linear address.

It is shown in this paper that substantial benefit can be delivered by MPC outside of the refining and petrochemicals sectors, and that it should now be considered a vital component of any plant control system.

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Acknowledgements

The authors' gratefully acknowledge the contributions and support of the following people to the various activities described above:
A.Morrow, C.Burns and D.Labbe(The Foxboro Company)
A.P.Burrows and A.G.Mitchel(PCL)
T.Kinney and N.Divittorio(Siebe Intelligent Automation, Technology Division)