Challenges and problems with advanced control and optimization technologies

Campos, M.*, Teixeira, H.*, Liporace, F. and Gomes, M.****

** PETROBRAS / CENPES / Engenharia Básica Abastecimento e Gás&Energia/ Automação, Equipamentos Dinâmicos e Confiabilidade, Av. Horácio Macedo, 950 - Cidade Universitária, Ilha do Fundão, Rio de Janeiro, 21949-915, Brazil (Tel:55-21-3865-6347; e-mail: mariocampos@petrobras.com.br).*
*** PETROBRAS / CENPES / P&D de Gás, Energia e Desenvolvimento Sustentável / Gás Natural / Célula de Otimização e Eficiência Energética, Av. Horácio Macedo, 950 - Cidade Universitária, Ilha do Fundão, Rio de Janeiro, 21949-915, Brazil.*

Abstract: Oil & Gas companies continuously try to create and increase business value of their installations (platforms, refineries, etc). Particularly the increasing energy consumption on a worldwide basis and, as a result, the substantial increase in prices volatility is a major drive for better advanced control and optimization technologies. Advanced control and optimization system can play an important role to improve the profitability and stability of industrial plants. This paper discusses the problems and challenges of advanced control and optimization in petroleum industries nowadays. It emphasizes the importance of control performance assessment technology to maintain a good regulatory control and the difficulties in using these technologies. It also shows the importance of malfunction detection and diagnosis advisory system for critical equipment in order to increase the operational reliability. Model predictive control (MPC) has become a standard multivariable control solution in the continuous process industries, but there are still many open issues related to accelerate a new implementation and maintain the controller with a good performance along the years. Real time optimization tools also impose new challenges for Oil & Gas industries application, which are discussed in this paper.

Keywords: performance assessment, regulatory control, advanced control system, real time optimization

1. INTRODUCTION

The advanced control and optimization systems in oil & gas and petrochemical plants are an industrial reality (Qin and Badgwell, 2003). These advanced systems provide many advantages for the process units, as improved stability and safety, respect to constraints and higher profitability. PETROBRAS has been investing in the development of these systems for several years. Advanced control system is already a consolidated technology in its refineries with many model predictive controllers implemented (Zanin and Moro, 2004). However, the application of real time optimization (RTO) is recent, although this technology can bring great economical earnings, besides to increase the energy efficiency and minimization of emissions.

To install and maintain these advanced systems with good performance is a great challenge. Its performance is influenced by instrumentation problems, bad tuning of the regulatory and advanced control, unreliable process dynamic models (Ender, 1993; Kern, 2007), unmeasured disturbances, etc.

This article will discuss the problems and challenges of advanced control and optimization in petroleum industries nowadays. It discusses some tools for diagnosis and tuning of the regulatory and advanced control, and the challenge associated with the real time optimizers. In spite of the several tools in the market that deal with industrial control and optimization solutions, PETROBRAS has decided to invest on the development of its own tools and solutions in many situations, usually in association with some Brazilian universities. The goal of this paper is to show some challenges faced, solutions and results obtained in PETROBRAS facilities.

2. REGULATORY CONTROL LEVEL

Process control aims to maintain certain variables within their desirable operational limits and could be visualized as a pyramid. In the base of this pyramid, the first level is the regulatory control, that uses PID controllers (Campos and Teixeira, 2006; Ogata, 1982) and is configured in the digital systems (DCS - Distributed control system or PLC - Programmable logical controllers). In a second level, we have the advanced control systems that use for instance Model Predictive Control (MPC). This algorithm considers the interaction between control loops, and includes an optimization layer of the industrial plant. These algorithms are usually implemented in a process computer that communicates with DCS or PLC systems by the use of OPC protocol (OPC, 2008). The outputs of this advanced control are usually the set points of the PID controllers. The architecture is conceived in such a way that if there is a failure in the advanced control level, the plant operation continues with the last PID set points in the DCS.

An advanced control system won't reach the expected benefits if is turned off constantly for the operators. Therefore, the instruments, valves and the regulatory control loops (PIDs) should operate appropriately. Hence, the performance of the regulatory control is fundamental for the success of the advanced control system. An industrial plant usually has hundreds of control loops, and less and less engineers to maintain the system. Therefore, the industries need tools to perform automatic analysis and diagnoses of the problems associated with the regulatory control. For example, these tools should be able to detect failures with the instrumentation (miscalibration, badly sizing, sensor noisy, out of scale, measurement resolution, etc.), non linear behavior in the process due to changes in the operational point, bad PID tuning (oscillation, stability, etc.) and control strategy problems (coupling between control loops, degrees of freedom, etc.).

There are several tools in the market that help engineers to maintain the regulatory control, but most of them require a well-trained engineers to interpret, analyze and define the correct actions, for instance: to change a control valve, tune PID controllers or to implement a new control strategy (decoupling, feedforward), etc. These engineers should also know very well the process in order to evaluate the better actions to be taken.

The great challenge for these tools will be to incorporate more "intelligence" to help engineers in the definition of the better actions. For instance, in certain case, only PID tuning could reach 80% of improvement in process variability reduction, and in some case, the process performance would improve only 10%. A lot of times in industries the engineer spends time and money with an action that won't bring great results. So, it is clear the importance of a tool that could perform the automatic diagnosis and assessment of the regulatory control (Farenzena et al., 2006). The most important features of this tool should be to have automatic ways to prioritize the actions for each process that might result in a better performance, and also to provide a standardized metric to compare different actions in different processes, even in different scales such as economical, environmental or safety (Harris, 1989; Kempf, 2003; Farenzena and Trierweiler, 2008). These features are a great development challenge for these tools.

Despite the several tools in the market, PETROBRAS and Federal University of Rio Grande do Sul (UFRGS) have developed their own tool, the software called “BR-PerfX”. Its main purpose is to compute some universal key performance indicators that reduce the subjectivity in the analysis and help engineers in their assessments and decisions about problems affecting the regulatory control.

In order to face the PID tuning problem, PETROBRAS and Federal University of Campina Grande (UFCG) developed the software "BR-Tuning" (Schmidt et al., 2008; Arruda and Barros, 2003), which is comprised by a group of techniques regarding open and close loop identification and the proposition of new tuning parameters. It communicates directly with the process automation system (DCS or PLC) using the OPC protocol.

As it was said previously, the challenge is to develop an "intelligent" layer that helps to make a diagnosis based on several indexes or indicators. The integration between different tools is also an important concern. The use of the OPC standard for the exchange of information could be an option. So, each tool could make available their indicators to others tools through OPC. This way, the engineers' work would be facilitated, avoiding losses of time and money.

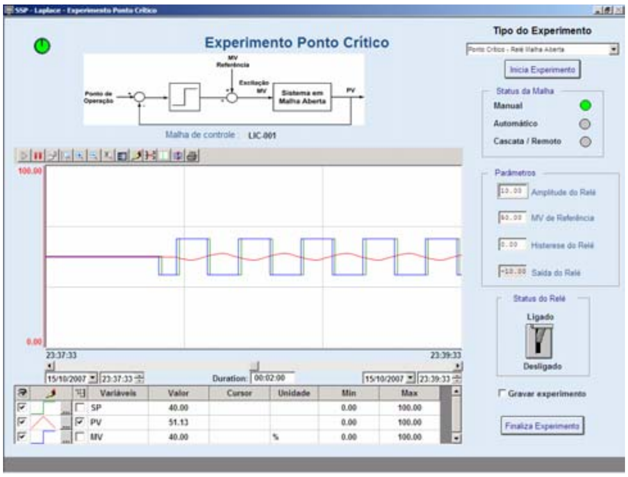

Fig. 1. BR-Tuning interface**.**

The challenges in relation to controllers' tuning are associated mainly with the identification of the models, the determination of the process non-linearities, interaction between control loops, as well as defining the desired performance for each control loop.

There are some processes where the disturbances’ pattern can change with the time, as in some off-shore petroleum platform. The slug flow can change its intensity for example due to changes in the gas-lift. So, we don't have a PID tuning parameters that are good for all these different situations. In this case, it was developed an "intelligent" system that supervises the process plant and changes the PID tuning automatically when necessary. This control strategy is equivalent a "gain-scheduling" where the control performance (deviation between the process variable and the setpoint) is evaluated during a time, and the system decides what is the best tuning for that moment. All the possible values for the PID tuning are chosen off-line. This system was installed in several PETROBRAS' platforms. The figure 2 shows the system changing the PID tuning parameters and the level performance. This project used a tool called MPA, which was developed by Catholic University of Rio de Janeiro (PUC-RJ) to PETROBRAS.

Another challenge is the development of non-linear controllers for some special cases, for example to pH control in certain plants, although PID will continue to be the algorithm more used in this regulatory layer control for several years.

Researches and developments for the regulatory control level are still necessary, and they can bring great economical earnings. For example, an application of these tools (evaluation, tuning and changes in control strategy) allows an increased of about 9% in the production of LGN (Liquefied Natural Gas) in a natural gas plant (Campos et al., 2007).

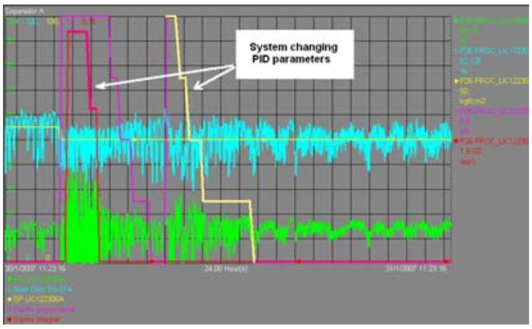

Fig. 2. Performance of this control strategy in production platform (1 day).

3. ADVANCED CONTROL SYSTEM

The multivariable predictive controllers (MPCs) are powerful tools for the process optimization and are available in many industrial plants. This system can increase feed and preferred product rates, reduce energy consumption and waste material. These benefits are more visible in complex processes where challenging dynamic responses (significant time delays, non-minimum phase responses, control loop interaction, etc.) due to disturbances (feed flow and composition, energy integration, usefulness, etc.) that must be dealt with while taking into account process constraints and trying to pursue the best economic performance. As an example of the benefits achieved, figure 3 shows an increase of about 16% in the LPG yield due to the implementation of an Advanced Process Control (APC) system in a natural gas plant.

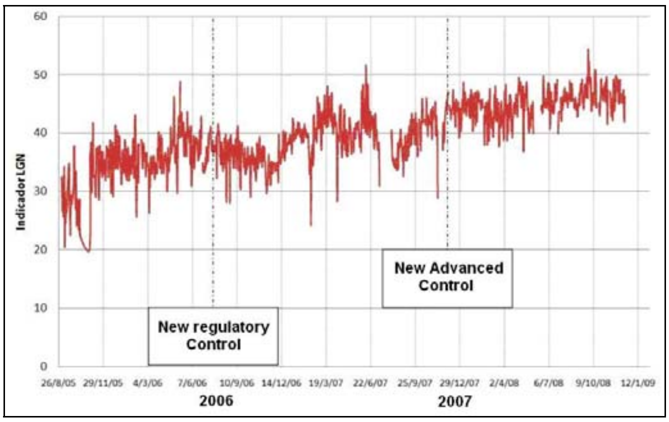

Fig. 3. LPG yield increase in a natural gas plant due to MPC.

However, even if MPC systems are nowadays seen as a commodity, there is still much to be done, due to the significant gap between the recent MPC technologies development in the academy and those effectively used on industrial plants. Most industrial MPC applications are based on the most traditional approaches: linear algorithms based on step-response models obtained through traditional step tests.

MPC maintenance

MPC performance decay throughout time is a well-known and widely reported fact (figure 4). If no maintenance work is done, the operators end up turning them off. There are many causes for this behaviour:

- Changes in the units operational objectives;
- Equipments efficiency losses (fouling);
- Changes in the feed quality;
- Problems in instruments and in the inferences;
- Lacks of qualified personnel for the controller's maintenance.

Therefore, the first great challenge associated with MPC control is to have reliable tools to keep performance and diagnose problems.

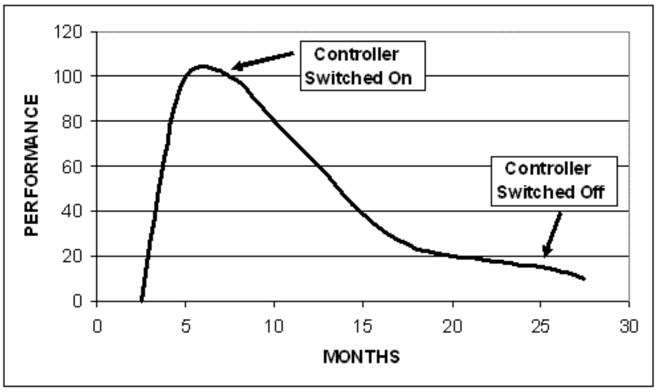

Fig. 4. Advanced Control Performance during the time.

Therefore, industry needs better tools to help maintenance personnel to answer the following questions:

- Is advanced control system accomplishing their objectives?
- What is its performance?
- Is the process optimized?
- What are the benefits?
- How is the level of disturbances?
- What is operational factor of the controller?
- How are the operators adjusting the limits of the manipulated variables?
- Are manipulated variables very limited?
- What is the variability of the main controlled variable?
- Is the process operating close to the constraints?

It is necessary a tool not only to answer these questions, but the system point out the causes of the bad performance: bad models, bad controller tuning, inference problems, non-linearities, frequent changes in the operation point, new constraints not considered in the design?

Nonlinear models, Identification and Model mismatch

Many different and even sophisticated approaches have been proposed in order to allow MPC algorithms to cope with process nonlinearity. Bequette (2007) presents a recent review on the subject. However, despite all this effort, industrial Nonlinear MPC (NMPC) applications are relatively few, and most of these are based on the simplest approaches.

One possible reason for that might be simply that the nonlinear behaviour is not known, and any lack of performance is seen as a typical model mismatch.

Another possibility might be that the nonlinear behaviour is known, but can not be easily determined with traditional plant tests. One way to overcome these problems might be the use of rigorous dynamic simulators, to improve the understanding of the process behaviour. Information obtained with dynamic simulation could be combined to the existing linear model in order to provide a reliable nonlinear one. Dynamic simulation might be useful also to find out the best way to characterize the observed nonlinearity. Once more, although there is availability of dynamic simulators, there is not much use of them in industrial applications.

Process identification of complex processes is still a hard task, where a significant part of the effort on MPC implementation is spent.

In order to address this problem, some commercial tools have been conceived in this decade for closed-loop identification. These tools are based on efficient ways to perform step tests allied to modelling strategies for minimization of the model order. While this approach has proved to be useful and promising, it is still a hard task to apply these techniques to complex processes, especially when dealing with noisy data. It seems to be a lot of space for development in this area.

Another interesting way to reduce implementation time can be the use of algorithms for automation of the plant test.

Tuning

MPC tuning is another interesting issue, where new technologies might help to reduce implementation time and also on the maintenance task.

Some interesting ideas have been proposed (Trierweiller and Farina, 2003) that try to combine desired and achievable performances. However, the controller tuning still consume time and is critical points for controller performance. Normally, all MPC tuning methods consider a square controlled variables x manipulated variables matrix, but, in fact all controller has a rectangular matrix that means different tuning scenarios depending on which constraints is active.

Another big challenge is to reduce the application time and maintenance time. For this, it is believed that the main critical points are:

- Tools for the development of inferences:
  - Use of rigorous dynamic simulators, or statistical methods for better inferences using less laboratory analysis data.
- Dynamic models identification:
  - Automation of the identification tests, minimizing problems and loss of data;
  - Efficient tools for closed loop identification;
  - Characterization and identification of the non linearities of the process.
- Better tools for tuning the predictive controller:
  - How to define the priorities in the several operating points of the controller and change automatically the tuning parameters. This activity is still done by trial and error in many industrial cases.

New advanced controllers that contemplate these aspects will help the users to implement and maintain these industrial systems.

4. REAL TIME OPTIMIZATION

Real Time Optimization (RTO) technology is a powerful tool for the continuous search of the most profitable way to run petroleum and petrochemical process units. Cutler and Perry (1983) state that despite being a hard and complex task, its potential benefits are relevant and might provide profit increases around 6 to 10% when allied to Advanced Process Control (APC).

The task of an RTO application is to make the best of an existing process unit, adjusting its process variables for every new change of external conditions, like operational variables, feed compositions and process constraints. The RTO benefits are usually associated with the maximization of products and minimization of the specific energy consumption and other resources, depending on the following factors:

- Market availability
- Products prices and feed costs
- Safety and environmental constraints
- Product specifications

The central figure of an optimization application is the mathematical model. It is expected to represent the process behaviour on a wide range of operating conditions with good accuracy. It should not only guarantee that the predicted potential profitability matches that of the real process, but also that when the optimal solution is implemented the process constraints must not be violated. Most RTO systems used nowadays are based on rigorous, steady-state, first-principles mathematical models.

The good performance of an RTO system depends on a reliable mathematical model and on reliable input data. In order to obtain that, many procedures must be executed before the economic optimization problem can be solved:

- Gross Error Detection
- Steady-state Detection
- Data Reconciliation
- Parameter estimation

Once that a reconciled data set and a fitted model have been obtained, the process optimization can be performed. The optimization problem usually consists of the maximization the operational profit (or minimization of operational costs) subject to a set of constraints. On most situations the optimization problem is posed as a non-linear programming problem (NLP). Most commercial applications are based on variations of the SQP (Successive Quadratic Programming) algorithm. This algorithm is also used to solve the previous Data Reconciliation and Parameter Estimation problems.

Real Time Optimization at PETROBRAS

Since 2004, RTO has been classified by PETROBRAS and its Strategic Downstream Committee as a “High Sustainable” technology. It means that RTO is seen as a key technology to improve PETROBRAS performance and profit, and therefore significant effort and resources will be spent on this subject.

PETROBRAS implementations on RTO covered a wide range of alternatives, focusing both on profitability and on the search of the best way to deliver the technology:

- Fluid Catalytic Cracking (FCC) and Crude Distillation Units (CDU);
- Proprietary and commercial process models and RTO systems;
- Sequential Modular (SM) and Equation Oriented (EO) approaches (Alkaya et al., 2003).

The first RTO initiatives were taken using PETROBRAS' in-house process simulator for FCC, with a small scope covering only the reactor/regenerator section. The proprietary process model used is based on a Sequential Modular (SM) approach. Though many difficulties were found (see next section), this initiative made possible to test the technology as well as to help our engineers to take a step further.

Distillation Unit / SM approach (2004)

This implementation took place at the Crude Distillation Unit (CDU) and the two Solvents Units of RECAP refinery (Gomes et al., 2008).

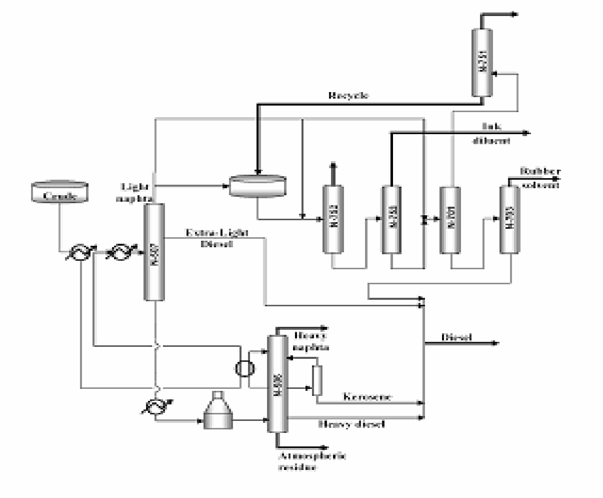

Fig. 5 - Scheme of the CDU and the Solvents Units of RECAP/PETROBRAS.

The process model was built using PETROX, a proprietary sequential-modular process simulator from PETROBRAS. The simulation comprises 53 components and pseudo-components and 64 unit operation modules, including the 7 distillation columns and a recycle stream. All modules are built with rigorous, first-principles models.

For optimization applications, PETROX was linked to NPSOL, an SQP optimization algorithm. Procedures for Steady-state and Gross error detection, Data Reconciliation, Parameter Estimation and Economic Optimization were implemented. The economic optimization problem consisted of the maximization of the operational profit, constrained by limits related to product specifications, safety constraints, feed rate and performance parameters. The whole optimization problem involves 19 decision variables and 21 constraints.

Most of the reported problems of optimization based on sequential-modular models were observed in this application:

- Low computational efficiency, due to slow recycle loops and the numerical derivatives that imply running the SM model several times. These derivatives are also inaccurate, which slows down the optimization process even more.
- Lack of reliability: the SM model is computed many times and must converge always. If a single failure happens during the optimization, all the effort is lost.

In order to minimize these problems, a lot of effort must be spent on the conception, customization and tuning of the SM model. However, that is no guarantee of success. When the Data Reconciliation and Parameter Estimation problems were implemented, the same problems were observed.

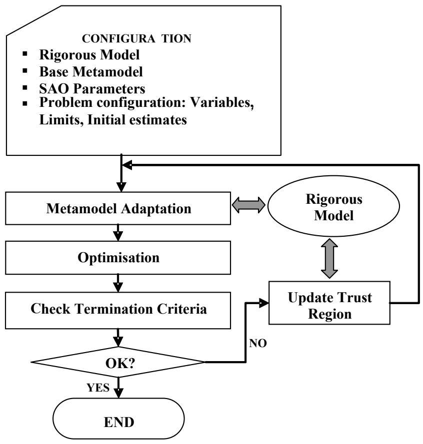

Fig. 6 - SAO strategy applied to the metamodel-based optimisation.

Metamodel approach

In order to overcome some of these shortcomings, a metamodel approach has been studied. Metamodels or surrogate models (Gomes et al., 2008) are reduced models whose parameters are obtained with data that is generated with rigorous, first principles models. In this work, an optimization procedure was developed, combining metamodels and rigorous models with a Sequential approximate optimization (SAO) algorithm. The optimization problem is solved based on the metamodel that is updated with data obtained from the rigorous model throughout the optimization procedure. The RECAP optimization problem was addressed with this approach, with kriging models and neural nets used as metamodels. Accurate results have been obtained with considerable reduction of the computational effort on most of the studied cases.

Distillation Unit / EO (2005 to 2006)

This was the first EO RTO project PETROBRAS implemented. After an International Bid, where 3 well-known companies were invited to submit their proposals, AspenPlus Optimizer (Aspentech, Inc.) was selected. The project scope included all 3 preheat trains as well as Pre-flash, Naphtha Stabilizer, Atmospheric, Vacuum and Pre-vacuum distillations towers. The unit was fully modeled with the RTO software, which allowed for instance the understanding about the implications that changes on the preheat train, like feed distribution, have on the Atmospheric tower. Or to study the best pumparound heat removal distribution along this tower and its effects on the preheat train. In order to do that, all pumparounds were modeled as external streams from the tower and not as an internal model within its model (see Figure 7), as it is common on SM simulators.

The system is running on open loop since 2007. A few closed-loop tests were performed, but the unit had some operational problems which were solved on this last Oct/08 turnaround. PETROBRAS intends to close loop in 2009 after making model tuning adjustments in order to incorporate the new atmospheric trays and other unit improvements. Nevertheless, by keeping the system running open loop (around 9 runs / day), we were able to improve our knowledge of the system itself, how to overcome non convergence problems (feed reconciliation and optimization) and attaining expertise on how to maintain such a real time, strongly data and instrumentation dependent system as well as evaluate potential benefits (around 13 000,00 dollars / day).

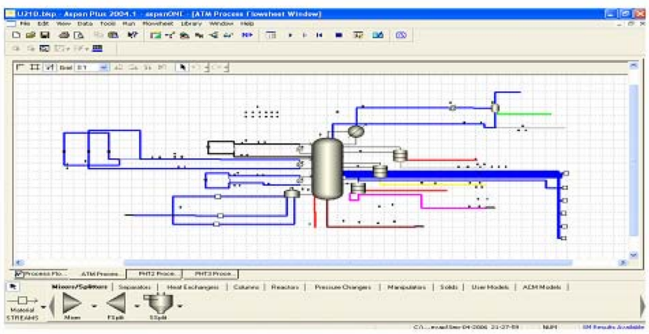

Fig. 7 - Aspen Plus Optimizer Screenshot - Atmospheric tower.

FCC Unit / EO (2007 to 2008)

Following the success on the distillation unit implementation, PETROBRAS moved forward to implement an RTO on another very important unit. Again, after an international bid, ROMeo (Invensys, Inc.) was selected.. The project scope included the Reactor / Regenerator section, Main Fractionator and Gas Recovery Plant. Again the unit was fully energy and mass integrated modeled.

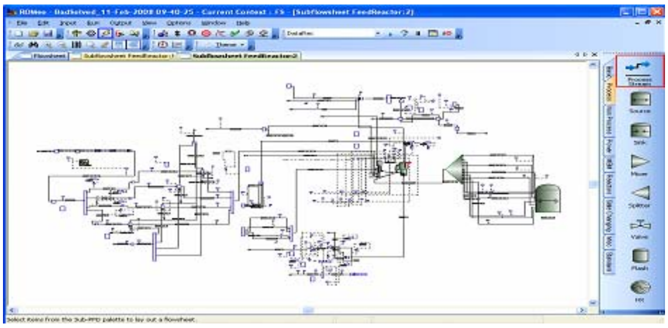

Fig. 8 - ROMeo screenshot - Reactor/Regenerator Section.

The system is running on closed loop (around 8 runs / day) since June/08 with most of the independent variables active. On average, around 60% of the successful runs are being accepted by Operations and targets are being sent to Advanced Control. PETROBRAS has evaluated an average gain of US$ 0.12 / bbl of FCC feed for this application, by comparing the unit performance with and without RTO.

A few comments on both projects:

- Lack of instrumentation on preheat train (FCC) – implied on simplifications, which has impacts on Main Fractionator heat balance and, thus, must be evaluated from time to time;
- Low feed lab analysis frequency – There is a need for a better way to estimate feed characterization;
- Non-convergence problems - Mainly, due to instrumentation faulty and/or out of service heat exchanger or other piece of equipment. Although there is a kind of standard procedure to deal with them, it is not possible to automate it. So each problem must be solved on a case to case, hands-on basis.

These facts enforce the need for a fully dedicated RTO engineer for each application, not only to assess its results and make sure they are being implemented, but to keep the system running despite of the many daily issues the application faces.

Modelling approach

PETROBRAS experiences showed that the Equation Oriented (EO) approach is more suitable for RTO, when compared to the Sequential-modular process models, especially when process unities of higher complexity are addressed.

Challenges associated with RTO

Non-convergence tracking

When the optimization process brakes down due to non-convergence, it is sometimes a hard task to find out the origin of the failure, especially when the cause of the problem is not related to instrumentation or well-known process problems. Therefore, there is a need for better procedures or even an expert system that might identify the numerical failures and provide high-level analysis to support the user on the best actions to take.

The improvement of the initialization techniques (Fang et al., 2009) might also be useful to avoid convergence problems, especially for the data reconciliation problem.

Scaling

Scaling of variables is a subjective issue. Despite the available heuristic rules provided by the technology licensors, the users are sometimes required to define scaling factors or limits. However, it is possible that a numerical analysis of the system of equations to be solved might provide the best scaling factors.

Integrating multiple process unities

In order to take the most of process flexibilities, it might be important to expand the scope of the optimization problem to involve more than just one process unit. However, the increase of the problem size and the consequent shortcomings can be a challenge to be faced. In this case, the non-converge tracking procedures would become a key issue.

Steady-State detection

The steady-state detection procedures used nowadays in the commercial solutions require the definition of several parameters, which is a very subjective issue. This task demands from the user not only process experience, but also a long time of observation. It would be useful to have procedures that could drive a straightforward choice, especially when dealing with multiple-process optimization applications.

Multi-scale optimization

The integration and information exchange between different optimization levels is an issue that requires more attention.

Multi-level optimization concepts could be applied in order that procedures for model re-fitting or tuning and the redefinition of search spaces could be done automatically, while the different optimization problems are being solved.

Dynamic RTO

Dynamic Real Time Optimization (DRTO) is an open issue. The use of rigorous dynamic models for large-scale applications might allow the simultaneous solution of process optimization and control problems. Ideally it would also avoid the requirement of steady-state detection procedures. However, with the present resources, DRTO solutions would demand a significant computational effort and, possibly, many numerical issues should be addressed before this technology can be widely used in industrial applications.

5. CONCLUSIONS

This article has discussed some challenges associated with advanced process control and optimization in petroleum industries as well as how PETROBRAS is overcoming them. Our vision is that there is still plenty of space for further nd research and development on the improvement of those technologies. The best accomplishment of this task will come if Industry and Academy work together.

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