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REAL TIME OPTIMIZATION AS A TOOL FOR INCREASING PETROLEUM REFINERIES PROFITS

Saeid Shokri *, Reza Hayati, Mahdi Ahmadi Marvast, Mohammad Ayazi, Hamid Ganji

Research Institute of Petroleum Industry (RIPI), Tehran 14665-1998, IRAN
Email: shokris@ripi.ir

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Abstract

The increasing competition in refinery industries, reducing refinery plant's costs, minimizing measurement errors and environmental issues lead to growing interest in modeling, simulation and optimization of refineries. Real time optimization (RTO) of the process units is one of the most effective ways for enhancing economic performance and reducing overhead costs of chemical plants. This method has a fully automated system, which intelligently collects and processes main outputs of the plant. Modifications of plant operating conditions have been implemented in order to reduce costs and meet constraints. Many objectives can be reached by implementation of RTO in refinery industries such as: automatically optimizing plant's performance, automatically performing fault detection, elimination and modification of random errors (Data reconciliation), modification of nonrandom errors (Gross Error Detection), intelligent computation of data which are not measurable, calculating and reporting consumption of raw materials, products production and energy consumption of the entire plant and the equipments at any time. In this article we studied the RTO implementation profits in oil industries and the effect of different parameters on the refinery processes performance. The medium term plan of the Research Institute of Petroleum Industry (RIPI) on developing RTO technology in IRAN oil industry is presented.

Keywords: Simulation; Real time optimization; Profit, Refinery.

1. Introduction

Chemical and petrochemical process industries are increasingly compelled to operate profitably in a very dynamic and global market. The increasing competition in the international arena and stringent product requirements mean decreasing profit margins unless plant operations are optimized dynamically to adapt to the changing market conditions and to reduce the operating cost. Hence, the importance of real-time or on-line optimization of an entire plant is rapidly increasing. Applying this technology to oil refineries has the potential to provide competitive benefit for oil refiners.

Real Time optimization (RTO) is an effective approach for economic improvement and source reduction in chemical and petrochemical plants. Real Time optimization uses an automated system which adjusts the operation of a plant based on product scheduling and production control to maximize profit and minimize emissions by providing optimal set points to the distributed control system. This optimization approach is an attractive research field of computer aided process engineering (Marlin & Hrymak[9], Perkins[12]. The decrease in hardware and software costs has resulted in several implementations of this technology, showing quite attractive economical results (Basak et al. [2], Lauks et al.[6],White[14]). The efforts in this area have been focused on specific components of the system, to mention data acquisition and validation, gross error detection, data reconciliation and, of course, modeling and optimization (Bagajewicz[1], Brown & Rhinerhart[3], Crowe[4], 1996). Besides, particular attention has been paid to the effects of uncertainty and noise over the final implementation (Forbes & Marlin[5], Loeblein & Perkins[8], Miletic & Marlin[10], Yip & Marlin[15]). Also numerous successful applications of the RTO in oil refinery industry have been reported (Lid & Strand[7], Zanin et al.[16]).

The objective of this paper is to demonstrate that using real time optimization technology in some industries can improve the their performance and increase profit by reducing the offset and maintain the process in optimum condition in spite of unknown disturbances or changing in desired operating point.

2. Elements in the RTO loop

Real-time operations optimization relies on model updating as feedback that corrects for model errors and disturbances and enables the RTO system to closely track the true plant optimum. A typical structure of an RTO loop is shown in Fig. 1.

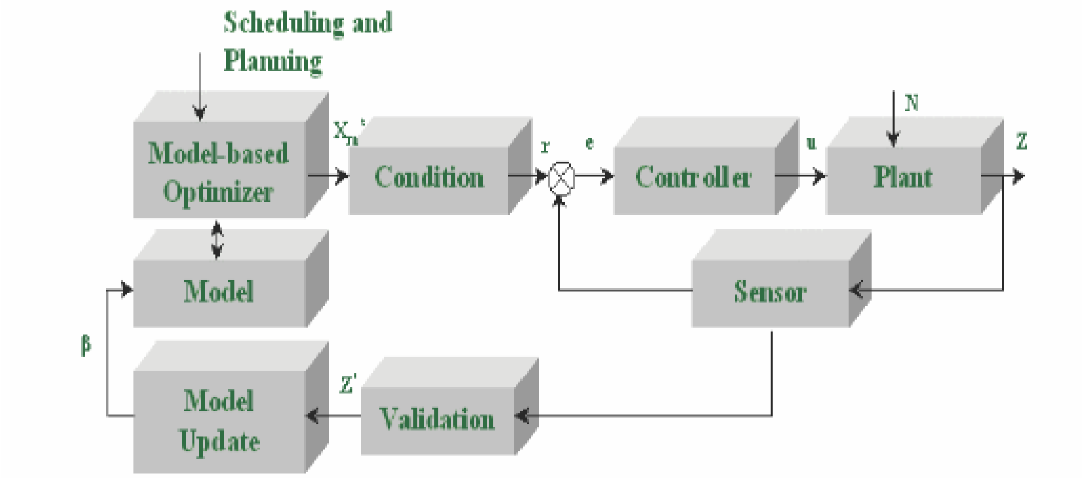

Figure 1. Typical Architecture of Real-Time Optimization

The main elements in the RTO loop consist of the model updater, model-based optimizer, results analysis and process control. Real-time measurements, z, are collected via the distributed control system, checked for reliability and low pass filtered. Then, the process parameters, β, are estimated using the data in the model updater. The estimated parameters are then sent to the optimizer, in which model-based optimization is performed. In the results analysis, statistical tests are used to evaluate the optimizer results before the values are transmitted to the process controllers. Only significant changes in optimization variables are forwarded to the process controllers for implementation.

Main applications of real time optimization can be stated as follows:

- Elimination and modification of random errors
- Dynamically describing performance deviation of key equipment from their set points.
- Automatically optimizing plant's performance
- Automatically performing fault detection (instrumentation's mal function, leak)
- Intelligent computation of data which there measurements are unavailable (temp. pressure, flows)
- Calculating and reporting consumption of row materials and production of product at any time
- Assessing energy consumption of the entire plant and the equipments at any desired time instant
- Determining equipment's performance loss over time (reactors, exchangers, columns)
- Studying and monitoring history of the equipments and monitoring.
- Sending computed data and results via computer networks to the desired locations in the plant.

3. Data Reconciliation

Real Time optimization heavily relies on process measurements and accurate process models. Process measurements are inevitably corrupted by errors during the measurement itself but also during its processing and transmission stages. The total error in a measurement, which is the difference between the measured value and the (definitely unknown) value of a variable, can be conveniently represented as the sum of the contributions from two types of errors: random and gross errors. Random errors which are inherent to the measurement process are usually small in magnitude and are most often described by the use of probability distributions. On the other hand, gross errors are caused by nonrandom events such as instrument malfunctioning, miscalibration, wear or corrosion of sensors and so on. The nonrandom nature of these errors implies that at any given time they have certain magnitude and sign which may be unknown. Thus, if the measurement is repeated with the same instrument under identical conditions, the contribution of a systematic gross error to the measurement value will be the same (Narasimhan & Jordache[11]). It is the reason why gross errors are also called systematic errors or biases.

The process in which the accuracy of data could be improved by detecting two mentioned types of error and eliminating them is currently known as Data Reconciliation (DR) which is an important foundational activity and performed in Validation block shown in fig. 1. The estimates of unmeasured variables as well as model parameters are also obtained as a part of data reconciliation problem.

There are several proposed methods for accomplishing this important stage but we are not aim to explain them here. This paper just aim to show the importance of doing this data processing phase.

4. Some Industrial Cases

Some industrial units using RTO as tool for increasing their economic profit are mentioned in Table1. Some important points could be implied from data collected in this table:

1. Against the most of new technologies tested in developing countries for insuring profitability, RTO technology was implemented on units in developed countries even for testing. It shows that applicability of this new technology is trustable and scientists and engineers who live in developed countries need not to test this method on the industrial units of developing countries.
2. These results are reported by industrial units on which RTO technology has been implemented not companies who are the owner of this technology so these results are very likely to be correct.
3. It could be seen that the payback period of RTO technology is short. It has positive impact on general improvement in overall industry economics.

Table 1 Some industrial units using RTO

Company	Process	Location	Capacity	RTO Technology	Benefit	Year	Payback	Reference
Borealis Group Tech nology	Ethylene Plant	Finland	300000 tpy	Neste Jacobes	12.5 M$/yr	2004-2005	One - month	www.Hydrocarbon processing.com
Not report	Low –sulfur gasoline HDS plant	France	870000 metric tpy	Axens	1.1 M€/yr	2006	Not report	www.Hydrocarbon processing.com
Eastman Chemical	Utility plant	USA	3.6M lb/hr of steam, 176MW of electricity	Emerson (AMS suite)	1M$/yr	Not report	Not report	www.pmo.assetweb.com
ConocoPhillips	Alkylation's plant	USA	Not report	Emerson (AMS suite)	1.2 M$ / yr	Not report	Not report	www.pmo.assetweb.com
BASF, Seal Sands	Chemicals Optimization (acrylics & nylon polymer)	U.K.	Not report	Emerson (AMS suite)	Not report	Not report	Less than 1 year	www.pmo.assetweb.com
Shell Nederland Chemie, Moerdijk,	Petrochemica ls Optimization	Nederland	Not report	Emerson (AMS suite)	Not report	Not report	Less than 6 months	www.pmo.assetweb.com
Sannazzaro refinery	Refinery (Fcc unit)	Italy	200000 Barrels per day	Aspen Tech Inc (ASPEN HYSYS)	10 cents /barrel	Not report	Not report	www. Aspen tech .com

Company	Process	Location	Capacity	RTO Technology	Benefit	Year	Payback	Reference
Refineria Isla, Curacao	Crude Unit	Nederland	180000 Barrels per day	SimSci& Foxboro (ROMeo &MRA)	2 M$ / yr	2001-2002	Not report	www.eptq.com
Yeosu Yeochun	Ethylene Utilities	Korea	Not report	Emerson (AMS suite)	1.038M$ / yr	Not report	Not report	www.pmo.assetweb.com
Hyundai Petrochemical Co.	Olefins Plant	Korea	350000 ton/yr	M.W.Kellog Co.	12%(increased profit)	Not report	Not report	Oil & gas journal
ConocoPhillips,	Refining Closed-Loop Optimization	U.S.A	Not report	Emerson (AMS suite)	Between 600,000$ -1.2 M$/yr	Not report	Not report	www.pmo.assetweb.com
Not report	Boiler Performance Monitoring, Entergy	U.S.A.	Not report	Emerson (AMS suite)	240,000$/yr	Not report	Not report	www.pmo.assetweb.com
Sriracha Refinery	Refinery Utility	Thailand	Not report	Emerson (AMS suite)	1M$ /yr	Not report	Less than 3 months	www.pmo.assetweb.com

5. The potential of applying RTO in Iran refineries

RTO technology could be implemented in some cases which have certain conditions as explained below:

1. The frequency of occurring disturbances is sufficient so that one could give a good reason why applying RTO is necessary or sensible.
2. Total profit should considerably change with changing in optimization parameters.
3. Determining the appropriate value for optimization parameter should be more complex and not determinable with common methods.
4. An operator faces a numerous numbers of data so that he/she cannot trace

The plant which RTO technology will be implemented on, should has some conditions explained below:

1. Access to plant data should be possible
2. The process has potential to use Distributed Control System (DCS).

With regard to conditions mentioned above, refinery distillation units, hydrotreating units, olefin units and ethylene units in petrochemical complexes have several decision variables to apply real time optimization technology.

So some units without DSC technology are not capable of implementing mentioned technology.

Based on statistical data collected from chemical and petrochemical industries, the most of RTO consumers in the world are gas and petroleum refineries because these companies have wide range of decision variables, which affect process optimization considerably. In addition there are a wide range of products in these units which provides suitable conditions for applying RTO. Table 2 is the list of Iranian companies with the capability of applying RTO technology.

Table 2: Gas and oil refining company in Iran since year 2007 which have DSC

Bandar Abbas Oil Refining Company
Arak Refinery Company
South Pars Refinery Phase 1
South Pars Refinery Phase 2 & 3
South Pars Refinery Phase 4 & 5
South Pars Refinery Phase 6, 7 & 8
South Pars Refinery Phase 9 & 10
Parsian Refinery 1
Parsian Refinery 1

6. Conclusion

In this work, the concept of Real Time Optimization (RTO) technology is presented and the potential of applying this method is evaluated. It is concluded that there are many refining companies in Iran which RTO could be implemented on to maximize their profitability, reduce off spec products and minimize energy consumption.

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