REAL TIME CONTROL AND OPTIMISATION – CURRENT STATUS, NEW DEVELOPMENTS AND FUTURE POSSIBILITIES

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Multi-variable predictive control (MVPC) can now be considered to be a mature technology with proven benefits, particularly in the Hydrocarbon Processing Industries. This paper outlines the current status of this technology and its typical applications. New directions are described, including multi-unit optimisation, the use of non-linear models in linear control, improved tools for inferential calculations, more efficient step testing, the human machine interface and performance monitoring of an MVPC. Future challenges for the technology are discussed.

Keywords: Model based control, Multivariable control, Global optimisation, Non-linear control systems, soft sensing, human machine interface

1. INTRODUCTION

Linear multi-variable predictive control may now be considered a mature technology, particularly in the Hydrocarbon Processing Industry. Over 2500 applications of linear MVPC are reported in the refining and petrochemicals fields (Qin and Badgwell, 2003). Typical payback periods for such applications are in the region of two to twelve months (Taylor *et al.*, 2000). The applications typically utilise a linear plus quadratic program to move the process toward local optimal operation. Many applications use some form of soft sensor to provide missing physical or chemical property values.

More recently focus has been placed on the area of multi-unit optimisation, in an attempt to reach a globally optimal operating point (Friedman, 2000). Non-linear MVPC remains a relatively new field, with 35 applications reported in refining and chemicals (Qin & Badgwell, 2003).

Emphasis is now being placed on more efficient project execution, in order to reduce costs of implementation. The models required for the MVPC are typically obtained by step testing the plant, followed by model identification. Suppliers of MVPC are currently attempting to streamline this process, by employing constrained stepping techniques, using psuedo-random binary signals (PRBS) to move more than input, and by performing identification during the testing procedure.

The development of an operator friendly human machine interface (HMI) has been a neglected area. Research in this field indicates that operators control by exception and require an HMI that allows this.

It has often been observed that the benefits provided by an MVPC application degrade with time. This can be due to process changes causing model mismatch, changes in operating points, under trained operations personnel or many other factors. Techniques for monitoring the performance of the application easily are required, so that busy control engineers can focus their efforts on the poor performers.

The remainder of this paper explores the newer areas described above in more detail. Directions for future developments are suggested. These are focussed on continuing to achieve benefits for the users of MVPC, rather than purely on application of new technology.

2. MULTI UNIT OPTIMSATION

One of the main challenges limiting the increased application of MVPC techniques is the extension of the optimisation scope. Typically one or more MVPCs will be applied on one processing unit, and the unit will be locally optimised. In general the unit is part of a larger processing plant, and there is no guarantee that the local optimum for the particular unit is globally optimal for the area.

One approach to this problem is to build a rigorous non-linear model of the area, and to use it to define target setpoints for the individual units. This approach is attractive because non-linear effects are included. From a practical perspective this technique has largely been unsuccessful. The single biggest drawback has been the high cost of developing and maintaining the model. In addition the models used are generally of the steady-state variety. Any dynamic effects are neglected, and this causes a mismatch between the calculated setpoints and the current operation of the MVPCs. The calculated solution may not be feasible in a dynamic sense. The result is that the setpoints have to be filtered in some way before being implemented, meaning that the solution is non-optimal. A further limitation is that the applications have to perform some form of steady-state detection before executing. If steady-state is not detected optimisation is skipped. Since the applications typically run on a one to two hourly basis, this has a deleterious effect on the optimisation of the area.

A more recent approach to this problem has been discussed by Friedman (2000). For this method the existing linear dynamic models in the MVPCs are combined into a dynamic optimiser. This approach has the disadvantage that the representation is linear. The advantage is that the existing models are re-used, implying a lower development cost. The integration of the global optimiser and the MVPCs mean that the calculated targets are feasible. Figure 1 shows a schematic view of this approach.

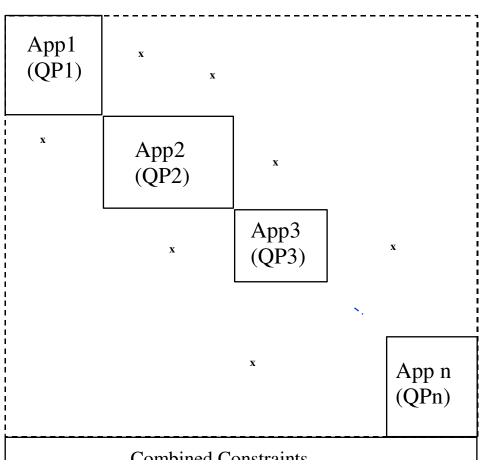

Figure 1 Global Optimisation Matrix

The matrix is largely diagonal. The off-diagonal elements represent the linkages between process units, for example where the product from one unit is the feed to another. Combined constraints occur when the sum of some inputs (e.g. steam usage or feeds) must be kept above or below a certain value.

This method has proved successful in constraint pushing type optimisation, and has recently been applied in a large South African plant to maximise production through the whole facility.

3. NON-LINEAR CONTROL

As mentioned previously the vast majority of MVPCs applied in the chemical industry have employed linear models. These processes are almost all non-linear. The fact that these applications yield measurable benefits implies that the non-linearities are not of sufficient scale to render the linear controllers inoperative.

Nevertheless there are processes for which non-linear techniques are required. The production of polymers has traditionally led in this field. The reasons for this include the fact that the reactions involved are extremely temperature sensitive, and that grade changes are fairly frequent.

Three general approaches have been used to model non-linearity:

a) Update the gains in a linear controller with gains calculated from a non-linear model (gain scheduling);
b) Develop a rigorous non-linear model of the process, and apply it to determine some reference trajectory for the process;
c) Develop an empirical model (typically neural network based) from plant data, which is then inverted for control purposes.

From a practitioners point of view the first of these is the least complicated to implement. The models required can be quite simple, since only the key non-linearities in the process need be modelled. This method can be easily combined with the optimisation technique discussed above (Nath *et al*., 1999).

Rigorous non-linear models are based on the mass and energy balances for the process. Model parameters are either estimated from plant data or online using extended Kalmann filters. These models have the advantage of not requiring plant step testing. Since they are based on first principles, these models are likely to be more reliable than empirical models when extrapolation is necessary. This method is discussed in more detail by Young *et al.* (2001). The initial development of the model remains a costly exercise.

Empirical non-linear models are used in various forms. One approach is to use a non-linear neural network (NNN) to represent the steady-state of the system, and to model the time varying behavior using either first or second order terms. The dynamics of the system are essentially fixed, while the gains vary as a function of the operating point. It is claimed that the NNN may be derived from plant data, while step testing is still required for the dynamic portion. As is discussed by Zhao et. al. (1998), the model identification is a complex exercise.

4. INFERENTIAL MODELS

Inferential models are used in advanced control schemes when online measurement of a key value is not possible or is too expensive. It has been estimated that some eighty percent of all refinery MVPC applications employ one or more of these models. The model is updated with laboratory values, providing a slow feedback mechanism.

Development is performed using historical plant data, and can be time consuming. The ability to visualise data is key to the choice of a suitable model and powerful new methods are now available. An example is shown in Figure 2. This is a standard XYZ plot, with the addition of color to display a fourth variable. A further view of the same data is shown in Figure 3. This parallel plot is valuable for revealing normal versus abnormal operation. Tools are now available to quickly perform ordinary, weighted or partial least squares regression and to simply implement the models obtained online.

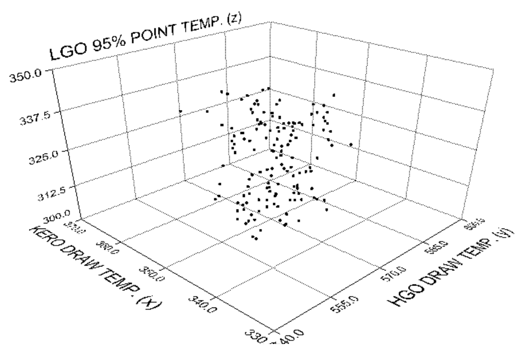

Figure 2 Star Plot

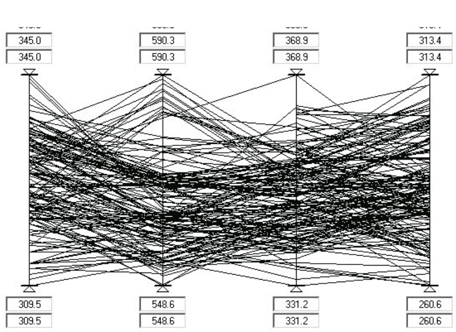

Figure 3 Parallel Plot

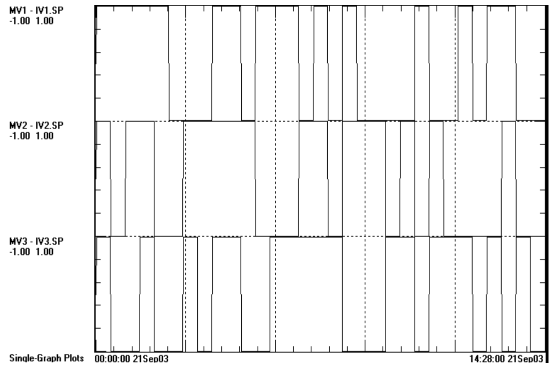

Figure 4 PRBS Step-Testing

5. PLANT TESTING

Plant testing is another time consuming aspect of the implementation of MVPC solutions. For an average sized controller two weeks of round the clock step testing may be required. There is a strong economic incentive to perform the testing as efficiently as possible. One advance has been the use of pseudo random binary sequences (PRBS), which have allowed more than one independent variable to be moved simultaneously. Figure 4 shows the sequence for three independent variables. There is a limit to how many variables can be moved simultaneously, since correlated moves can be introduced.

The real issue with step testing is that it is difficult to ascertain when the testing for a particular variable is complete. This question can be answered by performing online model identification during the step testing. A statistical test can be applied to the models obtained. When the models meet some confidence limit, step testing can be terminated on this variable, and started on a new one. This has the potential for saving significant time and money.

6. THE HUMAN MACHINE INTERFACE

Traditionally the human machine interface (HMI) for MVPC applications have been listed based, with some use of colour to indicate variables near to or outside of limits. Generally they have not been integrated into the underlying distributed control system displays. Recent research into the way that operators control their units indicates that the process involved is one that could be called ‘control by exception’. In other words the operator needs to be informed when something is unusual – otherwise the information is not useful. Graphical interfaces that display this type of information can be developed, and can go some way to reducing the perception that advanced control schemes make the operator’s job more complex.

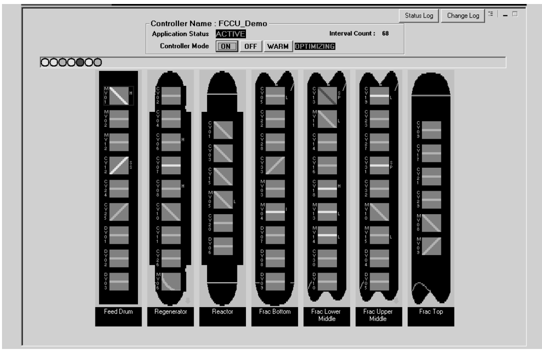

Figure 5 Graphical User Interface

An example of such an interface is shown in Figure 5. Color is used to indicate variables that are out of range, and the slopes of lines indicate current direction of movement. The operator can click on any particular variable to investigate in more depth.

7. PEFORMANCE MONITORING

It is a well-known phenomenon that the performance of an MVPC scheme tends to degrade with time. Reasons for this include process modifications, changes in unit operating point and new operating personnel. For whatever reason performance degrades, the situation can be reversed if recognised. It is thus important to institute a program to continually monitor the performance of the MVPC in order to maintain the benefits.

Maintaining an MVPC can be a labour intensive process. Tools are required that can give a quick overview of the health of the schemes on a plant, and to quickly identify those that are not delivering their full benefits. Much like the HMI discussed above, tools must also be available to drill down to trace the source of the performance degradation.

Controller:ISRX_CTL DAILY APC SCOUT REPORT - Monday, November 5, 2002
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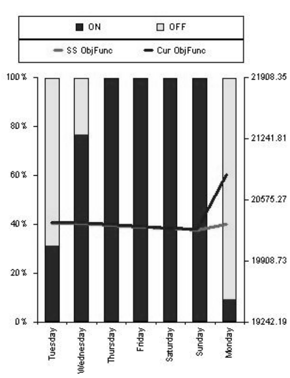

Figure 6 MVPC Performance Monitoring

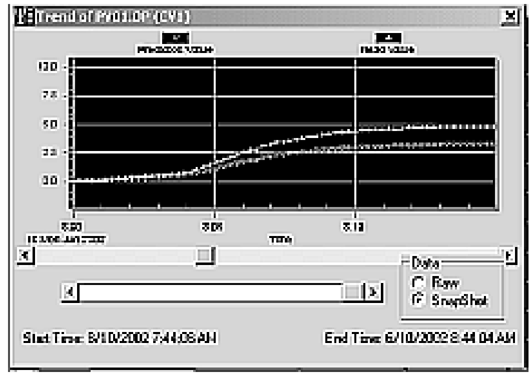

Figure 7 Model Predictions

Fortunately the applications themselves generate the correct data to perform this task. The challenge is in turning this data into information and in presenting it in an accessible way.

Figure 6 shows a very simple graph, which displays online times and values of the objective function in the controller's linear/quadratic program. A drop off in either of these metrics is a first warning sign of problems with the application.

The control engineer can dig deeper. If she suspects that the controller models have degraded, a plot of the model predictions and actual values can be obtained. As can be seen in Figure 7, this can indicate that a change in the model gains may be required.

Plots of the independent variables and their limits can indicate if the operators are clamping the range in which the MVPC can operate. This is often a sign that operator re-training is required.

8. FUTURE CHALLENGES

Having proved its value, MVPC now faces the challenge of how to extend the scope of its implementation, and to extend the benefits achievable. Some of the developments the author sees in future are discussed below.

8.1 MVPC in the Control System

Currently most MVPC applications execute in a separate computer to the plant control system. Integration with the distributed control system (DCS) is achieved using an interfacing protocol. This adds a degree of complexity to the implementation.

Many users would prefer to have the MVPC algorithm embedded in the DCS. It would then be as simple to implement, as it is to configure a PID loop.

8.2 Self training models

As mentioned before, plant testing is a time consuming exercise. A method where the models could build themselves would be welcome. The practical difficulties of achieving this goal are significant.

A more tractable problem is the online estimation of the gains of the models. This is essentially a steady-state estimation process, and as mentioned in section 3 is already performed for some non-linear controllers. If a control engineer detects that the gains of the models are inaccurate, she may then be able to instruct the controller to re-calculate them. Changes in dynamics are much more difficult to detect. Step testing is designed to provide a source of high power uncorrelated signals for model identification. This data is seldom available from day to day operation.

8.3 Automatic Mode Switching

Some units may operate in distinctive modes, depending on current plant state. For units such as these, MVPC applications that can detect the change in mode and alter their structure accordingly, would significantly increase their availability. Currently the applications are normally switched off when the unit is not in its typical mode. Agile manufacturing is a term much used, and the MVPC applications should likewise be suitably agile.

It could be argued that current technology can achieve this goal using model-scheduling techniques. In this method multiple plant models are derived for the different modes. This can be complicated to implement, and the model-switching criterion is often heuristic. A more integrated approach is required to bring this method into more common use.

8.4 Start-up, Shutdown and Abnormal Situations

The management of start-up, shutdown and abnormal situations is a problem somewhat similar to mode switching. The majority of current MVPC applications have limited turndown ratios, and are switched off during abnormal plant operation. It is exactly at these times that an advanced control system can yield large benefits, since plant operation is most difficult at these times.

Non-linear control will almost certainly be required to achieve this goal. From an economic point of view the applications will have to minimise the start-up period. During abnormal situations the aim should be to stabilise the unit, while still aiming for the most profitable operation possible. During shutdowns the focus would be on maintaining unit production at specification for as long a possible.

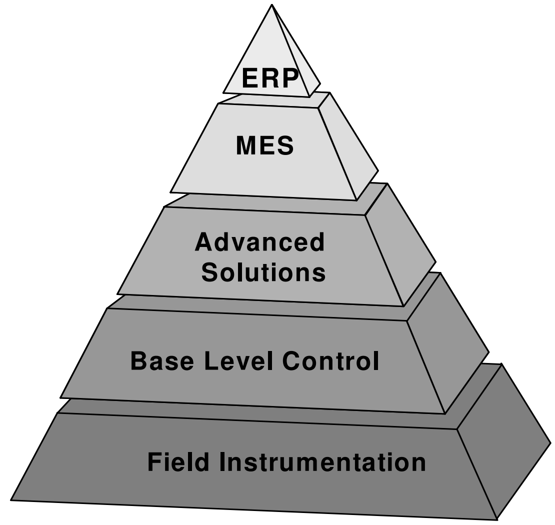

Figure 8 The Pyramid of Control

8.5 Integration with Plant Planning and Scheduling Systems

Many chemical processing plants use some form of linear programming (LP) model to plan and schedule production. Operating targets for the various units are communicated to operations. These targets can include parameters such as unit feed rates and product specifications. Yield accounting is used to reconcile the flows through the plant, and the actual flows are compared with the planned flows. These applications together are often referred to as the Manufacturing Execution System (MES), and can provide information to the organisation's Enterprise Resource Planning (ERP) systems. This is shown diagrammatically in Figure 8, the so-called pyramid of control

Despite the fact that some of these targets may be under the control of an MVPC, an automatic link is seldom implemented. In order to implement a fully integrated system it will be necessary to have some form of the multi unit optimiser (discussed in section 2) in place. This is a matter of time scales; the plant LP operates on a time scale of days or weeks, and the MVPC of hours. The multi unit optimiser bridges the gap between these, and should ensure that targets are feasible

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9. CONCLUSIONS

MVPC is no longer a new technology, and has proved its value in the processing industries. It however largely remains a technology applied by specialists, on a unit-by-unit basis. It is perceived as a technology separate both to the plant control system, and to the plant planning system. Yet in reality it should be integrated with both. The challenge going forward is not so much which particular flavour of MVPC should be applied, since this is likely to vary on a case-by-case basis. Rather it is in achieving the seamless integration implied in Figure 8.

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