Industrial Plant Optimization and Advanced Control Application

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Abstract

In today's globally competitive marketplace, industrial plants are looking at new ways to increase plant efficiency, production rates, safety and reliability. Engineer education and training, monitoring, diagnosis and plant optimization play a key role in satisfying technological, economical and environmental constraints. Furthermore, control system optimization is the basis for system improvement and advanced process control (APC) implementation.

Very few plants use modern software for control quality monitoring, controller tuning, APC or optimization. The reasons are absence of engineering knowledge and unavailability of practical and robust process control software tools for system identification, parameter optimization and control quality monitoring, running plants conservatively due to fear of causing shutdowns and plant problems.

Process control software tools for quick and easy system identification using available data from the plant's historian can help tremendously improve the control quality and the plant's profit margin. It is possible to analyze multivariable systems, complex, nonlinear and slow processes with long dead times and long time constants commonly encountered in process industry.

Optimization of primary and advanced control schemes stabilizes the process and allows the plant to run closer to process, equipment and economic constraints. This increases production rates, minimizes operating costs and improves product quality. The overall control system performance is significantly improved which ultimately has a positive effect on product quality and energy consumption thus proving application of control system diagnostics and optimization usefulness.

1 Introduction

Application of advanced control methods has rapidly increased since the 1990s in the chemical, petrochemical, and oil refining industry. The terms DCS, PLC and PID can be found in many articles like: Henriquez et al. [1], Van Schuppen et al. [2], Cauffriez et al. [3], Campelo et al. [4], Rullán [5], Valencia-Palomo et al. [6], Bolton [7], Reznik et al. [8], Panda [9] and Escobar et al. [10].

Also, the terms APC, model predictive control (MPC) and MBC are mentioned many times in literature as in: Lababidi et al. [11], Dobos et al. [12], Zhi Gao et al. [13], Willersrud et al. [14], Al-Gherwi et al. [15], Peng et al. [16] and Malchow et al. [17].

As can be seen, these terms are ubiquitous in chemical process control literature. A prerequisite for APC/MPC success is a well-designed primary PID control platform with optimized parameters. Increasing application of AP schemes places higher demands on the skills and experience level of process control engineers and technicians in the control rooms.

This paper nicely explains the application of the powerful 3G optimization method [18–20] which helps the control engineer and technician to design and implement control schemes inside the DCS, optimize the controller performance and increase the plant's profit because of improved plant operation.

Application of process control software tools for system identification, PID tuning optimization and APC calculations is still not too common in the control room environment in manufacturing plants. The reasons for this is that most current software tools and dedicated optimization algorithms are too complex, rather expensive, and neither robust nor practical for the control room environment.

Further, applications of the newly developed 3G algorithm are illustrated. It can accurately identify process models admist the presence of large unmeasured disturbances or oscillations and high noise from the data, all in complete closed-loop mode without conducting any additional new step-tests in the plant. Current system identification and optimization algorithms such as: autoregressive–moving-average model with exogenous inputs (ARMAX), step response coefficient models, Box and Jenkins, etc., are rather sensitive to the presence of noise, disturbances and drifts in the data.

In the PID and APC parameter optimization area, the application of internal model control (IMC), Lambda tuning, Ziegler-Nichols, Cohen Coon, and other methods, still produces conservative and not optimal control action. The 3G algorithm can accurately calculate PID/APC parameters for the processes where currently known heuristic-based methods have failed.

2 Process control application hierarchy

Fig. 1 shows the common industrial process control hierarchy split into three major categories. At the lowest level are the primary control loops – mostly PID controllers for controlling flow-rates, pressures, levels, temperatures and other variables in the industrial plant. To handle slow process dynamics, multivariable interactions, long dead times and complex control loops, pure PIDs alone cannot effectively provide the best control quality, and APC applications are necessary. Further, to incorporate market, economic conditions, process and equipment constraints and nonlinearities, a third application level – real time optimization can further provide monetary benefits.

Primary control and DCS-based APC, if correctly implemented, can significantly increase the plant's profit margins. Optimized primary and advanced control stabilizes process operation and pushes the operation closer to process, equipment and economic constraints. This increases production rates, minimizes operating costs and improves product quality [21].

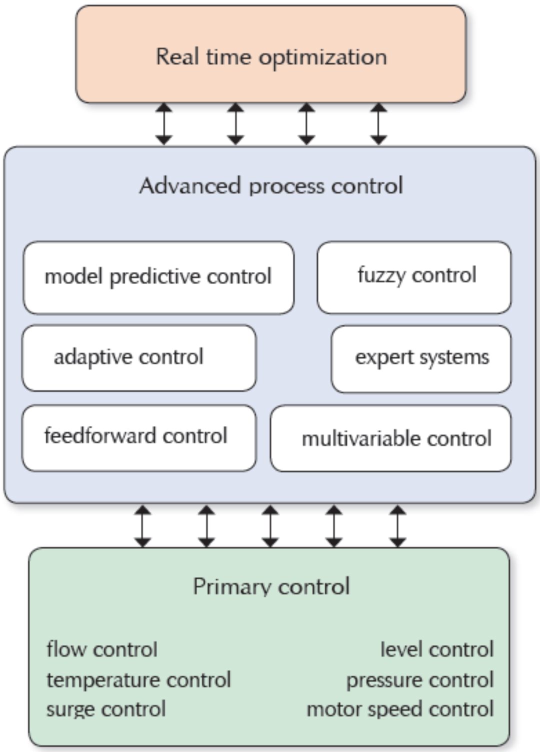

Figure 1: Process control hierarchy.

3 Challenges and opportunities in modern control rooms

The increasing use of primary and advanced control poses the following challenges in the control rooms:

1. New control and process engineers and DCS or PLC technicians come into the plant on a regular basis. They need to be trained in practical primary and advanced process control.

2. Many DCS-based APC concepts cannot be taught practically at schools and colleges. Learning practical process control skills quickly is not easy and simple.

3. Changes in process or operating conditions, complexity, nonlinearities, external unmeasured disturbances, high signal noises can impact closed-loop control quality resulting in inefficient operation including lost production, and could even cause equipment shutdowns and safety/reliability incidents.

4. Constant software and hardware upgrades add to the maintenance challenges in the control room.

Using modern DCS and/or PLCs, various powerful, robust, money-making control schemes can be implemented. This paper also describes the following powerful techniques for designing and implementing DCS or PLC-based APC schemes, which are optimized using the 3G algorithm:

1. Process dynamics identification,

2. Primary PID and APC optimization,

3. Online adaptive control,

4. Model-based control for product quality and production rate maximization.

4 Process dynamics identification

Process measurement ranges can be from as fast as milliseconds on compressor surge control and motor control to as low as many hours in tall super-fractionator distillation columns. In modern control rooms, there are plenty of data sets available containing the controller output (OP), process variable (PV) and set point (SP). Data may contain OP step changes with the controller in manual mode, or may contain SP changes in auto mode. There are many opportunities in the plant where the operator may have made changes to the SP or OP. All these data sets are abundantly available from the plants data historians that continuously archive the data.

From collected data it is possible to identify process dynamics i.e. the dynamic relationship between the controlled variable (CV) and manipulated variable (MV) for each control loop. Most chemical processes can be characterized by one of the common industrial process models (zero, first or second order) [22, 23].

Pitops [24] identification and optimization software tool was used to identify the model parameters using existing data of distillation column pressure controller from an olefins plant, which were stored in the plant's data historian. Fig. 2 shows pressure control (PC) data when the loop was in manual mode. The PC's output (OP), i.e. the valve position, was moved a few times which caused the pressure PV to respond. Identified first order process model parameters are shown on the right top side of the Figure: Time delay = 1.3 min; Process gain = –1.017 bar / %; Time constant = 5.4 min.

The blue trend in the top window shows the model prediction which follows the red trend of the actual column pressure data in the top window and the bottom trend is the control valve position.

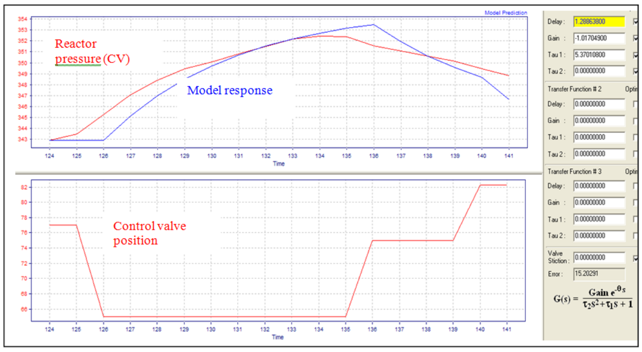

Figure 2: Pressure control loop model identification [24].

The next example shows model parameter identification using closed-loop data (controller in auto mode), as shown in Fig. 3. This example involves a temperature controller which is manipulated by a steam flow controller in a distillation batch process. The TC output is often zero (there is no steam flow). When the process is ready for increasing the temperature, a batch sequence logic tag changes the TC's set point. Optimal tuning of the TC was demanding because the TC is not always in control during the day shift.

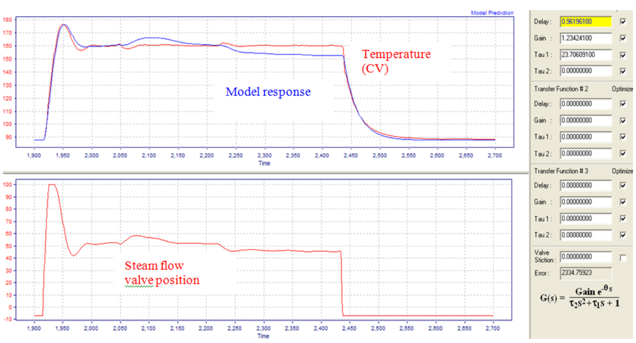

Figure 3: Temperature control loop model identification – closed loop mode.

Using temperature PV and steam flow-rate SP data in a closed-loop control, the first order model was identified. The identified process parameters are: Delay time = 1 min; Process gain = 1.234 °C / (kg h−1); Time constant = 23.7 min.

The last example shows a multivariable model-predictive controller from a chemical plant manufacturing catalyst in closed-loop mode, simultaneously manipulating three MVs: distillation column feed, side product flow-rate and reflux flow-rate, as shown in Fig. 4. The product impurity is impacted by all three MVs (red trend in the top window). All three second-order models are identified simultaneously using the data from the closed-loop mode. This identification can be used to improve the step response coefficient or any other kind of models used in the commercially multivariable model-predictive controllers in order to improve the controller performance.

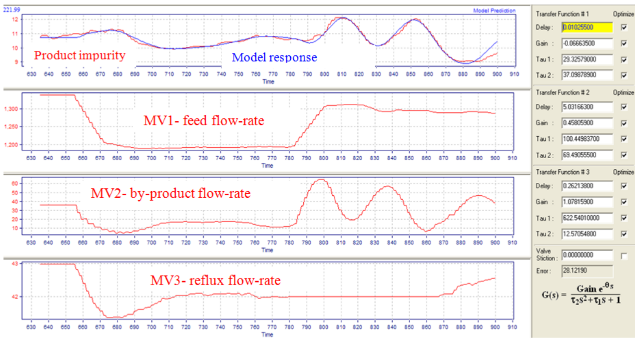

Figure 4: Multivariable control loop model identification – closed loop mode.

5 PID Controller Tuning and Optimization

Knowing the process model helps to optimally tune base-level and cascade/advanced controllers. Fig. 5 shows an industrial pressure control (PC) example, which is the same as in Fig. 2. The bottom window shows the PC's output. The top window shows the SP (blue trend) and PV (red trend).

The PC's objective is to not only provide crisp SP control but also to respond aggressively when hit by a disturbance. Disturbances can come and go anytime and it is important for the PC to respond quickly by closing or opening the valve immediately. The key is that such aggressive control action needed during disturbance rejection should not result in sustained oscillations at steady state.

The 3G optimization algorithm generates such tuning parameters that give crisp, non-oscillatory SP control while responding quickly during fast and large disturbances. This resulted in increasing the controller proportional gain from 2 to 11 in one step and the integral from 8 to 3 minutes.

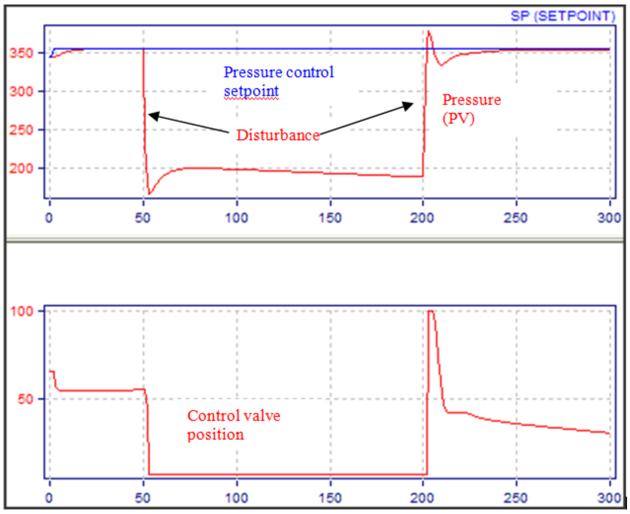

Figure 5: Optimized pressure controller in presence of disturbance.

Without modern optimization tools that use the 3G optimization algorithm, control engineers confronted with tuning such a PC would not have the confidence to increase the controller gain drastically from 2 to 11 in one step. They would have crept up the gain from 2 to 2.5 and 3 etc., over a much longer time period. And since the disturbance does not come all the time, it is hard to manually tune the loop for optimal control without the help of modern tools.

The following text explains the optimization of the cascade control which is common in all chemical processes. Cascade controllers can be fast as in PC to FC chains or slow as in AC to TC or TC to TC cascades controlling product stream quality measured by on-line analysis or temperature inferential controllers. The optimizer can identify both slave and cascade process dynamics and then optimizes cascade PID parameters. Fig. 6 shows an example of a master AC and its slave TC from the simulator, which mimics a distillation column cascade example.

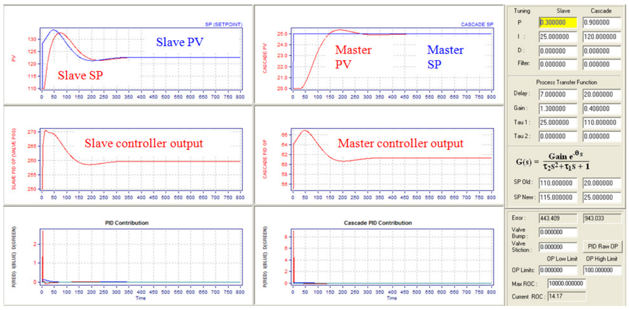

Figure 6: Optimized PID controller in presence of SP change.

One of the most powerful schemes to maximize plant profits is implementing production rate maximizer schemes in the DCS or PLC, as illustrated in Fig. 7. As many as ten or more constraints can be implemented as part of the constraint pusher schemes. The optimizer can identify the process dynamics for all the constraints and then precisely optimize all the tuning parameters.

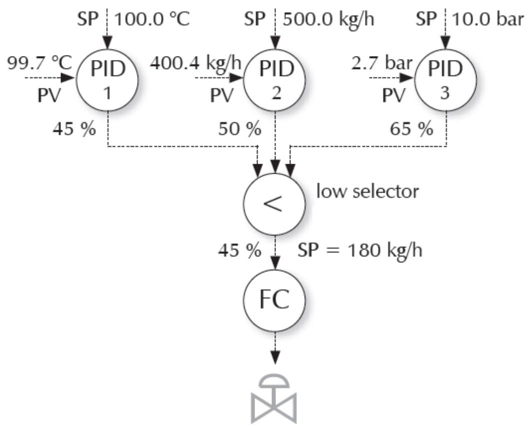

Figure 7: Production rate maximizer controllers.

6 Feedforward control and model-based control

In all chemical processes, control quality can be significantly improved on various important control schemes using feedforward control. Unfortunately, almost all feedforward tuning parameters are estimated today in the control room by trial-and-error or "best-guessed" estimates.

The 3G algorithm provides powerful functionality to mathematically identify the feedforward parameters: lead, lag, gain and dead time. Understanding how feedforwards work allows building custom new applications all inside in the DCS or PLC for numerous other innovative purposes.

By mastering the quantitative details of how feedforwards work, an engineer, operator or technician can easily build powerful feedforward control schemes inside the DCS or PLC with numerous benefits. Fig. 8 shows a sample calculation overview of a feedforward control scheme using the 3G algorithm.

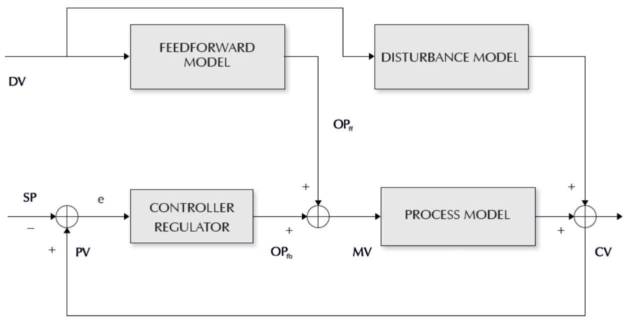

Figure 8: Feedforward control simulation and optimization scheme

Another great opportunity is the implementation of model-based controllers in the DCS or PLC. Any model based on rigorous, empirical, semi-empirical or regressed models can be implemented in the DCS using once through or iterative calculations. Such models can be used to implement closed-loop controllers in the DCS or PLC. Furthermore, measurement feedback such as from online gas chromatographs or laboratory analysis can be incorporated into the predictive models. This model-based controller design with predictive, corrective and feedback closed-loop control action can also be nicely built using the new 3G optimization algorithm. Model-based structure is shown in Fig. 9.

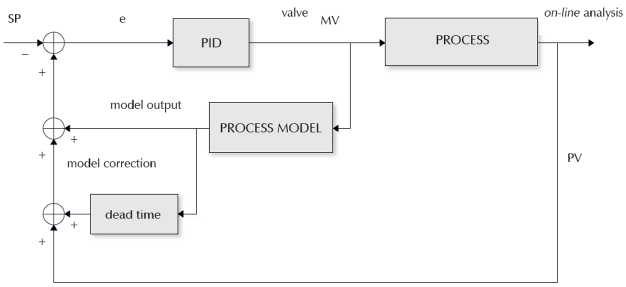

Figure 9: Model-based control scheme for dead-time compensation.

7 Conclusion

Application of the newly developed identification and optimization 3G algorithm is presented. It can be implemented in the DCS or PLC with increased recurring average annual profits ranging from 50 000 to 3 million dollars, depending on the size and type of the plant. Using the 3G algorithm, it is possible to identify process dynamics in the presence of disturbances and noise, design primary and advanced process control schemes, and optimize their PID/APC parameters. The ability to identify system dynamics using this 3G approach allows successful identification using ultra-short duration data amidst disturbances and allows optimization of PID tuning and APC implementation inside an existing DCS or PLC in a remarkably short duration, at a lower cost and higher accuracy.

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