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Model Predictive Control in Industry: Challenges and Opportunities

Michael G. Forbes* Rohit S. Patwardhan Hamza Hamadah** R. Bhushan Gopaluni*****

**Honeywell Process Solutions, North Vancouver, BC V7J 3S4, Canada*
***Process & Control Systems Department, Saudi Aramco, Dhahran, 31311, Saudi Arabia*
**** Department of Chemical and Biological Engineering, University of British Columbia, Vancouver, BC V6T 1Z3, Canada*

Abstract: With decades of successful application of model predictive control (MPC) to industrial processes, practitioners are now focused on ease of commissioning, monitoring, and automation of maintenance. Many industries do not necessarily need better algorithms, but rather improved usability of existing technologies to allow a limited workforce of varying expertise to easily commission, use, and maintain these valued applications. Continuous performance monitoring, and automated model re-identification are being used as vendors work to deliver automated adaptive MPC. This paper examines industrial practice and emerging research trends towards providing sustained MPC performance.

Keywords: industrial control, process control, model-based control, predictive control, adaptive control, performance monitoring, control applications, human factors.

1. INTRODUCTION

Model predictive control (MPC) is an industry accepted technology for advanced control of many processes. Recall that DMC (dynamic matrix control) was introduced around 1980 (Cutler and Ramaker, 1980); by 1997 a number of commercial MPC software packages were available (see, for example, Qin and Badgwell (1997)). Industrial expectations for MPC have increased from providing superior control for multivariable systems to doing so with minimum set-up effort and ease of maintenance. In today's process industries, MPC is often considered a required solution for many applications. At the same time, resources of expert practitioners to commission, monitor, and maintain MPC are increasingly limited. For this reason, both vendors and customers are looking for ways to sustain MPC performance with minimum manual intervention. In this paper, some established and emerging trends in the industrial application of MPC for sustained performance are discussed. Section 2 gives considerations in commissioning MPC for long term success. Section 3 examines ease of operation as a contributing factor to successful applications. Section 4 discusses industrial MPC maintenance practice, with a focus on performance monitoring and adaptive control. Section 5 reviews emerging research trends for industrial MPC.

2. COMMISSIONING AN MPC APPLICATION

Sustained performance of an MPC depends on many important decisions made during commissioning. An MPC that is easy to configure, operate, and maintain has a good chance of long term success. While examples are given in the following subsections, the main themes of this section are:

- MPC structure and use of features affect maintainability,
- Difficult MPC set-up may cause less robust tuning and model mismatch due to software use errors. Chances of sustainable performance are immediately reduced.

2.1 MPC Structure

One benefit of MPC is that it determines the optimal actions to take for large multi-input, multi-output (MIMO) systems. MPC simultaneously adjusts all inputs to control all outputs while accounting for all process interactions. As a result, MPC often takes actions that improve plant performance beyond what a skilled and experienced operator can achieve.

However, there are also drawbacks to the use of a single MPC to control an entire MIMO system, which may inhibit the success of an application. One obvious alternative to putting all variables into a single MPC is to break up the problem into a number of smaller systems which have limited interactions. In the following points, some of the potential drawbacks to including all process variables in a single MPC are listed, along with the comparative advantage possible if the MPC is broken into several smaller systems:

- A single MPC can optimize an entire process, but it may also be difficult to understand and monitor performance of a large application due to the large number of interactions between variables. Splitting the MPC into smaller systems, may make it easier to judge the behaviour of each MPC.
- When a large application performs poorly due to model mismatch, it may be difficult to determine which submodel(s) need updating. Often, plant experimentation and identification for all models is time consuming, or introduces unnecessary variability to the process. With multiple small MPCs, when one of the small MPCs is not performing, there are fewer models to evaluate.
- If the controller cannot be used for some reason (a set-up error for example), then no controlled variables (CVs) are controlled. With multiple small systems, one MPC can be turned off independently of the other MPCs, leaving most CVs under control. Some commercial packages have

features to handle this issue; practitioners should determine how to best utilize such functionality.

- If some CVs and/or manipulated variables (MVs) are dropped from the controller, the likelihood of unexpected MV movements, as the MPC re-optimizes using the remaining process variables, is relatively high for a large system. (These different movements may be correct, but they also may be undesired consequences of an unusual operating mode. Even if correct, different MV movements may be questioned by an operator.) If CVs and/or MVs are dropped from a smaller MPC, it may be easier to anticipate how the MPC will re-optimize, and there will be less MVs to monitor for unanticipated movements.

2.2 Process Modeling

Success of model-based controllers, such as MPC, depends on having reasonably accurate process models. Often a designed experiment is run to generate the data containing sufficient process excitation needed to accurately identify models. A common problem with this approach is that the type of plant experiments that yield the best data are also likely to perturb the process beyond current operating limits. This issue is well known, and sometimes is mitigated by clever experimental designs. In other cases plants accept some small short term deviations in production or quality in exchange for the long term benefits of a successful MPC application. However, there is another aspect of process modeling that can impact the long term sustainability of MPC performance, which may not be as widely considered: ease of identifying the model.

Most industrial MPC packages include model identification software. This software helps the user to take plant data and develop the models needed for MPC. The ease with which the software can be used can have a big effect on how well MPC is maintained. Identification software can suffer from:

- Poor workflow, requiring many steps, menu selections, button clicks, and so forth, to go from raw data to a final model. Each step is the opportunity to make an error.
- High complexity, which allows for a great deal of flexibility in the model building process, but which may overwhelm the occasional, inexpert user, again offering opportunities for mistakes to be made.

These challenges may not be a problem during the commissioning process where often an expert user performs the model identification. However, maintenance of the MPC, including re-identifying models, often falls to a non-expert. The difficulty of the identification task may then prevent MPC performance from being sustained because:

- Non-intuitive identification software hinders user confidence and willingness to update process models as often as needed,
- Incorrect use of complex identification software leads to poor model selection,
- Most users will not be able to judge, by inspection, if higher-order model parameters are valid.

To help overcome some of these issues, it is common (but not universal) for MPC practitioners to use first-order plus deadtime models unless there is strong evidence that a higher order model is required. The advantage of using these simple models, even at the expense of some model-plant mismatch, is that someone who is not a controls expert can 'sanity check' these models, and judge if the gain, time delay, and time constant are plausible. Additionally, if a review of the model predictions versus data reveals poor identification of model parameters, most users can manually adjust gain, time delay, and time constant. The use of this simple model form comes with the expense of providing a very good but not optimal process model, but reduces the risk of large model errors due to user unfamiliarity with higher-order models.

Another approach to process model maintenance is to use an adaptive algorithm to automatically detect controller performance degradation due to model mismatch, generate data with a new plant experiment, and identify and deploy a new model. Adaptive control is discussed later in this paper.

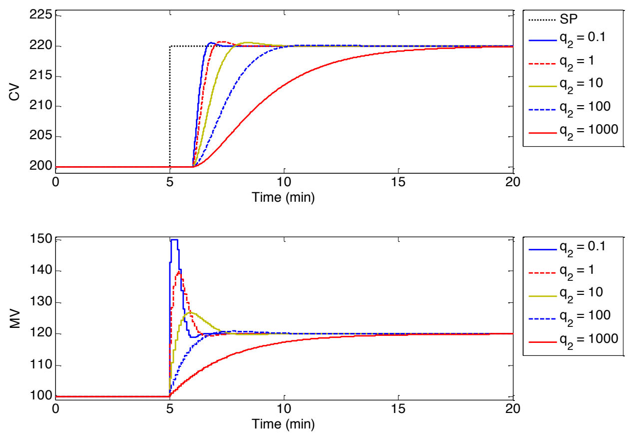

Fig. 1. Setpoint change for SISO MPC for different MV movement cost weight (q2)

2.3 Controller Tuning

For basic MPC there are many tuning parameters: prediction horizon, control horizon, setpoint tracking cost weights, and input movement cost weights. More advanced MPC may have additional tuning parameters relating to reference trajectories, output funnelling, blocking, etc. While there is often a clear explanation of what these tuning parameters are meant to influence in the MPC formulation, it is not always easy to find the parameter values that achieve a desired controller performance. Fig. 1 gives an example of a basic single-input single-output (SISO) MPC executing a step setpoint change for different choices of the input movement cost weight, q_2. The five example responses each have a different character, but to achieve these different behaviours it is necessary to change the input movement cost weight by an order of magnitude. Even if the two most aggressive tunings are rejected as extreme, it is still necessary to pick a value for this tuning parameter from the range of 10 to 1000. This is a big challenge, resulting in much trial and error, for tuning. In the more general case where there are multiple input movement cost weights, plus other parameters to select, even an expert user can struggle to find the right combination of parameters to achieve the desired MPC performance.

In an effort to simplify MPC tuning, many vendors provide tuning defaults, automated tuning, or simple variables that indirectly set the MPC tuning parameters. Simplified tuning helps expert users to easily and quickly tune the MPC during commissioning. For the non-expert who occasionally retunes the controller, a simplified or automated approach will make the user more confident in making changes to the system, avoiding confusion and possible errors in tuning. All of this helps to set the stage for sustained MPC performance.

2.4 Nonlinearity Across Operating Points

Most industrial processes exhibit some nonlinearity; while most industrial MPC software uses linear process models. Often, this mismatch between the actual process behaviour and the process model does not cause much degradation in MPC performance. In other cases, the linear MPC must be extended to account for different process behaviour at different operating points. A common and effective approach to applying linear MPC to nonlinear processes is to use a gain scheduling technique, where process operations are divided into a set of operating regions based on the values of one or more key process variables. For each region, the process model parameters are identified, and the controller is tuned appropriately. As process operations change, moving the process from one region to another, the MPC is updated to use the appropriate parameters for the new region. To balance the effort of maintaining this more complex controller against reduced need for maintenance due to poor performance, a judicious division of the process operating space into a sufficient but not excessive number of regions is needed. Switching seamlessly between linear controllers requires care in implementation. Recent research results on this topic include Stewart (2012) and references therein.

Paper machine control offers a particularly tidy example of use of this technique (see, for example, Gheorghe et al (2009)). Typically a paper machine will make a number of grades of paper at different times. The paper grades sometimes vary significantly in weight (and other factors) leading to important differences in process behaviour. Grades that are close in weight can be grouped together to form weight-based grade groups. Process models and controller tunings can be made based on a representative grade within each group. The MPC is then updated with the appropriate models and tunings whenever paper machine operations switch between grades from different groups.

3. OPERATING AN MPC APPLICATION

During MPC commissioning, there may be excitement about the potential for a more stable process, better quality product, better throughput, etc. However, MPC may automate tasks that were previously handled by the operator. In these cases, the operator will scrutinize the MPC, expecting high performance. Issues that are not corrected early in the commissioning will cause operators to lose confidence in the MPC, with some undesirable outcomes possible:

- The operator may turn off the MPC each time he/she does not understand the control actions, possibly leaving it off for the rest of the shift,
- The operator may yield all responsibility to the MPC and blame all process problems on the MPC.

Of course, the MPC has to work well, but even a high-performing MPC could fall victim to the above scenarios if the operators do not understand and trust the application.

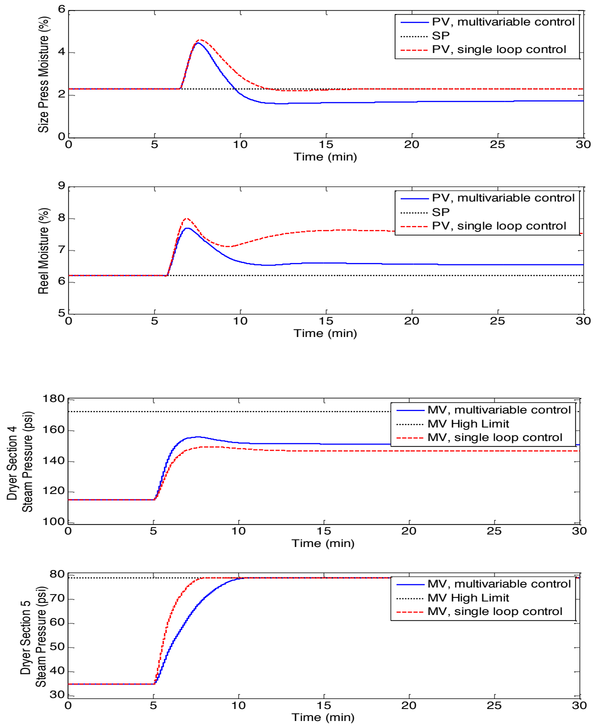

Fig. 2. CV movements for single loop and MPC control.

One characteristic of MPC operation that can cause operators to object to MPC is that MPC may move process inputs differently than the operators themselves would, or the previous control loops did. Consider Fig. 2 where two types of control of a 2-input (dryer section 4 steam pressure and dryer section 5 steam pressure) 2-output (size press moisture and reel moisture) process are shown. In one case the system is controlled by 2 SISO loops (dryer section 4 steam pressure – size press moisture, dryer section 5 steam pressure – reel moisture), while in the other case a full multivariable MPC is used. When a disturbance pushes both ouputs off target, in the single loops case the first loop brings the first output back to setpoint. The second input becomes saturated and thus the second output is not brought back to target. In the MPC case, when the second input becomes saturated, the controller makes a trade-off, allowing the first output to come off setpoint which allows for the second output to be closer to setpoint. Some operators will immediately understand what has happened, but many will not understand this outcome. In particular, for someone used to single loop control, it may appear that the controller has somehow overreacted so that the first output ends up below setpoint. It may not be obvious that having the first output below setpoint is allowing the controller to bring the second output closer to setpoint. This is just a simple 2x2 system. The challenge is much greater when trying to understand or explain the actions of a larger system.

Operators need to be prepared for MPC. There are a number of ways to do this, including:

- Providing predicted values to show the operator where the MPC will be taking the process,
- Highlighting constraints and limits so that the reason for a CV staying off target will be clear,
- Noting, sharing, and discussing simple examples, such as the one above, of unexpected but correct MPC behaviour.

These types of practices help build operator understanding and trust of the MPC. An operator who has confidence and intuition for how MPC acts is likely to keep it running, and can identify situations where the MPC is underperforming.

Human factor considerations are sometimes overlooked by MPC experts, but are highly important to MPC success. Guerlain et al (2002) give a good overview of this topic; with an example effort in interface redesign to support operator understanding and use of MPC.

4. MAINTAINING MPC PERFORMANCE

4.1 Monitoring

MPC technology is widely accepted by industry practitioners as a necessary profitability enhancement tool. Paradoxically, MPC performance deterioration is of growing concern among end-users. For instance, changes in feedstock rates and quality, degradation of instrumentation and process equipment and changes in operating strategies impede sustainable MPC performance. Without reliable monitoring of MPC technology, a significant portion of the initial benefits is at risk; consequently, there is remarkable interest in performance monitoring solutions among practitioners. Canney (2003) considered monitoring as an active area of MPC technology progression over a decade ago. Systematic monitoring is a necessary pre-requisite for MPC application reliability. While MPC performance monitoring is an area of increasing interest from researchers, the successful application of these techniques in industry is far from complete. Kano et al (2010) reported that 33% of surveyed MPC users in Japan identified response to performance deterioration as a major problem. This is a complex and multi-layered undertaking. The large number of control loops and associated MPC variables leads to “big” data that makes monitoring cumbersome and necessitate organized, structured and methodical approach (Paulonis et al, 2003).

MPC monitoring has evolved significantly since early applications. Industry practitioners report several challenges influencing monitoring. Firstly, what aspects of a MPC should be monitored? Interestingly, to this day industry has not seen consistent and standardized approach for MPC performance monitoring and benchmarking. A number of basic indicators are widely used by industry practitioners such as service factor, controller saturation, model quality, etc. Proper division of labour is another challenge. Roles and responsibilities for monitoring are vague among MPC technology stakeholders. Each organization has its own unique culture and structure which influences monitoring as a key function. Due to its complexity, awareness and understanding of MPC, let alone monitoring it, among end-users present key challenges. Effective monitoring and utilization of MPC is highly influenced by technology complexity as well as scarcity of domain expertise.

Practitioners generally value economic performance, which indicates what financial value MPC brings to the table. This will eventually signal and guide the need for servicing technology. Interest in economic performance monitoring for process control has been rising among academicians as well. For instance, Bauer and Craig (2008) point out the lack of theoretical basis and heavy reliance on oversimplified assumptions as key shortcomings in industry MPC economic assessments. However, incorporating industry-relevant economic performance monitoring indicators for MPC, such as profit/loss meters, has not seen as much interest despite its clear need. This is increasingly important for industry users, as it translates performance of MPC into monetary benefits. Also, the rising popularity of economic MPC formulations (Section 5) further underpins such need. Furthermore, servicing MPC to improve performance is another contemporaneous challenge. This will be more thoroughly addressed in the following section. Consistency among end-users within the same organization is another challenge. Corporations with considerable MPC install-base face the challenge of inconsistency arising from both software functionality and usability. Different MPC technologies and versions have different configurations which subsequently affects their monitoring. Different users of the same software in the same organization may monitor applications with different conventions. This is especially apparent in large corporations with large numbers of MPCs in separate facilities. The challenge of software connectivity and data accessibility is exacerbated by rising cyber-security risks. Network architectures are becoming increasingly complex with reduced accessibility. This affects usability of both embedded and stand-alone monitoring technologies. Base-layer control monitoring is a paramount pre-requisite for MPC monitoring. PID control monitoring is widely implemented in industry; however its influence on MPC performance is underestimated and poorly acknowledged.

Table 1. MPC monitoring for different stakeholders

Monitoring Hierarchy	Level of Complexity	Emphasis	Frequency
Management	Low	Application Use; Financial Impact	Quarterly-biannually
Engineering	High	Core Technology	Monthly-Quarterly
Operations	Medium	Service factors, Base-layer control	Daily-weekly

Large corporations such as Saudi Aramco responded to the need for continuous monitoring and assessment of MPC performance via establishing a company-wide monitoring framework. A similar approach for monitoring is reported by Eastman chemical company (Paulonis et al, 2003). Such frameworks ought to engage all MPC stakeholders within the organization with documented work processes, identified key performance indicators and mutually accepted roles and responsibilities. Stakeholders include operators, plant engineers, maintenance staff, plant managers, central engineering subject-matter experts, and technology providers.

An effective monitoring framework addresses the multifaceted nature of MPC utilization in industrial settings, and is actionable rather than only informational. Base-layer control must be monitored also. Paulonis et al (2003) gives an Observe-Orient-Decide-Act monitoring approach aimed to alleviate servicing. Three key layers of MPC monitoring exist: managerial, engineering, and operational (Table 1):

- *Management monitoring* briefs management on MPC utilization and economic performance, company-wide, in order to secure resources and communicate financial benefits. Corporate-wide performance benchmarking is illustrated by Fig. 3.
- *Engineering monitoring* encompasses model and economic performance. It is targeted to examine core technology performance which requires profound knowledge of MPC technology in order for subject matter experts to provide engineering solutions. This primarily addresses quality of controller models and inferential property estimators. The frequency of such reports is typically monthly-quarterly.
- *Operational Monitoring* is performed by front-line engineering support staff in order to probe effective utilization operationally. This focuses on low-level indicators such as service factors and variables saturation on more frequent basis (daily-weekly). Persisting anomalies are typically incorporated in engineering monitoring reports for higher level engineering support.

Saudi Aramco maintains over 100 MPCs spread over 20 operating facilities across the hydrocarbon value chain. A small group of experienced APC (advanced process control) engineers oversees management and engineering monitoring while site APC engineers conduct more frequent operational monitoring. APC engineers utilize embedded MPC monitoring software which accompanies MPC packages such as AspenWatch®. Furthermore, technology point-solutions such as Honeywell ® Controller Performance Monitoring, Yokogawa MDPro ®, are utilized. Those typically acquire data from MPC servers through PI (a process historian) and are capable of providing more comprehensive assessment and accessibility than embedded software.

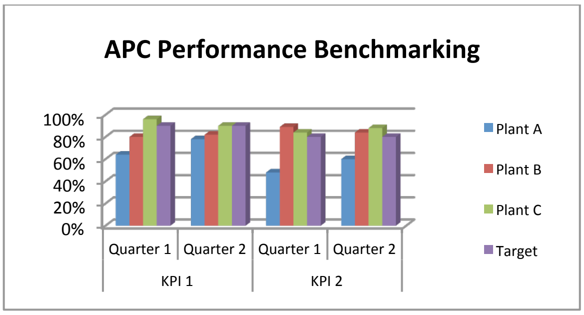

Fig. 3. Corporate APC performance benchmarking example.

4.2 Maintaining the benefits

MPC is complex and high maintenance technology. In an ideal setting, servicing is driven by operational and engineering monitoring as illustrated in the previous section. Inadequate monitoring at site presents a challenge, typically arising from lack of expert users. Technology monitoring is paramount to identify model-mismatches and to properly tune controllers on on-going basis.

The increasing complexity of MPC is affecting serviceability and maintainability. Qin et al (2003) notes that increasing technology capabilities come at a cost of more complexity. This reinforces the need to configure MPCs with inherent simplicity to enhance serviceability as discussed in section 2.

Another emerging challenge in servicing MPCs is paucity of skilled resources. The technology complexity requires matching level of expertise for end-users to be able to maintain application reliability. Skilled APC engineers are becoming rare commodity for two reasons: multiple skill set and technology complexity. The former rises from fundamental need for APC engineers to be competent in two equally important fields: process and systems engineering. Often experienced engineers involved in initial commissioning are not available to service MPCs deeming them to be more susceptible to performance degradation. Lack of skilled resources is driving MPC users to be more vendor-dependent. By and large, vendors have responded to skill scarcity through increasing application usability with more emphasis on embedding process knowledge, which is analogous to automation technology trends reported by Jokinen (1996). While academicians focus on monitoring and servicing from algorithmic perspective (i.e., model performance), industry users demand ease-of-use and emphasis on basic factors such as software utilization, usability and monitoring of economic benefits. Qin et al (2003) argue that research on control engineering issues such as closed loop stability is far more relevant to practitioners than increasing algorithmic complexity.

Risk of diminishing operator confidence is another issue. Operators are the true end-users of MPC and they need to be well prepared for it. They need to trust the application and develop intuition for how MPC acts, as stated earlier. In the experience of authors working at Saudi Aramco, for example, clearly superior MPC utilization is observed in facilities where operators attend basic MPC training and where operator-engineer communication is well-established. Operator feedback is vital for servicing MPCs effectively. MPC providers respond to this reality through developing more operator-friendly GUIs as stated earlier.

4.3 Towards Adaptive MPC

Automated step testing and modelling tools are increasingly available off the shelf with the mainstream MPC technology. Closed loop identification was first introduced by Zhu (1998) to industrial practice. Since then multiple applications have demonstrated the feasibility of doing closed loop step testing and modelling (Celaya et al. 2004; Kalafatis et al. 2006; Zhu et al. 2013). In the authors' experience, closed loop testing works well and saves significant amount of engineering time in addition to reducing lost benefits due to reduced MPC uptime. There are subtle differences in the implementation of the closed loop testing with the different technologies (TaiJi, Profit Stepper and Smart Step/Calibrate) but they work on similar principles. Small steps are injected at the input in order to excite the process. The step tests are designed to focus on the low and mid frequencies that are of interest for closed loop control. The magnitude of the perturbations is varied as the step test progresses to ensure sufficient excitation. The signal-to-noise ratio is assessed based on the quality of the models developed from the closed loop data. The step testing technologies make every attempt to ensure the injected signals do not result in input/output constraint violations.

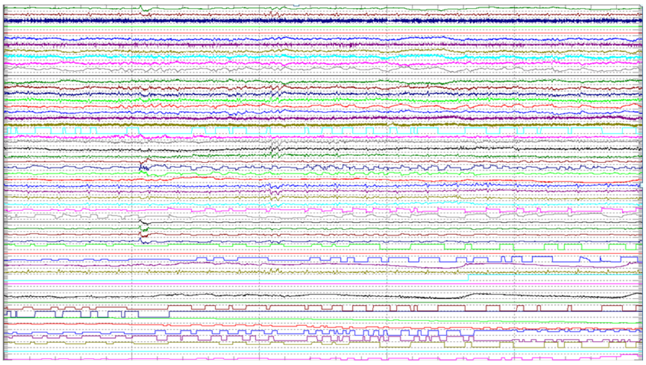

Fig. 4. Closed loop step test data for a CCR MPC.

Fig. 4 shows data from a closed loop step test implemented on a Continuous Catalytic Reformer (CCR) MPC in a Saudi Aramco refinery. The bottom part of the graph shows the steps inserted by the testing software while the top part of the figure shows the effect of these steps on the process outputs. Seven inputs were simultaneously moved during the test. The step test lasted for about 4 days which was a significant reduction from the original open loop test. The step testing/modelling software was run on a standalone virtual server that is separate from MPC server. The data communication between the step testing software and the MPC was via OPC. All of the data needed for modelling purposes was collected and managed by the step testing software. Model development was initiated after the first day of step testing and was conducted from the step testing environment.

Models can be developed relatively quickly or even scheduled to be automatically estimated. Newly developed models are assessed by (a) the level of parameter uncertainty, (b) quality of predictions and (c) comparison with previous models. Most commercial technologies provide a single measure of model goodness based on (a) and/or (b). The APC engineers themselves engage in a sanity check for (c). At least one vendor (reference AspenTech manual) allows users to provide bounds on the parameters estimates, gain ratios to ensure infeasible parameters are not allowed at the outset.

All of these technologies rely on direct identification to estimate models from closed loop data. Some use a combination of a high order modelling followed by model order reduction (Zhu, 2001; MacArthur and Zhang, 2007), to prevent bias due to structural mismatch while minimizing variance errors. Others use subspace identification based approaches, again avoiding the bias errors through a high order parameterization. All of the modelling tools have evolved to a point where delay estimation is automated with closed loop data. In the authors' experience, the delay estimation is not always accurate and leads to model errors due to structural mismatch especially with closed loop data.

While model uncertainties are now available as part of the model estimation process in almost every MPC software, the controller algorithms do not use uncertainty estimates in any explicit way. As a result, the most an APC engineer can do with high uncertainty models is either detune the affected input/outputs or discard them in favour of models which have a high degree of certainty. The rich body of robust MPC theory, developed to take advantage of uncertainty information, remains largely unavailable to the practitioner.

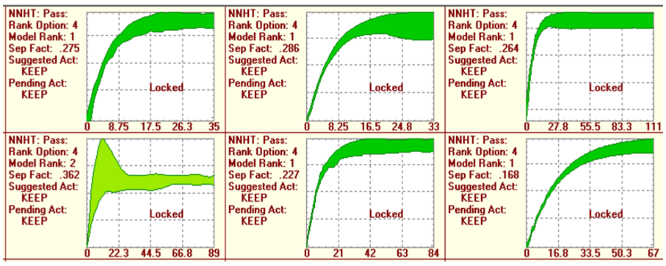

Fig. 5. Models estimated from closed loop step test data.

An important aspect of the modelling activity is the selection of appropriate data windows from the step test data. Presence of outliers can skew the modelling results. Though the model parameter estimation may be automated, the selection and slicing of data, is largely based on the engineering judgement of the APC engineer. As data accumulates during a closed loop test, care has to be taken to ensure that the data slicing is applied correctly prior to modelling. Some vendors offer automated slicing tools that recognize poor quality data and automatically ignore it for identification. These are not yet mature and results need to be vetted further by practitioners.

Fig. 5 shows model uncertainties and ranks for a section of CCR APC models. These models were estimated using the Profit Stepper tools for closed loop modelling. Green bands indicate the uncertainty in the estimated step responses. Models are automatically ranked from 1-5 with 1 being best model rank and 5 being the worst. Model ranks are based on a combination of parameter uncertainty and prediction errors.

While model estimation is relatively automated, implementation can be non-trivial. Most packages allow users to automatically download the new models to a running controller. While this is a vast improvement from past work practices, a significant amount of engineering work is still needed to get the models to a stage where they are ready to be downloaded. In particular, models which are likely to have a strong impact on the closed loop performance of the MPC have to be thoroughly scrutinized. An effort must be made to understand the underlying process changes responsible for the model changes. Without this understanding, the ability of the process control engineer to support the updated models and controller is limited. In summary, advances in the theory and practice of closed loop identification have brought the vision of adaptive control closer to reality. However, the engineer in the loop is there for a reason, and his/her understanding of the key process relationships is vital to the overall success of the control application. Moreover most chemical processes do not change very quickly or frequently, and as such the need for fast and automated adaption, in the processing industry, is not as prevalent.

To the authors' knowledge no automatic adjustment methods are available to update the tuning parameters in an online fashion. Practitioners can change any of the myriad tuning knobs for MPC in real time but not automatically. Typically one may adjust factors such as move suppression, LP (linear programming) costs, or gain multipliers on a need-to basis. Some degree of automation may be available at the time of commissioning to select best practice tuning values for the various parameters. While all vendors have made an attempt to simplify the selection of these parameters, the number of tuning knobs remains large and at times intractable in terms of their impact on real time performance of a running controller. One of the main reasons MPC is implemented is its ability to reduce variability and operate the unit at a near optimal position. However once an MPC application has been operating for few a years, the baseline conditions are often no longer valid due to process changes in the intervening time. Thus the ability to gauge the impact of the tuning parameters on the "before" MPC variability is obfuscated.

Often a major part of an MPC is a set of inferential models that predict quality variables which do not have frequent online measurements. Secondary measurements such as temperatures and pressures are used to develop a steady state and/or dynamic model. The model predictions are corrected via a lab or analyser update once it becomes available through a bias update scheme. The power of inferential models is in their ability to predict the quality variable changes between updates. These models need to be periodically assessed and updated to ensure that this predictive power is retained. Automated modelling and adaptation of the inferential models would greatly aid in the pro-active sustainment of MPC performance. This capability would definitely be of great value to the practitioner.

5. ACADEMIC RESEARCH AND INDUSTRIAL PRACTICE

Owing to its popularity in the industry several variants of traditional MPCs are being actively investigated by the academics. However, there is significant gap between the state-of-the-art research and applications. The research can broadly be classified into two categories: research on MPC algorithms and that on applications of MPC to linear, nonlinear, time invariant, time varying, hybrid and stochastic models. Each of these models, their unique characteristics, and the challenges they present are driving the need for new MPC algorithms.

The traditional industrial MPCs are linear but applied on large-scale systems. However, research in the last decade allowed extending MPC applications to nonlinear systems and to a certain extent to uncertain systems. While there is no exact solution to the nonlinear MPC problem, several approximations have been developed and successfully used in the industry (Mayne et al 1990; Chen et al 1998; Qin et al 2000). Approximate nonlinear MPCs attempt to obtain a feasible solution rather than an accurate solution. This trade-off, while not providing the optimal control performance, makes the nonlinear MPC tractable in practice (Lee 2011). Many successful industrial applications of nonlinear MPC have been reported in the literature (Qin et al 2000). However, lack of high fidelity nonlinear models remains a challenge to wide spread application of this technology.

Robust Model Predictive Control is another technology that is studied widely in the literature. Several solutions have been proposed using specialized descriptions of model uncertainty. Uncertainty descriptions are increasingly available in commercial identification software; however, they are not currently exploited using the advances in robust MPC. Another barrier to quick adoption of this technology is the need to solve online a non-convex optimization problem.

Large-scale applications of MPC are rather common in the industry. However, due to the difficulties involved in maintaining and operating extremely large MPCs, they are often split into smaller MPCs that are installed on sub-systems of the original process. This approach where the MPCs act independently of each other and on the subsystems is called decentralized MPC and is widely used in the industry. However, related recent developments in distributed MPC with cooperating controllers, is a novel concept that is yet to take root in the process industry (Camponogara et al 2002; Christofides et al 2013).

Recently, there has been a flurry of research activity on a novel idea called Economic MPC (EMPC). The central idea in EMPC is to use a single MPC objective function to control and to optimize economic conditions (Ellis et al 2014). This approach is promising, but so far few applications have been reported. In the recent years, a stochastic variant of Robust MPC called Stochastic MPC has been formulated. As the name suggests, Stochastic MPC is based on the stochastic uncertainty of a process model. The expected value of the MPC objective is minimized and the constraints are assumed to be soft (Mesbah et al 2014). This approach has the potential of maintaining the controller performance while satisfying the robustness conditions for the controller on "most" occasions. However, it is still a nascent idea that has not yet been tried on commercial applications. These emerging areas offer exciting new opportunities to improve performance, robustness and reliability of industrial MPCs.

6. CONCLUSIONS

Industrial appreciation of model predictive control has reached the point where it is simply expected that MPC will be used for many applications. Concerns have shifted away from whether MPC will deliver expected performance to how easily it can be installed, how intuitively operators can interact with it, and how long term performance can be monitored and maintained with limited resources. In this paper some approaches of industrial practitioners (vendors and industrial process control engineers) towards meeting these current industrial MPC challenges have been shared. Technology providers are attempting to provide tools to simplify and automate commissioning and maintenance tasks; however, they have yet to satisfy fully the needs of industry. At the same time, academic research continues to develop new techniques that may eventually help industrial applications achieve higher levels of sustained performance.

REFERENCES

Bauer, M. and Craig, I.K. (2008). Economic assessment of advanced process control–A survey and framework. *Journal of Process Control* Vol. 18(1), pp. 2-18.

Camponogara, E., Jia, D., Krogh, B. H., & Talukdar, S. (2002). Distributed model predictive control. *Control Systems, IEEE*, Vol. *22*(1), pp 44-52.

Canney, W. (2003). The future of advanced process control promises more benefits and sustained value. *Oil & Gas Journal*.

Celaya, P., Tkatch, R., Zhu, Y. C., & Patwardhan, R. (2004). Closed-loop identification at the Hovensa Refinery. In Proceedings of the NPRA plant automation & decision support conference San Antonio, TX, USA.

Chen, H., & Allgöwer, F. (1998). A quasi-infinite horizon nonlinear model predictive control scheme with guaranteed stability. *Automatica*, *34*(10), 1205-1217.

Christofides, P. D., Scattolini, R., Muñoz de la Peña, D., & Liu, J. (2013). Distributed model predictive control: A tutorial review and future research directions. *Computers & Chemical Engineering*, Vol. 51, pp 21-41.

Cutler, C.R. and Ramaker, B.L. (1980). Dynamic matrix control - a computer control algorithm. In *Proceedings of the joint automatic control conference*, Vol. 1, pp. Wp5-B.

Ellis, M., Durand, H., & Christofides, P. D. (2014). A tutorial review of economic model predictive control methods. *Journal of Process Contro*, Vol. 24(8), 1156–1178.

Gheorghe, C., Lahouaoula, A., Backstrom, J., and Baker, P. (2009). Multivariable CD Control of a Large Linerboard Machine Utilizing Multiple Multivariable MPC Controllers. In proceedings from PaperCon 2009.

Guerlain, S., Jamieson, G.A., Bullemer, P., and Blair, R. (2002). The MPC Elucidator: A Case Study in the Design for Human-Automation Interaction. *IEEE Trans. Systems, Man, and Cybernetics – Part A: Systems and Humans*, Vol. 32(1), pp. 25-40.

Jokinen, P. (1996). A life-cycle approach to automation information management in process industries. *ISA Transactions* Vol. 35, pp. 285-296.

Kano, M., and Ogawa, M. (2010). The state of the art in chemical process control in Japan: Good practice and questionnaire survey. *Journal of Process Control* Vol. 20, pp. 969-982.

Kalafatis A., Patel K., Harmse M., and Zheng Q. (2006). Multivariable step testing for MPC projects reduces crude unit testing time. *Hydrocarbon Processing*, pp. 93–100.

Lee, J. H. (2011). Model predictive control: review of the three decades of development. *International Journal of Control, Automation and Systems*, Vol. *9*(3), pp 415-424.

MacArthur J. W., and Zhan C., A practical global multi-stage method for fully automated closed-loop identification of industrial processes, *Journal of Process Control*, Vol. 17(10), pp. 770-786.

Mayne, David Q., and Hannah Michalska. (1990). Receding horizon control of nonlinear systems. *IEEE Transactions on Automatic Control* Vol. 35 (7), pp 814-824.

Mesbah, A., Streif, S., Findeisen, R., & Braatz, R. D. (2014). Stochastic nonlinear model predictive control with probabilistic constraints. In *Proc. of the American Control Conference. Portland, Oregon*.

Paulonis, M., and Cox, J. (2003). A practical approach for large-scale controller performance assessment, diagnosis, and improvement. *Journal of Process Control* Vol. 13, pp. 155-168.

Profit Stepper User's Guide. (2012), Honeywell International Inc., Release 410, Phoenix, Arizona.

Qin, S. J., & Badgwell, T. A. (2000). An overview of nonlinear model predictive control applications. In *Nonlinear model predictive control* (pp. 369-392). Birkhäuser Basel.

Qin, S.J., and Badgwell, T.A. (1997). An overview of industrial model predictive control technology. In *AIChE Symposium Series*, Vol. 93(316), pp. 232-256.

Qin, S.J., and Badgwell, T.A. (2003). A survey of industrial model predictive control technology. *Control Engineering Practice* Vol. 11, pp. 733-764.

Stewart, G. E. (2012). A pragmatic approach to robust gain scheduling. *7th IFAC Symposium on Robust Control Design.*

Zhu, Y.C. (1998). Multivariable process identification for MPC: the asymptotic method and its applications. *Journal of Process Control*, Vol. 8(2), pp. 101-115.

Zhu Y.C., Patwardhan R.S., Wagner S.B., and Zhao J. (2013). *Toward a low cost and high performance MPC: The role of system identification.*Computers and Chemical Engineering Vol. 51(5), pp. 124–135.

Zhu, Y.C. (2001). Multivariable system identification for process control. Oxford, Elsevier Science.

Zagrobelny, M., and Rawlings, J.B. (2012). Quis Custodiet Ipsos Custodes? *4th IFAC Nonlinear Model Predictive Control Conference*.

Kothare, M.V., Balakrishnan, V., and Morari, M. (1996). Robust constrained model predictive control using linear matrix inequalities. *Automatica* Vol. 32(10), pp. 1361-1379.

Mayne, D.Q., Kerrigan, E.C., and Falugi, P. (2011) Robust model predictive control: advantages and disadvantages of tube-based methods. *In Proc. of the 18th IFAC World Congress* Milano.

Rawlings, J.B., and Mayne, D.Q. (2015). *Model Predictive Control: Theory and Design.* Nob Hill Publishing, Madison, Wisconsin.

Richalet, J., Rault, A., Testud, J.L., and Papon, J. (1978). Model predictive heuristic control: Applications to industrial processes. *Automatica* Vol. 14(5), pp. 413-428.

Camacho, E.F., and Alba, C.B. (2007). *Model predictive control*. Springer, London.

Maciejowski, J.M. (2002). *Predictive control with constraints*. Prentice Hall, London.

Mayne, D.Q., Rawlings, J.B., Rao, C.V., and Scokaert, P.O. (2000). Constrained model predictive control: Stability and optimality. *Automatica*, Vol. 36(6), pp. 789-814.

Grüne, L., and Pannek, J. (2011). *Nonlinear model predictive control: Theory and Algorithms*. Springer, London.

