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INTEGRATION OF PROCESS SIMULATORS IN ADVANCED PROCESS CONTROL SOLUTIONS

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This paper presents a novel approach to test and to pretune advanced controllers to reduce the onsite work of control engineers and to train operators using advanced control solutions. Following the proposed approach a simulation framework has been developed where detailed process model realized in Matlab which is connected via OPC (Object-Linking and Embedding for Process Control) to the Profit Controller of Honeywell. With the application of the resulted simulation system the model predictive control (MPC) of a nonlinear crystallizer has been analysed. The case study demonstrates the efficiency of the proposed approach and the illustrative results show that the linear and robust MPC is an adequate controller of nonlinear crystallizers.

Keywords: Process simulator, Model Predictive Controller, OPC

Introduction

The interest for the use of dynamic simulation techniques in process industry is growing continuously, new fields of applications appear and become more reliable. Areas such as engineer and operator training [1,2], design or test before commissioning of a new control system are only some examples where simulation-based methods are being applied. In particular, process simulators are found in those industries where training is essential for plant security or process operation. The use of simulators facilitates a deeper knowledge of the process and its behaviour in different operating conditions, so that it can be manipulated without risk and minimizing production losses. All these factors have an impact in the global improvement of plant performance.

For control applications, fairly simple models obtained by identification from plant data can give good results, but a simulation for operator training should be based on a first-principles model, able to reflect many details of the process and to cover a wide range of operating conditions [3]. Process modelling is a powerful technology that enables managers and engineers to link critical business objectives to improve the design, operations and optimization of a plant [4, 5].

In the literature it is possible to find examples where steady state and dynamic modelling have been used to improve unit operation and control scheme design, even in industrial cases [6, 7]. Unfortunately, in these papers very limited information is published concerning the applicability of process simulation tools at the plant level. Apart from some specific examples related to operator training [8, 9], the advantages of using state-of-the-art commercial simulation tools at the plant level, e.g. for the improvement of process behaviour, are not well presented. However, it should be noted that the process industry has already started to move towards a more direct application of modelling tools and some engineering organizations have set up guidelines for the use of computer software in the design of process plants [10].

According to these experiences, the possible benefits of the simulation based process development are the following:

- Maximizing the return on capital employed by predict the future of the plant today
- Allowing the usage of what-if scenarios and sensitivity analyses to identify the optimal design, based on operational and business targets [11]
- Ensuring that process equipment is properly specified to assure desired product throughput and specifications
- Preparing plant assets for profitable, reliable and safe production [12, 13]
- Improving profitability by using simulation online for enhanced process control and optimization [14]
- Allowing the evaluation of the effect of feed changes, upsets and equipment downtime on process safety, reliability and profitability
- Training plant staff to ensure they can react to abnormal situations and run the plant at safe, yet optimal levels of production
- Improving the design of regulatory and advanced control strategies for better plant control and operability

The goals of the development approach proposed in this paper are mainly the last two; design a simulation framework that is able to test and pretune advanced controllers to reduce the onsite work of control engineers, and to train process operators how to use the controller.

In the developed tool a detailed engineering (first-principles) process model is implemented in Matlab. This model is connected via OPC (Object-Linking and Embedding for Process Control) to a model predictive controller (MPC). Since the aim of the tool to pre-test the efficiency of the advanced control solution in industrial environment, the studied controller is the Profit Controller of Honeywell which is widely used in the process industry.

In the following section an overview of the structure and the elements of the proposed framework are highlighted, where the model in general, the model predictive controller and the OPC connection between these elements are presented. This section is followed by a case study where the details of the simulator and its implementation are showed through the control of a continuous vacuum crystallizer.

Structure of the proposed simulation environment

The proposed simulation system is based on the synthesis of the process (model) and the controller.

Components of the combined simulation system are (see *Fig. 1*):

- the detailed engineering model of the technology, realized in Matlab (of course other simulation tool could also be used),
- the controller model, which is a real-time, industrially used model based controller (In this study predictive controller (MPC) is used as advanced control solution.),
- and the connection of the two elements above, which is the standardized OPC (originally OLE-Object Linking and Embedding for Process Control).

As it is shown in Fig. 1, the model is considered to act like the real plant, the manipulated variables (mainly the setpoints for the controllers, e.g. temperature controller) are the inputs of the model, while the outputs of the controller are the controlled variables (e.g. delivery). The value of these variables are transferred from the model to the controller via OPC.

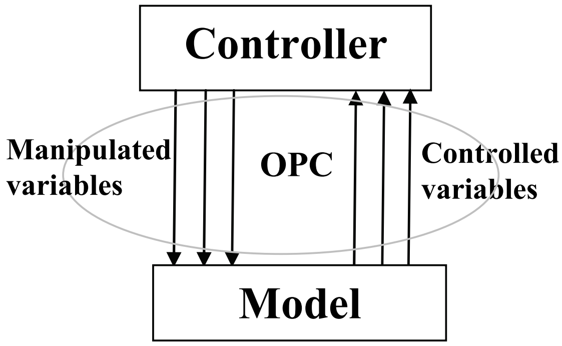

Figure 1: The sheme of the simulator system

In the next section the elements of the system are presented. Following this overview the details of the implementation are presented in a case study through an example connected to a particular model of a crystallizer and controller.

Model

"Modelling means the process of organizing knowledge about a given system" [15]. "A model (*M*) for a system (*S*) and an experiment (*E*) is anything to which *E* can be applied in order to answer questions about *S*" [16]. "By performing experiments, we gather knowledge about the system. However, at the beginning of this process, this knowledge is completely unstructured. By understanding what are the causes and what are the effects, by placing observations in a temporal as well as spatial order, we organize the knowledge that we gathered during the experiments" [17].

For different functions in different environments, different models have to be applied. Models can be used during the whole lifecycle of a plant, e.g. in the design, the operation and in the optimization phase as well. Such simulation lifecycle is presented in *Fig. 2*.

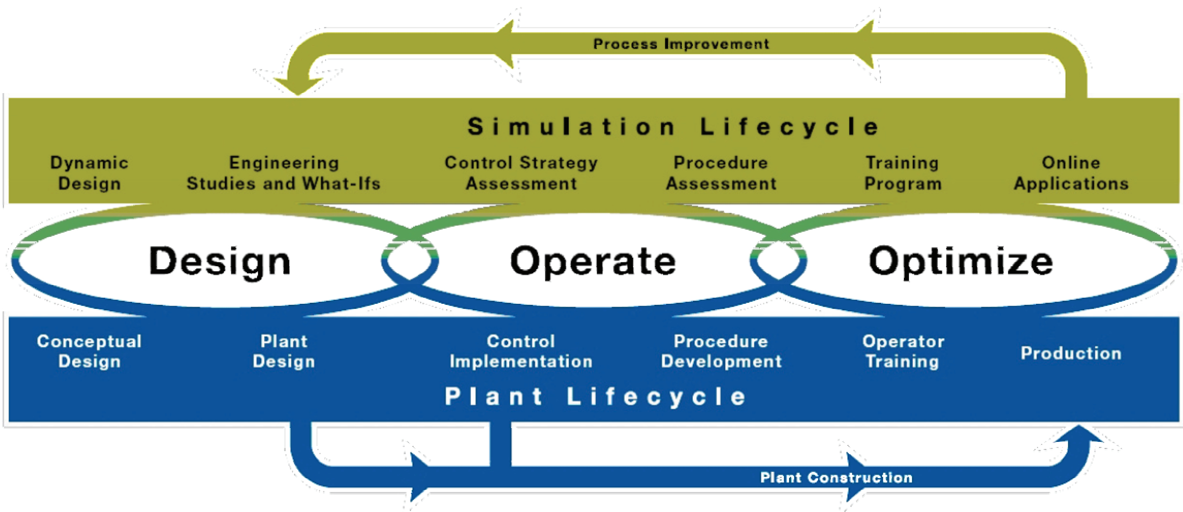

Figure 2: The simulation lifecycle at Honeywell

In this paper the model has not only to be able to cover a wide range of operating conditions, but it has to be also adaptable to the process control system via OPC.

Controller

Model predictive control refers to a class of computer control algorithms that utilize an explicit process model to predict the future response of the plant [18]. The technique was originally developed to meet the specialized control requirements of power plants and petroleum refineries [19]. MPC technology can now be found in a wide variety of application areas including chemicals, food processing, automotive and aerospace applications.

In model predictive control, the control action is provided after solving – in real time at each sampling instant – an optimization problem, and the first element in the optimized control sequence is applied to the process (receding horizon control). The “moving horizon” concept of MPC is a key feature that distinguishes it from classical controllers, where a pre-computed control law is employed. A major factor in the success of model based predictive control is its’ applicability to problems where analytical control laws are difficult, or even impossible to obtain.

A model is used to predict the future plant outputs, based on prior and current values and on the proposed optimal future control actions. These actions are calculated by the optimizer, taking into account the cost function (where future tracking error is considered) as well as the constraints, for the details see [20].

In this paper a real, industrially used MPC, the Profit Controller was applied. The Honeywell’s Profit® Controller controls the process using the minimum manipulated variable movement necessary to bring all of the process variables within limits or to setpoints. This controller also optimizes the process with the remaining degrees of freedom in order to drive the process to optimum operation. Profit Controller uses Honeywell's patented Range Control Algorithm (RCA) [21]. RCA minimizes the effects of model uncertainty while determining the smallest process moves required to simultaneously meet control and optimization objectives.

The models for the prediction were also identified in Honeywell’s software environment. The overall process model is composed of a matrix of dynamic sub-process models, each of which describes the effect of one of the independent variables on one of the controlled variables [22].

Integration issues

The integration of a process simulator and the controller was performed with OPC. This standard specifies the communication of real-time plant data between control devices from different manufacturers. OPC was designed to bridge Windows-based applications and process control hardware and software applications.

During the integration, the variables have certain definite names (e.g.: MV01.ACTIVEVALUE) called tag. The communication can be asynchronous or synchronous, and the sampling time has to be set.

OLE for Process Control which stands for Object-Linking and Embedding for Process Control, is the original name for an open standard specification developed in 1996 by an industrial automation industry task force (See http://www.opcfoundation.org). The standard specifies the communication of real-time plant data between control devices from different manufacturers.

While OPC originally stood for “OLE for Process Control”, the official stance of the OPC Foundation is that OPC is no longer an acronym and the technology is simply known as “OPC”. One of the reasons behind this is while OPC is heavily used within the process industries, it can be, and is, widely used in discrete manufacturing as well. Hence, OPC is known for more than just its applications within process control.

The OPC Specification was based on the OLE, COM, and DCOM technologies developed by Microsoft for the Microsoft Windows operating system family. The specification defined a standard set of objects, interfaces and methods for use in process control and manufacturing automation applications to facilitate interoperability.

Case study

The proposed simulation framework was tested for the model based control of a vacuum crystallizer.

The crystallizer is a non-linear, multi input multi output (MIMO) object, with a high degree of interaction between the process variables. The control of this process has many difficulties, e.g. one can do nothing if the crystals grow beyond a certain size, there is no opposite way of change. For all of these problems, a Model Predictive Controller presents a good solution. MPC can handle the MIMO object; and it is predictive, so the controller “prevents” oversized crystals. For non-linearity within a certain range, a robust controller can be adequate.

These problems are tested below in the presented simulation environment.

Simulation details

Vacuum crystallizers are able to produce crystals of a certain quality as fast as possible using the minimum amount of energy. The description of the studied vacuum crystallizer and its model can be found in [23].

From controlling point of view a crystallizer the main quality criterions are the properties of the produced crystals, the size and the size-distribution. The delivery of the crystallizer can be also controlled.

So, the outputs (the controlled variables, called CVs) calculated from the moments are the following:

- Mean crystal size
- Standard deviation of the crystal size distribution
- Delivery of the crystallizer

From the process point of view, in a continuous vacuum crystallizer, the pressure, the temperature and the residence time can be changed in practice. In the environment of the model the inputs (the variables to be manipulated, called MVs), are the following:

- Pressure; can be controlled with partial pressure by the valve of the vapour outlet
- Temperature; can be changed with the inlet suspension temperature
- Residence time

There is a strong coupling between the inputs and the outputs, for example any change of the residence time in the vacuum crystallizer not only changes the size but the size distribution (and of course the delivery).

To summarize, the above presented crystallizer is a non-linear object, with a high degree of interaction between the process variables.

The robustness of the controller is tested in the following case study, where a non-linear process is controlled by a linear MPC. This solution is widely applied in the industry, since the non-linearity of the process can often be handled by the linearization of the process model or the process is operated within a relatively narrow range where the process may act linearly.

Implementation details

The first-principle model of the process has been developed in Matlab simulation environment. The Honeywell environment of the Profit Controller is also set up as OPC server. According to this solution, the OPC Read and OPC Write toolboxes of Matlab are used to connect the Profit Controller of the crystallizer (Hci.CRYST).

Matlab Simulink view of this solution can be seen in *Fig. 3*, where the red boxes are connected to the Profit Controller. In this platform, some measurement noise is added to the controlled signal to get closer to a real-time environment. During the simulation, this Simulink program is sending and getting the data from the controller at every minute.

Profit Viewer is used to supervise the parameters and performance of the Profit Controller [21], the online model predictive controller of Honeywell. This program serves as a Windows based graphical user interface, see *Figs 4* and *5*. In the CV Summary display the operator can change the limits or the setpoints of CVs. The VALUE comes from the process unit (now from the model), the SS VALUE is the predicted steady state value while STATUS shows whether the CV is controlled by MPC or not. MV Summary screen shows the actual inputs (VALUE), how it has changed in the last execution period (MOVE) and the steady state values (SS VALUE). In normal conditions, the operators do not change the limits of MVs.

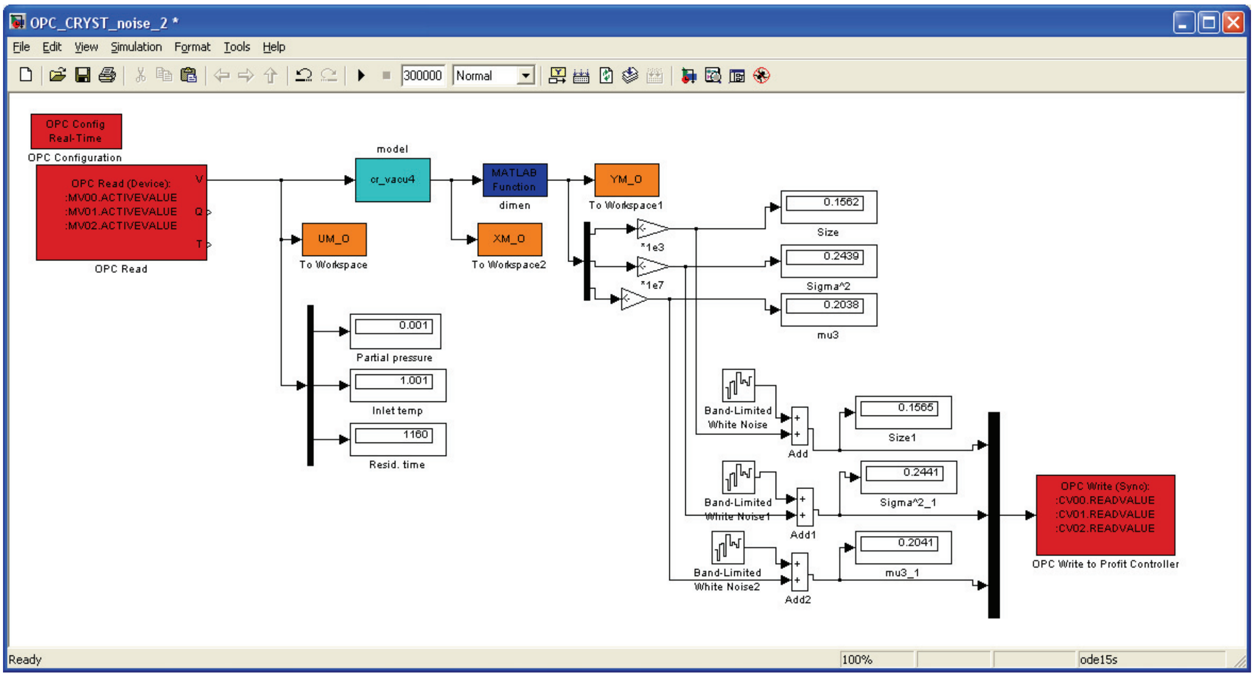

Figure 3: Matlab Simulink view of the process, connected to the controller

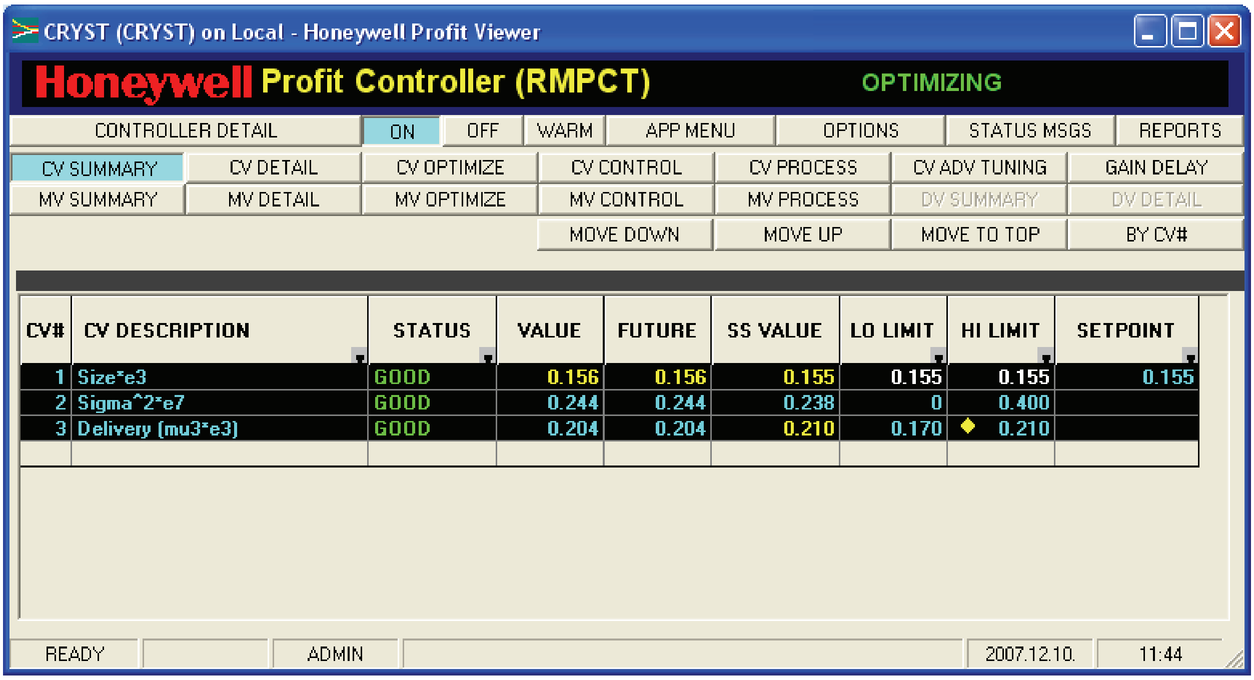

Figure 4: One of the main Profit Viewer screens, CV summary

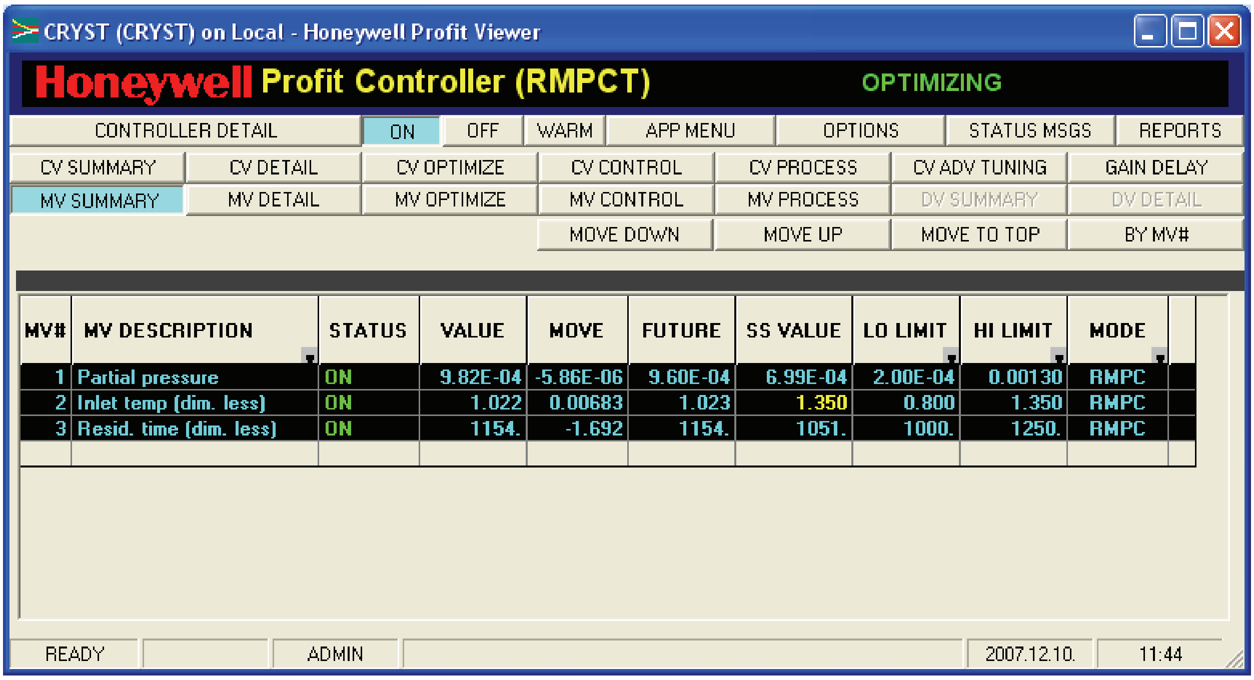

Figure 5: One of the main Profit Viewer screens, MV summary

Results

The main goal of the model predictive controller was to follow the setpoint that defines the desired size of the crystals. The standard deviation of the size distribution was minimized within a certain range, but the maximization of the volume was set to be a more important priority than this goal.

The default control horizon (where the manipulated variables change in the prediction) in the Honeywell controller contains 10 movements of the MVs. The prediction horizon (where the prediction is calculated) is identical to the open loop response interval which is about 1.5 hours in this case.

Weights, rate of change limits, ramping limits and other tuning parameters were set up in the Profit Controller manually, based on the results of previous simulation experiments.

The optimization speed factor was set to three (fast), which resulted in an optimization horizon approximately two times of the CV overall response time. The CV overall response time was defined as the average of the longest CV response time and the average CV response time, 123 minutes in this case.

The simulation results are shown in *Figs 6* and *7*. The dashed lines are the setpoint for CV1 and the minimum and the maximum limits of CV3. The limits of CV2 are irrelevant.

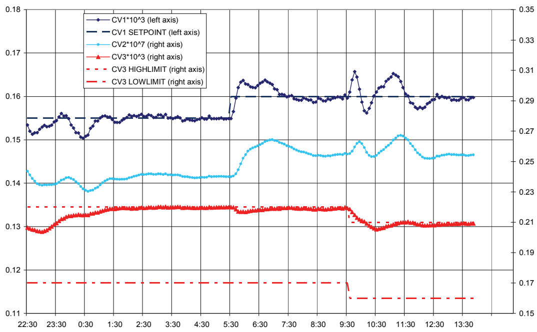

Figure 6: Simulation results for the controller, optimizer, with controlled variables (CV1 = crystal size, CV2 = crystal size-distribution, CV3 = delivery of the crystallizer)

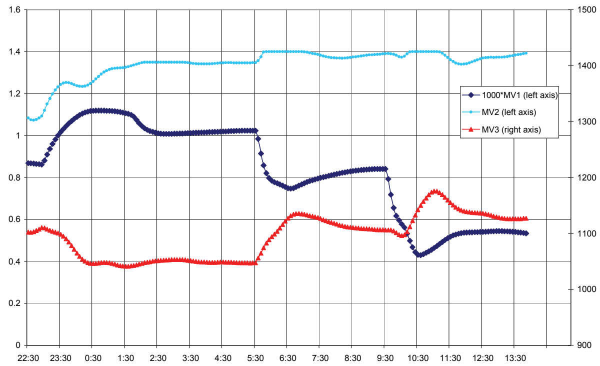

Figure 7: Simulation results for the controller, optimizer, with manipulated variables (MV1 = pressure, MV2 = temperature, MV3 = residence time)

In the test run the optimizer was turned on at 23:00, from that time the CV3 (delivery) increased significantly while the CV2 (size distribution) decreased a little to the optimal values. CV1 setpoint change was realized after a little overshoot, the changes of MVs (Fig. 7) show that the controller reacted rapidly.

When the range of CV3 was changed, the MVs also changed fast, and the control problem was solved. CV1 also changed significantly due to interaction, but it calmed down after a while.

The results shows that the controller optimizes and solves the changes in the range, the MVs react rapidly but smoothly, and the controller is robust.

The online measurement of size distribution can be difficult. With Profit Controller, the size distribution can be an inferred variable calculated from measurable variables. It is an often-used technology, for example, to control the cutpoints in the refineries.

During a real commissioning, engineers always check the unbiased model CVs, which are calculated from the linear model matrix. These model CVs should change parallel with the real CVs, it is the validation of the models. If the change is too big, then the gain is too big, if the unbiased model CV changes appear later, then the dead time is too big and the dynamics should be also more or less the same.

According to these rules, linear models were checked and changed where it was needed.

The results are very good, with the final models the unbiased and the read CVs are changing parallel. (See *Fig. 8*.)

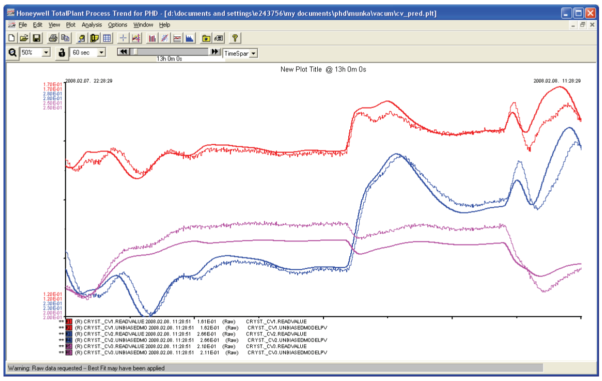

Figure 8: Validation of the models, the bold lines are the unbiased model CVs

Conclusion

The paper demonstrated a successful application of a novel simulation framework, where the detailed engineering model of a process unit is connected to a widely used advanced process controller (APC) via OPC. The solution system can be used to pretune the controller, test the controller solution or the operating strategy (e.g. grade transition), to train the engineers and the operators and in many other simulation cases.

In the case study, it was examined how a continuous vacuum crystallizer can be controlled by MPC using this system. The control of the crystallizer is difficult, because it is a non-linear MIMO object with strong coupling between the variables. The results showed that the linear, robust MPC is and adequate controller of a nonlinear crystallizer, it is adaptable in real unit. It was tested in regulatory and servo mode as well.

The simulation system has proved to be a very convenient tool to test the controllability in this special case. According to our knowledge this is the first successful integration of the MPC of Honeywell and the Matlab simulation environment. The experience gathered in this study can be applied in other projects as well.

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