New Technology for Closed-Loop System Identification, PID Control Loop Optimization and Advanced Process Control

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Abstract: Ability to identify open-loop transfer functions using normal process data from a running plant is immensely useful. Open-loop transfer functions help to optimize PID tuning precisely, implement Advanced Process Control (APC) inside the plant's DCS or PLC, improve Model Predictive Control (MPC-DMC/RMPCT) performance by improving models and also build dynamic process control simulator for training. This paper shows a new and novel method of using complete closed-loop data without any intrusive step tests for model identification. The technique identifies multivariable open-loop models with slave PIDs in auto or even cascade modes and then shows how to optimize PID tuning and improve MPC models.

Keywords: PID tuning software, PID tuning optimization, closed-loop multivariable system identification, dynamic modelling, Advanced Process Control (APC), Model Predictive Control (MPC), DMC (Dynamic Matrix Control)

1. INTRODUCTION

Most chemical plants today are controlled by a DCS (Distributed Control System) or a PLC (Programmable Logic Controller). Data historians store process data conveniently available in Excel format. During the normal operation of a plant, control room operators make setpoint changes to adjust process and operating conditions required for making the desired product grades and achieving the desired production throughput. Slave PID controllers can be in auto or cascade with their setpoints manipulated by an operator, a DCS-resident APC scheme or a MPC like DMC or RMPCT. Identification of open-loop dynamic models in either transfer function format or step-response coefficient format can be easily done by conducting intrusive step tests on a slave control loop in manual mode or even step tests on the setpoint in auto mode. Technology and tools for open-loop tests and model identification has been used successfully for decades with good results.

However, multivariable identification of open-loop dynamic models with multiple inputs with the slave control loops in cascade mode is difficult. Using current methods, at best produces open-loop models with low level of confidence and uncertain results.

This paper describes an amazing new method capable of identifying multivariable open-loop transfer functions using completely closed-loop data with slave control loops in cascade mode amidst high frequency noise, drifts and unmeasured disturbances. No intrusive open-loop tests are required. The normal plant operating data can be used.

2. OPEN-LOOP DYNAMIC MODELS

Almost 98% of all dynamic relationships in chemical processes can be characterized by zero-order, first-order, second-order or open-loop unstable type transfer functions as shown in Figure 1.

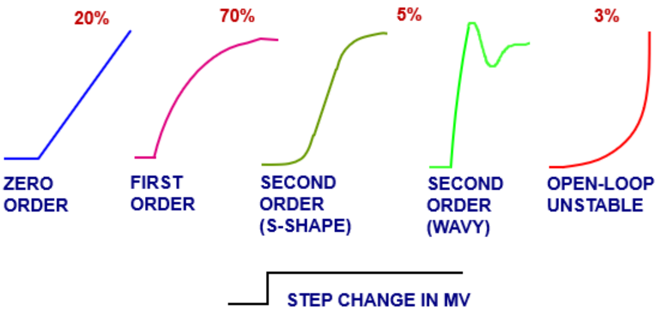

Figure 1. Open-loop dynamic models in chemical plants

The remaining 2% of models that show a very complex shape with inverse response and roller-coaster squiggly shapes are either not real, better off not used as a model in a MPC or could be represented as a reduced order model fitting one of the categories is Figure 1. Most higher order models can be reduced to lower orders by extrapolating the dead time and minor shape modification without losing significant model prediction accuracy.

Current system identification algorithms and software work well for simple cases shown in Figure 2 below. However, in many cases such intrusive step tests are hard to conduct due to process sensitivity and interactions. Step tests may cause product properties to change unacceptably. Normal plant operation involves ramping setpoints of slave PID controllers. With ramping there are no abrupt step tests and conventional open-loop model identification methods are not useful. During the normal plant operation, setpoints of multiple variables are changed often simultaneously. Multiple MVs can affect multiple CVs. Superimposed on these multivariable simultaneous changes are the menacing effects of unmeasured disturbances and noise. The new COLUMBO algorithm provides this new, novel breakthrough functionality.

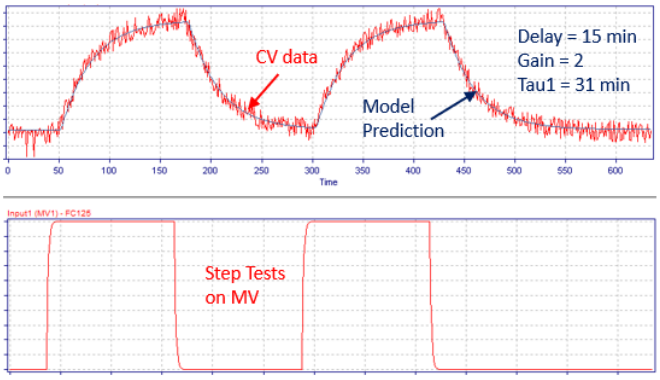

Figure 2. Conventional open-loop step tests

3. CLOSED-LOOP DATA FROM NORMAL OPERATION

Figure 3 shows control of hydrogen composition in a reactor. CV data are hydrogen composition. MV moves show hydrogen flow setpoint changes in cascade mode made by the hydrogen composition master controller in auto mode. This data is illustrative of typical and normal plant operation. At the very left is start-up followed by steady state and some planned setpoint changes. Strong unmeasured and unexplained disturbances are superimposed. This data would be considered “bad” or not “rich-enough” for identification of open-loop dynamic models. But the new COLUMBO algorithm is able to identify the open-loop transfer function as shown in Figure 3. The bottom-most trend shows the isolated unmeasured disturbance signal separated from the transfer function contribution.

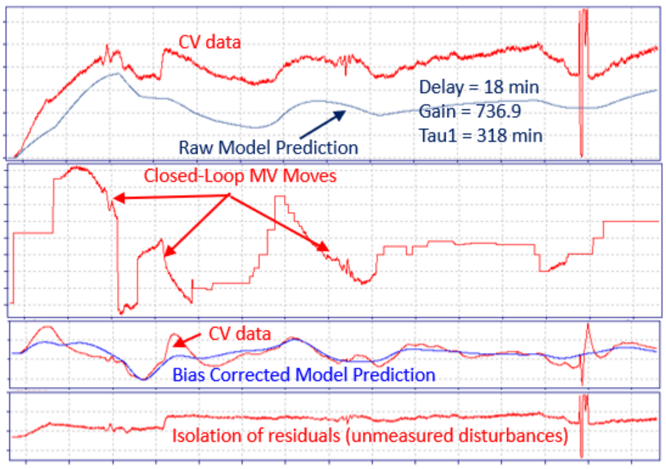

Figure 3. Closed-loop data from normal plant operation

Figure 4 shows another complex data set showing a master AC (analyzer controller) manipulating a slave FC controller. The changes in the CV value in the top trend is because of some setpoint ramping necessary for making the product grade changes. The data is oscillatory and full of unmeasured disturbances. The new COLUMBO algorithm is able to isolate the unmeasured disturbances (see the bottom-most trend in Figure 4) and identify the true open-loop transfer function model (delay = 15 min, process gain = 103.7 and first order time constant = 35 min). Conventional tools, algorithms and methodologies cannot make much out of such complex closed-loop data tainted by unmeasured disturbances and that’s why COLUMBO is a true breakthrough in process control with its ability to identify the true open-loop transfer functions using such closed-loop data.

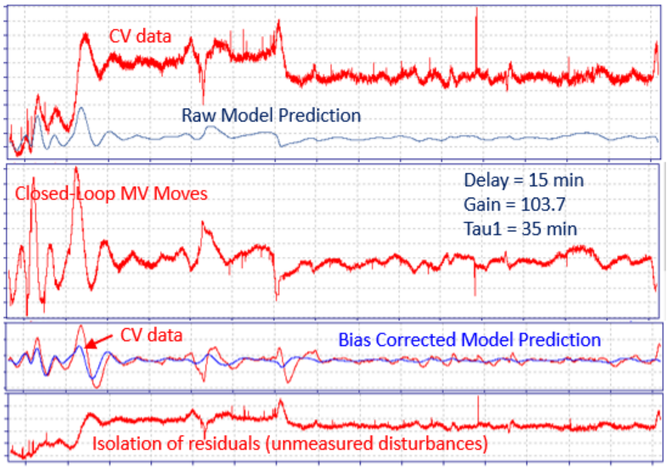

Figure 4. Closed-loop oscillatory data from normal plant operation

Figure 5 shows a master in auto mode and its slave PID in cascade mode. Some setpoint changes have been made to the master as part of the normal plant operation. There have been no new intrusive step tests conducted for model identification. Only normal plant data from normal planned operation is shown. With the slave PID in cascade mode and the master PID in auto mode, COLUMBO algorithm is able to identify both open-loop transfer functions: one from control valve to slave CV and the second from slave setpoint to master CV.

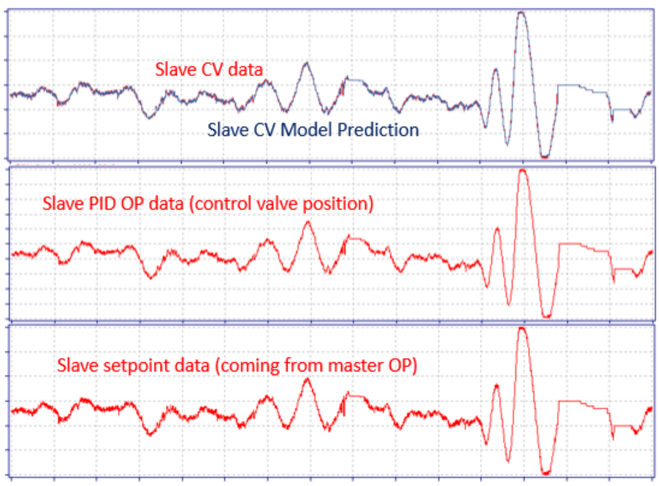

Figure 5. Master-Slave closed-loop data with master in auto and slave in cascade modes

Figures 6 and 7 show a spectacular example from a real plant distillation column. The column feed, reflux flow and reboiler duty change in a correlated manner – at the same time. A MPC (DMC) is on and makes changes to the slave setpoints with the slave PIDs in cascade/remote mode. Three open-loop transfer functions are simultaneously identified with completely closed-loop data. These identified open-loop transfer functions were used to modify models in the DMC. Control performance of the DMC improved after the models were changed with the newly identified models.

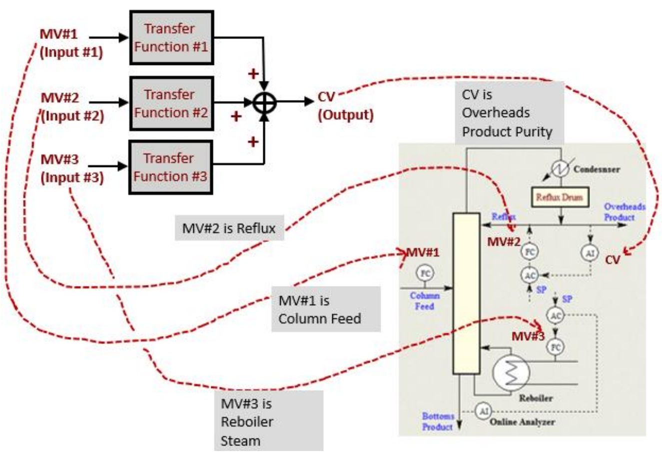

Figure 6. Multivariable closed-loop model identification

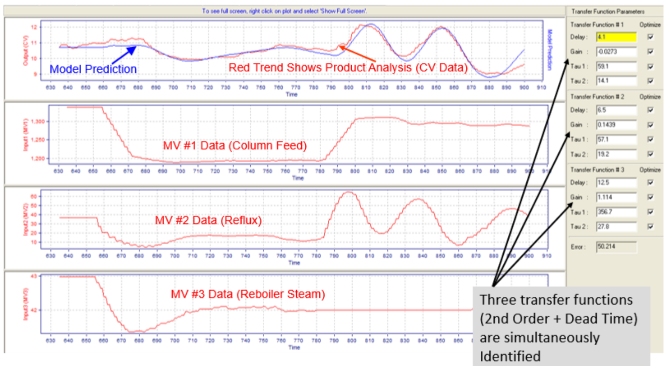

Figure 7. Multivariable model identification with complete closed-loop data

Figure 8 shows another spectacular example of the ability of COLUMBO algorithm to identify control valve stiction simultaneously along with the open-loop transfer function parameters with closed-loop data comprising of setpoint changes in auto mode. The ability of COLUMBO to identify control valve stiction with such normal operating data is extremely useful in chemical plants where old control valves can start deteriorating followed by loss of control quality. When slave PIDs deteriorate due to bad control valves, this also reduces control quality of an APC or MPC followed by lost profits and lost benefits.

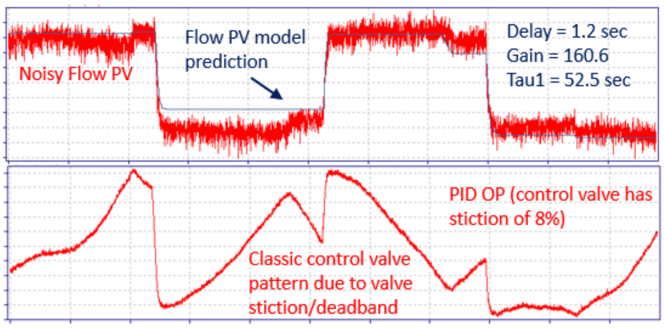

Figure 8. Identification of control valve stiction along with open-loop dynamic model for a flow PID control loop

4. ISOLATION OF RESIDUALS

Residuals are the unmeasured disturbances that creep into any process. A good example of an unmeasured disturbance is unknown and unpredictable changes in heating value of fuel gas to a furnace for temperature control. Current system identification algorithms are sensitive to unmeasured disturbances and can generate false models. COLUMBO has the amazing capability to isolate the unmeasured disturbances and high frequency noise while determining the accurate dynamic models. Figure 9 shows a simulation example comprising of a single step test on the MV. The CV rises and settles and then due to an unmeasured disturbance, the CV creeps down a little. Using conventional model identification algorithms will produce a low process gain but COLUMBO produces the correct process gain of 5 in this example and isolates the unmeasured disturbance shown in the bottom trend.

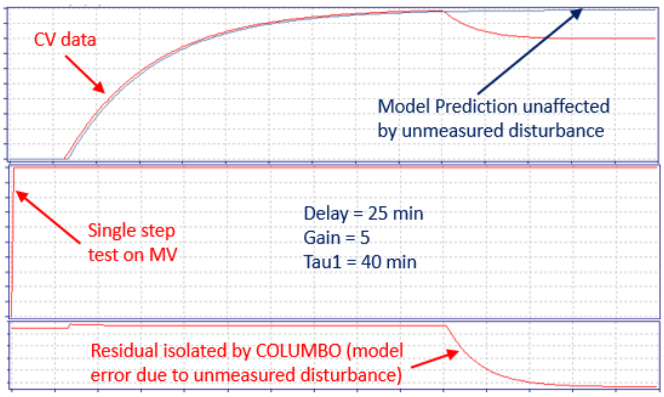

Figure 9. Isolation of unmeasured disturbances

5. PID TUNING OPTIMIZATION BASED ON CUSTOM SIMULATIONS

Most PID tuning done in the control room is still based on the age-old trial-and-error method or using some heuristics like IMC (Internal Model Control), Ziegler Nichols Open-Loop/Closed-Loop, Cohen Coon or Lambda tuning. These methods were satisfactory for many years but in recent times, plants are built to be more efficient using many recycle streams, process interactions and complex designs making some of the old PID tuning methods hard to use effectively. PITOPS tuning software offers new PID tuning algorithms and methodology that is easy to apply and effective on the newer, complex and interactive plant designs. Instead of using generic heuristic equations for tuning, PITOPS minimizes the error between the setpoint and PV based on configured custom simulation. A custom simulation comprises of typical setpoint changes done by the operators or a cascade PID, APC or MPC. Typical disturbances and noise seen in the real DCS or PLC screens and trends can be easily configured in PITOPS. Sometimes the goal is for the PID to respond well to step changes in the setpoint, sometimes may be the setpoint is ramped slowly. Sometimes setpoint of slaves need to respond fast based on their master PIDs. Sometimes, setpoints are never changed but the PID is often seeing severe disturbances that could be pulse, ramp or sinusoidal waves. External or unmeasured disturbances that appear as sinusoidal waves could be due to interaction from neighboring PIDs. Conventional PID tuning also leans on relative gain analysis and building two loops interacting with each other. The new and novel approach from PITOPS allows you to configure a typical setpoint change (step/ramp or complex trajectory), typical disturbances and typical noise followed by minimization of the error between the setpoint and the PV of the PID. This approach works well for slaves, masters, multiple PIDs, constraint override PIDs, any type and any combination of a chain comprising of one or more PID loops. Figure 9 shows a PITOPS PID tuning optimization example. Here the PITOPS optimizer minimizes the absolute error between the PV and setpoint for a simulation comprising of a setpoint change, ramp disturbance, pulse disturbance and noise in the sensor. The optimizer allows imposing a rate-of-change limit on the PID's OP so that abrupt valve changes will not disturb downstream units. PID tuning parameters from this approach are markedly superior to trial-and-error and heuristic-type of PID tuning methods.

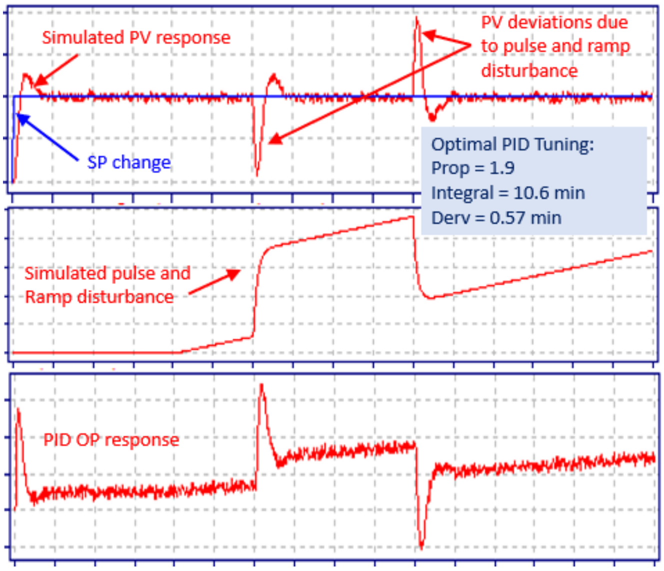

Figure 9. PID tuning optimization based on typical SP change, disturbances and noise as seen in real plant

6. Advanced Process Control (APC) Schemes inside a DCS or PLC

Knowledge of open-loop dynamic process models in the form of transfer function parameters can be used to design and implement powerful APC schemes inside a DCS or even a PLC. Many processes can benefit tremendously by implementing traditional APC comprising of multiple cascade PIDs, selector-based override constraint control schemes, model-based control schemes, inferential control schemes and virtual sensors. These can be built in a DCS or PLC without the need for a MPC. Many engineers resort to selecting and implementing an MPC instead of a DCS/PLC-resident APC because they do not have the skills and tools for identifying open-loop transfer functions for various MV-CV pairs. With COLUMBO for identifying transfer functions and PITOPS for APC design, compact, robust, reliable and easy-to-maintain APC schemes inside a DCS or PLC can be implemented at one fifth or less cost and effort compared to a MPC project. Many processes have a pseudo-diagonal control matrix where the density of the control matrix is low. Such processes are excellent candidates for a DCS or PLC-resident APC and can outperform a MPC and produce even more plant benefits and profits.

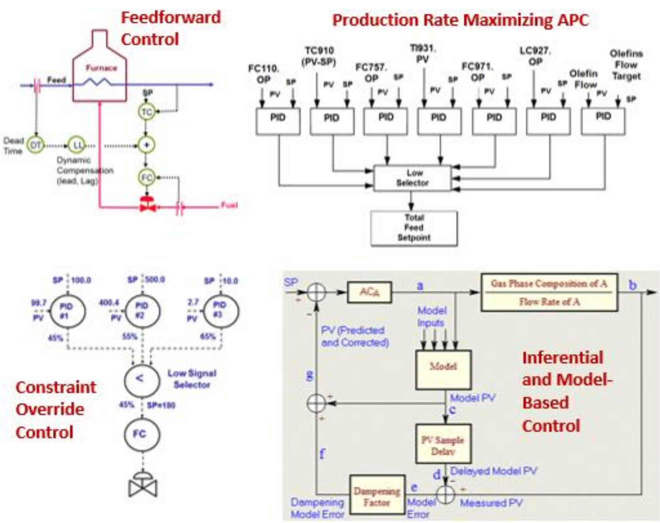

Figure 10. Traditional APC inside a DCS or PLC

7. IMPROVING MPC MODELS

MPCs like DMC, RMPCT, Connoisseur, PredictPro and others are based on dynamic process models based on step responses on various MVs. To generate good models, most MPC need uncorrelated step tests. Only one MV is stepped at a time. In order to identify the dynamic models accurately, holding each step anywhere from one-third to one-and-half times the time to steady state is recommended. Holding for such long time periods after each moves requires the step sizes to be small – typically only 1-3% of the prevailing values of the slave PID setpoints. When the MPC is on and working in closed-loop mode, the MV moves made by MPC can be significantly bigger compared to the 1-3% step tests during model identification. Nonlinearities and deviations from the simplified principle of linear superposition can cause the MPC models with larger and simultaneous MV moves to produce effects different from the identified open loop models. This is often why many MPCs need fine-tuning and improvements. COLUMBO is able to convert any MPC model into a best fit transfer function model. COLUMBO can use closed-loop data with a MPC running and improve the model prediction fit and subsequently the MPC models. This method is novel, unique and is the only method available for determining the real open-loop dynamic models based on large moves and correlated moves with several MVs moving simultaneously which is what happens when an MPC is on (active). See Figure 11 for an overview of COLUMBO.

8. COLUMBO and PITOPS Optimizers

Both COLUMBO and PITOPS are equipped with nonlinear constrained generalized reduced gradient (NC-GRG) optimizers. On top of the NC-GRG, PiControl has developed proprietary algorithms and code for working well with unmeasured disturbances, noise, closed-loop data with no step tests and processing of multivariable inputs. The technique has been proven and tested with real plant data with success.

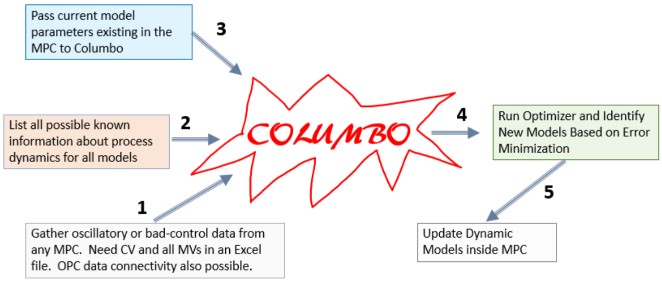

Figure 11. Steps using COLUMBO to improve MPC models

The COLUMBO approach offers a powerful unique capability that is truly a breakthrough. This is its ability to allow the user to fix or set constraint limits on the various model parameters. In some cases, the time constants can be calculated based on chemical engineering knowledge and first principles. E.g., knowing the gas phase reactor volume and dividing by the flow rate gives the time constant. Or dead time may be already known based on some prior tests. COLUMBO allows fixing certain known parameters and then searches for the unknown parameters. This approach helps to identify the true (more accurate) process gain of the model. Often, error in process gain estimation in dynamic models is the root cause of MPC or APC problems. Certain parameters can be fixed also based on information and knowledge of experienced process operators and engineers. Only COLUMBO algorithm allows reducing the uncertainty in the closed-loop optimization problem by incorporating process and dynamic knowledge based on various other sources and factors.

9. CONCLUSION

Most plants have the ability to generate Excel files containing MV, CV and FF (feedforward) data. The ability to identify open-loop transfer functions using complete closed-loop data with just the normal plant operation without any new intrusive step tests is a major improvement in the process control field.

System identification is inherently a complex area and COLUMBO makes the process easier and more successful compared to conventional competing approaches. COLUMBO offers the following functionalities:

- Identifies multivariable dynamic models
- Complete closed-loop data can be used from normal plant operation with some target changes
- Isolates unmeasured disturbances and noise
- Allows incorporating process knowledge, vessel geometry, chemical engineering first principles and vendor data and models into determining dynamic models and/or improving their accuracy.
- Works entirely in the time domain without need for complex math and no need for Laplace or Z (discrete) domain.

Pitops uses the NC-GRG (nonlinear constrained general reduced gradient optimization) method which does not need data conditioning or normalization (Sharmaa and Glemmestadb, 2013) compared to ARMAX, DMI, step response coefficient and impulse response methods (Peng et al. 2004).

REFERENCES

Chen, C.-L. (1989). A Simple Method for On-line Identification and Controller Tuning. *AIChE Journal*, Volume 35, Issue 12, 2037-2039.

Ljung, L. (1999). *System Identification: Theory for the User*, 2nd ed., Prentice Hall, New Jersey.

Escobar, M., Trierweiler, J.O. (2013). Multivariable PID Controller Design for Chemical Processes by Frequency Response Approximation. *Chem. Eng. Sci.*, Volume 88, 1–15.

Bucz, Š., Kozakova, A., Vesely, V. (2015). Ultimate Data Based Robust PID Design for Performance. 8th IFAC Symposium on Robust Control Design, *IFAC-PapersOnLine*, Volume 48, Issue 14, 221-228.

Wang, L., Freeman, C., Rogers, E. (2017). Experimental Evaluation of Automatic Tuning of PID Controllers for an Electro-Mechanical System. 20th IFAC World Congress, *IFAC-PapersOnLine*, Volume 50, Issue 1, 3063-3068.

Gao, X., Shang, C., Huang, D., Yang, F. (2017). A novel approach to monitoring and maintenance of industrial PID controllers. *Control Eng. Pract.*, Volume 64, 111-126.

Pitops user manual, "Process Identification & Controller Tuning Optimizer Simulator", version 1.4.5.0.

Sharmaa, R., Glemmestadb, B. (2013). On Generalized Reduced Gradient method with multi-start and self-optimizing control structure for gas lift allocation optimization. *J. Process Contr.*, Volume 23, Issue 8, 1129–1140.

Peng, H., Ozaki, T., Toyoda, Y., Shioya, H., Nakano, K., Haggan-Ozaki, V., Mori, M. (2004). RBF-ARX Model-Based Nonlinear System Modelling and Predictive Control with Application to a NOx Decomposition Process. *Control Eng. Pract.*, Volume 12, Issue 4, 191–203.