Management and Monitoring of Process Assets

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Abstract—This article discusses technology directions, emerging standards and organizational issues of process asset management and monitoring using the maintenance of advanced model predictive control (MPC) as an example of management of an economically important process asset. It places MPC performance monitoring technology within a wider context and attempts to identify new trends that may be of interest to researchers.

I. INTRODUCTION

THE goal of management and monitoring of plant assets is to enhance productivity and efficiency by optimizing the operation of installed industrial equipment. A definition of asset management for physical plant infrastructure is given in the PAS-55 specification “Optimized management of physical infrastructure assets” from the British Standards Institute as: The systematic and coordinated activities and practices through which an organization optimally manages its physical assets, and their associated performance, risks and expenditures over their lifecycle for the purpose of achieving its organizational strategic plan. The economic benefit was assessed by ARC Advisory group [1] who said Plant asset management is becoming a critical element of an effective automation strategy. They forecast the world market for plant asset management will be over US$2.4bn in 2011.

Present day oil, gas, chemicals, pulp and paper and other continuous process plants are generally regulated by Distributed Control Systems (DCS), either alone or supervised by model predictive control (MPC) and real-time optimization tools. High availability of plant assets such as power generation, electrical and mechanical equipment is required for optimal operation, and monitoring and management of these physical assets is a key industrial activity. Good performance of MPC and real-time optimization also requires access to reliable models and knowledge of constraints. The process assets that are critical for optimal operation therefore include algorithms, models and information as well as equipment.

New research directions are opening up in process automation in anticipation of the roll out over the next few years of a new type of industrial process control system called a Collaborative Production System, or Collaborative Process Automation System (CPAS) in the process industries. A CPAS will handle production and power management together with integrated control of process, electrical and mechanical sub-systems, and documentation such as plant descriptions. Deployment has barely started, but compared to the current state, the new CPA systems will contain abundant and well integrated information that can be exploited for prediction, detection, diagnosis and elimination of the root causes of breakdowns, disturbances and upsets to production caused by process assets.

Section 2 provides a technology survey that categorizes some of the functionality found on offer at the web sites of major technology vendors in early 2008. It puts process asset management into context and sets the scene by showing how technology vendors are integrating the components of CPA systems. Section 3 describes the state of the art in the performance monitoring of multivariable model predictive control systems as an example of process asset monitoring. These methods are at the cutting edge of academic and industrial research and the discussions shows how the technology fits within the broader framework of industrial process automation. The article ends with a summary which draws out some themes from the survey that might motivate future academic research.

II. THE INDUSTRIAL CONTEXT

A survey of commercial systems is presented in Table 1 (at the end) to show how asset monitoring and management fit into the overall picture. It also shows where MPC performance monitoring fits in. The survey is based on a web search from industrial commentators and control system suppliers.

Clearly the overall picture is huge. Each entry in Table 1 has its own research issues and it would take several articles to cover all of these thoroughly. Rather, the purpose of this paper is to focus on Asset Management and Monitoring with MPC Performance as an example. This section comments on the survey and then describes some issues relevant to Asset Management and Monitoring.

A. Summary of the automation survey

The Enterprise Resource Planning (ERP), Manufacturing Execution System (MES) and Production...
Control System (PCS) provide the three main components in a CPA system. ERP deals with business planning and management, the MES handles production operations while the PCS deals with real-time execution of production plans, control and monitoring. The ISA-95 standard (Enterprise Control System Integration) specifies the tasks to be carried out by each layer and how information is exchanged between the tasks in the different layers. Asset Management belongs in the ERP layer, while Asset Monitoring belongs in the PCS or MES layers. MPC monitoring tools belong to Asset Monitoring, with the advanced control system being regarded as an asset.

B. Issues in Asset Management and Monitoring

The Process Management and Control Subject Group of the Institute of Chemical Engineers held a meeting in London, UK, in January 2007 on management and monitoring of process assets. The report of the discussion session of the meeting [2] included a number of observations that are relevant to this paper, as follows:

- Improvements in condition and equipment monitoring technology will lead to a transition from reactive and scheduled maintenance towards predictive and proactive maintenance schedules.
- More interaction between the control room, maintenance and business activities will be beneficial. For instance, there is a need for systems that send alerts to the right people (e.g. to control room, to maintenance) with prioritization. Automation of this workflow can be expected when automatic asset monitors in the PCS layer communicate with Asset Management tasks in the ERP.
- Asset monitors include intelligent instrumentation, condition monitoring of rotating machinery and other equipment. Asset monitors can also be generated automatically from an electronic description of the connectivity of a process and its instrumentation. For instance, an asset monitor for a heat exchanger can be identified and implemented automatically [3].
- Wireless signaling is making more on-line data from machinery available and the cost of connection is much reduced. This will drive a trend towards much more on-line machinery and equipment monitoring including measurements from places that are infeasible to wire, e.g. inside rotating machinery.
- Wireless communications means that activities of field operators can be integrated with more information available to them from the control room and vice versa.
- Asset monitoring will draw on many resources in a future CPA system including historical process data, information about the connections between items of equipment, and between the equipment and the process. For instance, friction analysis and electrical measurements could be combined with advanced signal analysis methods to give early event detection and diagnosis for rotating equipment such as pumps, fans, compressors and gas turbines.

At present there is no agreed definition of a process asset, which gives scope for some novel notions of process assets:

- Models are valuable assets as repositories of knowledge that can make sense of data. Detailed simulation models are a source of knowledge that link operational data to decision making. Such models have to be managed and deployed so that they can be used by non-experts. Models for on-line control should automatically track process changes.
- Documents such as plant schematics and P&I diagrams are process assets, especially when stored in a format which allows process connectivity to be extracted.
- Knowledge of operating constraints is an asset, for instance who set the limits and why. They should be documented and reviewed periodically.
- Operating procedures are assets and should be easy to find, use and to maintain.

C. A new Standard for Asset Management

The PAS-55 specification from the British Standards Institute mentioned in the Introduction describes asset life planning, management and optimization, and includes a 21 point checklist giving a structured approach. The reason why PAS-55 is making an impact is that it helps organizations to adopt a rigorous approach and to implement and sustain good practices. There is evidence that companies are finding it useful, for instance Ofgem, the electricity and gas generator in the UK, is encouraging energy companies towards PAS 55 compliance by 2008 [4]. The rigorous aspects of PAS-55 include quantified risk management, analysis of lost opportunities and a procedure for continual improvement. It also discusses data bases and sharing of information and addresses human resource issues such as empowerment of technicians and how managers can communicate shared objective. For researchers, PAS-55 offers opportunities in the area of probabilistic risk assessment and strategies for repair and maintenance.

<table>
<thead>
<tr>
<th>Table 1. Survey of industrial automation systems</th>
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<tr>
<td><strong>CPAS</strong></td>
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<td>Collaborative Process Automation System (CPAS)</td>
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<td>Collaborative Process Automation System (CPAS) refers to a vision of a future central control system in a site which will handle production management, safety and critical control, advanced control, information management, smart instrumentation, smart drives, electrical power, energy management, equipment condition monitoring, asset management, and documentation management.</td>
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<tr>
<td>Components</td>
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<tr>
<td>Enterprise Resource Planning (ERP)</td>
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<td>An Enterprise Resource Planning system (e.g. SAP, Oracle, Microsoft) unifies data and processes including: business processes, cost management, decision support, finance, human resources, and operations such</td>
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A Manufacturing Execution System (MES) provides integration between the PCS and ERP according to the ISA-95 standard. It includes: data collection, equipment tracking, maintenance scheduling, material handling and tracking, production planning and scheduling, performance analysis, product tracking, quality assurance, regulatory compliance, resource management/allocation. Process optimization is considered an MES function.

Distributed Control System (DCS) is a system with a centralized processor and a network of remote sensors and actuators that provides monitoring and continuous control to a large manufacturing or processing site. DCS control algorithms include PID and advanced process controls. The communication system is hardened and may use IEC 61158 protocols (Fieldbus).

Supervisory Control and Data Acquisition (SCADA) is a centralized system that provides monitoring and control to a large site or network, for instance an electricity transmission or water network. The control tends to be discrete and the communication system may involve telephone (landline or mobile).

<table>
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<th>Modules</th>
<th>Description</th>
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<td>Advanced Process Control</td>
<td>Advanced Process Control manages regulatory control by selecting set points to achieve objectives such as economic optimization by driving a process towards constraints. It is generally model-based, making use of multivariable model predictive control (MPC) and model-based optimization. Other aspects include: fault detection, inferential control, multivariable statistical process control, neural network control, run2run control.</td>
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<td>Alarm Management</td>
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<td>Asset Management and Optimization</td>
<td>Asset management maximizes the utilization of plant assets by taking care of them in a risk-based way. Implementation requires a hierarchical data base of assets, early detection of developing problems based on analysis of data from field devices, identification of process and equipment faults, and notification of potential problems and scheduling of maintenance. Definitions and standards are emerging, e.g. the Institute of Asset Management has generated the PAS 55 Standard in BSI. An asset optimization system provides intelligent decision making to support actions, and automation of the workflow for instance by SMS messaging.</td>
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<td>Asset Monitoring</td>
<td>Asset monitoring provides data for asset management decisions. Examples include: control loop and MPC monitoring, equipment condition monitoring, integration/interpretation of routine measurements.</td>
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<td>Collaborative Production Management</td>
<td>Production management aims for paperless management of a production process based on process and business data, both current and historical. It covers production planning and optimization, tracking and reporting, analysis of operations, management of maintenance. A CPM system is able to integrate data from many sources and derive meaningful information. Condition monitoring comprises measurements on machinery such as: fluid flow, fluid leaks, mechanical noise, lube oil analysis, thermography, ultrasound and vibration analysis. It also includes active procedures such as visual inspection and non-destructive testing. The aim is to detect changes that indicate a developing failure. Condition monitoring underpins predictive and conditional maintenance schemes which take action only when maintenance is needed. A related topic is performance analysis where the efficiency and condition are assessed by comparing measurements against a benchmark or model. Non-process equipment includes: compressors, DC drives and motors, electrical switchgear, gas turbines, induction motors, low and medium voltage AC drives and motors, synchronous motors. Energy management refers to a programme of long term efficiency improvement especially in the energy-intensive oil &amp; gas and petrochemical sectors. Information management is the process of generating useful information based on data from disparate sources. The information is used in operations, maintenance, engineering, and management. Examples include: production status reports, FDA compliance reports, alarm and event reports. Integrated engineering facilitates large projects with a flow of information between contractors, suppliers and customers during engineering design, planning, installation, configuration, commissioning, operation and maintenance. The aim is to maintain a single source of truth for all data within the system. Operations management helps with meeting planning targets, key performance indicators (KPIs), standard operating limits, safety and environmental limits, and compliance with standard operating procedures. It should include analysis of the causes of deviations against plan and benchmarking of performance. A performance measurement system captures, validates, and analyzes data to provide key performance indicators such as Overall Equipment Effectiveness (OEE) and business margins. It supports a programme of continuous improvement. Power management is needed in a large site with its own electricity generation to ensure electrical power is always available. It includes: balancing of generation and loads, import and export of power from the electricity grid (e.g. load planning to make use of off-peak tariffs), load shedding, active and reactive power control. Services are offered by specialist third-parties to operating companies. Examples are: operations support service, remote services and continuous improvement services. Examples include control loop tuning, control loop performance assessment and alarm management. Smart sensors, transmitters, valves and valve positioners send signals to a DCS indicating their status and performance over a digital communication system such as Fieldbus. They can give early warning of abnormal equipment conditions to operators and plant maintenance personnel.</td>
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III. MPC PERFORMANCE MONITORING

Performance monitoring of Model Predictive Control (MPC) is discussed in this section as an example of process asset monitoring. Academic research described here is feeding into industrial tools such as Performance Analysis Toolbox and Solutions (PATS) from the University of Alberta and process controller performance benchmarking software from the University of Strathclyde.
A. Rationale

The performance monitoring of MPC requires special treatment to include constraint handling and economic optimization. It is debatable whether the classical performance benchmark such as minimum variance control is a suitable benchmark for MPC. The main argument lies in the fact that minimum variance control has a different control structure and objective from MPC; for example, it does not handle hard constraints.

For this reason, many alternative algorithms for MPC performance monitoring have been reported in the literature. They can be broadly classified into two groups: model-based and model-free approaches [5]. Among the model-based approaches, there are LQG (linear quadratic Gaussian)/MPC tradeoff curve approach, design objective versus achieved objective approach, historical-data benchmarking, on-line model validation, and model-based simulation approach. The common feature of this group of algorithms is the need for process models or interactor matrices. The model-free group includes impulse response curvature, prediction error curvature, Markov chains, and statistical data analysis. This group of algorithms does not assess control performance against a benchmark control. Since no models are needed they are attractive for practical applications. Most recently, economic performance assessment of MPC has also received attention [6].

Another interesting way of considering MPC performance monitoring is through on-line model validation. Since MPC is an optimizing algorithm based on models, a well formulated MPC will be optimal if the models are correct. Therefore, if the MPC objective function has been designed well, poor performance means the model that is being used by MPC needs attention. Following these arguments, monitoring of MPC performance boils down to two basic problems: evaluation and validation. Evaluation is for the MPC objective function and validation is for the model used by MPC. Parameters that affect controller objective functions are often called tuning parameters. Factors that may affect model quality include process nonlinearity, instrument malfunctions, time varying process and/or disturbance models being available, the actual trajectory of MPC can be simulated and statistical properties such as variance and covariance can be calculated for evaluation of MPC performance. If maintained as process assets, these models could be reused for other purposes, for instance disturbance models might be useful in a training simulator.

B. LQG/MPC Benchmark

Tighter quality specifications generally result in smaller variation in the process output but typically require more control effort. There is clearly an interaction here between asset management and control objectives because reduced control effort means less maintenance for a valve. It is useful to know how far the control performance is from the best achievable performance for any pre-specified control effort. A tradeoff curve of output tacking variance $E[(r_t - y_t)^2]$ versus input variance $E[u_t^2]$ is formed from LQG solutions, shown in Figure 1. Any linear controller can only operate in the region above the tradeoff curve. Given $E[u_t^2] = \alpha$, the minimum value of $E[(r_t - y_t)^2]$ can be found from this curve. This curve therefore represents the limit of performance and can be used for performance assessment purposes, particularly for constrained controls [7]. In an integrated CPA system, the tradeoff curve might offer new research opportunities, for instance perhaps it would be possible assess the impact of the modifications to the MPC tuning on valve maintenance schedules.

\[ \frac{\text{Achievable Performance}}{\text{Minimum variance}} \]

Figure 1. An LQG tradeoff curve

C. Simulation Approach

If process models are given, a natural approach towards performance assessment of MPC is through direct simulations. Ko and Edgar [8] studied this approach. The disturbance models can be unknown but may be estimated from the output data. With both process and disturbance models being available, the actual trajectory of MPC can be simulated and statistical properties such as variance and covariance can be calculated for evaluation of MPC performance. If maintained as process assets, these models could be reused for other purposes, for instance disturbance models might be useful in a training simulator.

D. Designed/Historical vs Achieved Performance

Design of MPC is an optimization of its objective function, typically in a quadratic form. Monitoring of MPC performance may be conducted by comparing the achieved MPC performance objective versus the designed one [9]. A performance index can therefore be defined as $\eta_{des} = J_{des} \cdot J_{ach}$. While $J_{ach}$ (achieved objective function) may be calculated from actual input-output data, calculation of $J_{des}$ (designed objective function) does need to have the complete process model. To avoid the modeling problem, $J_{des}$ has also been chosen as an estimate of $J_{ach}$ from a set of historical data with acceptable performance, which is similar to the historical benchmark [7]. Case studies were performed by Schafer and Cinar [10].
E. Historical Covariance Benchmark

Topics D above and this one both illustrate the need to maintain historical data as a process asset and to document it well. A historical covariance benchmark is proposed in [11], denoting benchmark data as period I and monitored data as period II. Detecting of the change of covariance is based on a ratio of the determinants of covariance matrices

\[ I_p = \frac{\text{det}(\text{cov}(y_H))}{\text{det}(\text{cov}(y_I))} \]

If the ratio is greater than one, the performance of the monitored period is in general worse than the benchmark period and the worst performance direction of the monitored period should be examined. The direction along which the largest variance inflation occurs is given by:

\[ p = \arg\max \frac{p^T \text{cov}(y_H)p}{p^T \text{cov}(y_I)p} \]

The solution is given by the generalized eigenvector problem \( \text{cov}(y_H)p = \mu \text{cov}(y_I)p \) where \( \mu \) is the generalized eigenvalue and \( p \) is the corresponding eigenvector. The solution maximizes the covariance ratio, indicating that the covariance of the monitored data deviates the most from the benchmark data along the direction of \( p \). This approach is used to identify the direction that has the most variance inflation.

F. Model Validation Approach

MPC is model critical by nature and model quality has been considered one of the two essential aspects in MPC performance monitoring. There are many model validation algorithms available in the literature. Most are designed for off-line model validation after model identification. For on-line monitoring purposes [12] proposed maximum likelihood tests for model parameter validation. Termined the local approach, the monitoring algorithm converts multiplicative parameter changes into equivalent additive changes which simplifies the on-line computations.

In practical applications it is desirable that the model validation algorithm should not give an alarm if parameter changes occur only in the disturbance models. Huang [13] has demonstrated that by associating the detection algorithm with the output error method as in system identification, the model validation algorithm based on the local approach is disturbance-dynamics independent. Along the same lines, if parameter changes do not affect control performance, then an alarm should not be issued. This leads to control-relevant model validation, specifically, MPC-relevant model validation [14].

G. Impulse-Response Curvature

An impulse response curve represents a dynamic relationship between the whitened disturbance and the process output. This curve typically reflects how well the controller regulates stochastic disturbances. In the univariate case, the first \( d \) impulse response coefficients are feedback-controller invariant, where \( d \) is the process time delay. Therefore, if the loop is under minimum variance control, the impulse response coefficients should be zero after \( d-1 \) lags. The normalized multivariate impulse response (NMIR) curve [7] reflects this idea. The first \( d \) NMIR coefficients are feedback-controller invariant, where \( d \) is the order of the interactor matrix [7]. If the loop is under multivariable minimum variance control, then the NMIR coefficients should decay to zero after \( d-1 \) lags. The sum of squares under the NMIR curve is equivalent to the trace of the covariance matrix of the data. Similar to the conventional impulse response curve, NMIR can be used to assess control performance of MIMO systems. Shah et al. [15] proposed to calculate NMIR from the closed-loop transfer functions directly, thus avoiding the use of the interactor matrix. This latter approach does not have a direct connection with the minimum variance control performance but does yield a convenient and approximate measure of control performance.

H. Prediction-error Approach

In the univariate control loop, one interprets output variance under minimum variance control as the variance of the optimal prediction error. If a closed-loop output is highly predictable, then a better controller should be able to compensate the predictable content and the closed-loop output would become less predictable. Therefore, high predictability of a closed-loop output implies that there is potential to improve its performance by control re-tuning. Huang et al. [16] analyzed the prediction error methods and proposed a curvature measure of closed-loop potential according to optimal prediction error. This method has been demonstrated by its application to model predictive control of a simulated as well as some actual processes.

I. Markov Chain Approach

A Markov-chain model is flexible in modeling nonlinear or non-Gaussian processes. The simple structure and rich class of a Markov chain makes it one of the most important models for random processes. Harris and Yu [17] applied the Markov chain approach to performance monitoring of MPC. By monitoring the degrees-of-freedom of constraints, they demonstrated how the Markov chains can be used to analyze industrial data.

The Markov chain model can also be used to monitor other properties of model predictive control systems, namely system stability and economic performance. Two indices have been defined in [18]: one is out-of-control index (OCI) and the other transition tendency index (TTI).
For a multivariable process, the OCI is defined as the number of out-of-control variables. The Markov chain analysis performed on the OCI can reveal the stability performance of the process under the model predictive control. The TTI is defined on the transition probability matrix of OCI. It provides a standardized index about the process transition tendency. By applying the Markov chain model to MPC objective functions estimated from data, similar analysis of economic benefits can be performed.

J. MPC Economic Performance Assessment

Recently, an algorithm based on the linear matrix inequality (LMI) for MPC economic performance analysis and for providing MPC tuning guidelines (named LMIPA) has been proposed. Mathematical details can be found in [6]. This algorithm, when provided with process data and the plant steady-state gain matrix, will perform economic performance assessment for MPC. It provides guidelines such as what is the maximum profit that MPC can achieve, and what is the potential of profit improvement with and without tuning control parameters respectively. It can also help determine how the MPC should be tuned to achieve a desired profit. The outputs from such an assessment have direct uses in an ERP system for business planning and making major decisions such as controller tuning projects.

IV. DISCUSSION

The above observations show that monitoring of MPC generates additional process assets such as models, information-rich statistics based on historical data, and indicators of the economic potential of the MPC asset. If maintained well, these things could give opportunities for use in other applications within a CPA system. For instance, models are useful in reduction of nuisance alarms since they include information about interactions, and comparisons of current and historical performance can feed into a predictive maintenance scheme. MPC also uses other process assets in the form of operating constraints to regulate the process within the constraints, so knowledge about such limits should be maintained properly. There seem to be many such possibilities for research if MPC models and the results of MPC monitoring were made available to other CPAS modules.

On the other hand, when MPC monitoring is placed in the context of Table 1, some limitations become apparent. In particular, it is limited to the monitoring of advanced process controls and has not yet crossed to monitoring of other systems such as compressor controls or power management systems. In a highly integrated future CPA system, there will be many research opportunities in transferring technologies such as controller performance monitoring to the mechanical and electrical plant systems. The survey in Table 1 and the discussions at the IChemE PMCSG meeting in London suggests that in future there will be much greater linkage between activities that have traditionally had little interaction. For instance, automated generation of plant asset monitors can be achieved when process control links with an electronically readable plant schematic, and information from continuous wireless condition monitoring of rotating machinery will have an impact on plant-wide disturbance diagnosis. Broader opportunities for researchers can be expected when process control meets condition monitoring, smart sensing and actuation, connectivity information from plant drawings, alarm management and power management in a future Collaborative Process Automation System.

V. REFERENCES