

On-line Fault Diagnosis Support for Real Time Evolution applied to Multi-Component Distillation

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Abstract

In this paper, the Real Time Evolution algorithm (Sequeira et al., 2002) is applied to the on-line optimization of a debutanizer distillation column. A fault diagnosis system (FDS) implemented within a supervisory module is responsible for handling incidences (faults and disturbances) happening in the plant by taking the appropriate corrective actions, including the activation of the RTE system. Thus, a more robust on-line performance is achieved. The implementation of the RTE scheme has been performed using Matlab© and the commercial simulation package HYSYS.Plant©, taking advantage of their communication capabilities (COM technology). Different possible plant incidences are addressed, involving different sources and types of disturbances. Results of RTE are compared with those obtained using the standard Real Time Optimization approach, showing better performance in most of the cases.

Keywords: On-line optimization, Real-time evolution, Multi-component distillation, Fault diagnosis.

1. Introduction

On-line optimization is a very important issue in chemical and petrochemical plants since it allows immediate response to internal or external disturbances in order to continuously maximize the economic and environmental performance of the whole process.

Real Time Evolution (RTE) introduces a new approach to on-line optimization that overcomes the drawbacks reported for the classical RTO approach. According to Friedman (1995), the steady state data required in a common dynamic environment needs heavy filtering and leads to long waiting. Furthermore, detailed process models are demanded whereas a proper trajectory for the implementation of the manipulated variables to reach the optimum is usually not provided.

The aim of this work is to show the concept of Real Time Evolution supervised by a fault diagnosis system in a multi-component distillation column. This system operates under a more robust framework, able to distinguish between incidences susceptible to be optimized (disturbances) and incidences that require alternative actions to keep the

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process stability (faults). This new structure decides continuously whether to operate under RTE or to activate alternative actions depending on the fault diagnosed.

2. Real Time Evolution

RTE responds quickly to disturbances (both, external or internal) by a continuous adjustment of the set-point values based on a steady state model. The plant parameters evolve smoothly, but continuously, towards the objectives without performing formal optimization. RTE is able to deal with continuous disturbances because it does not need to reach the steady state to trigger the improvement mechanism, leading to a better overall process performance. Plant model updating is only carried out when the steady state is reached.

RTE relies on four main aspects: improvement algorithm, RTE neighbourhood, time between successive executions and steady state model. The improvement algorithm is based on the way that the new points in the surroundings of the current set point values are selected. This neighbourhood is defined as the maximum allowed changes in the process variables to be evaluated. A successful RTE application requires an appropriate parameter tuning and selection of these elements (Sequeira et al, 2002).

3. Supervisory Control

The optimization technique described in the previous section runs under a supervisory fault diagnosis system. This supervisory module is the core of the on-line response system against deviations from the normal behaviour of the plant making the overall process more reliable and safe.

The supervisory module organizes the global performance of the plant, in such a way that differentiates the incidences that can arise in the plant, classifying them into two main groups. Incidences affecting the profit of the plant are classified as disturbances and are susceptible to operate under on-line optimization by the RTE, while incidences that affect the safety and good performance of the plant are named and classified as faults that may generate different responses of the supervisory module, i.e. activating a set of corrective actions to prevent more critical situations by monitoring different alarms and advising operators in the way they should act against this abnormal events.

Incidence detection is carried out through a MSPCA (Multiscale principal component analysis) (Bakshi, 1998), which is based on PCA (principal component analysis), one of the most applied multivariate statistical techniques (Kourti and MacGregor, 1995). Through the structure of MSPCA, the capacity of PCA to extract the relationship between variables is combined with the capacity of wavelets to separate deterministic features from stochastic processes. It approximately decorrelates the auto-correlation among the measurements.

Incidence isolation and diagnosis is carried out by a feed forward neural network trained in order to classify the signals received from the plant. Most possible disturbances and faults are tested, to extract enough data for properly training the artificial neural network. Then, it is prepared to classify new data from an abnormal behaviour of the plant.

4. System Architecture

The supervisory control decides at each moment if data received from plant correspond to normal behaviour or an abnormal situation (figure 1). When an abnormal event arises, it decides if this incidence is critical for the good performing of the plant (fault) or the plant is susceptible to be optimized (disturbance). In this case, RTE is automatically activated by the supervisory control. The time for diagnosing the fault must be minimized to take advantage of the benefits gained by an early reaction of RTE. First, current conditions from the plant are collected and applied to the steady state model. With this model, the improvement algorithm explores the surroundings of the current set-point values evaluating the resulting objective function. The combination improving the objective function value is chosen and immediately applied to the plant through the control system.

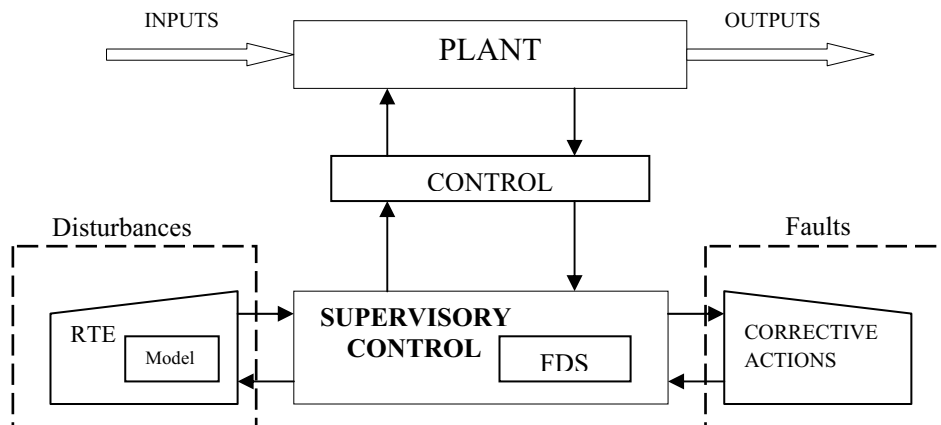


Figure 1. RTE supported by fault diagnosis system

When the plant reaches its optimum operation conditions and no disturbances occur, the value of the proposed set-points will not change. Therefore, no action will be done in the plant.

In case a fault is diagnosed, the supervisory control shows warnings or advices to the operator. Depending on the nature of the fault, it also can execute a previously designed protocol consisting of corrective actions to be applied to the process.

The implementation has been done with a Matlab function. It acts as a data manager establishing the communication between the plant (Hysys in dynamic mode), the model (Hysys in steady state mode), the optimization algorithm (Matlab), and the supervisory module (Matlab). Communication between Matlab and Hysys.Plant® is executed by mean of COM technology.

5. Case Study: Debutanizer Column

The debutanizer column provided by AspenTech® at their World Wide Site documentation (<http://support.aspentech.com>) has been chosen for this paper in order to make the results more reproducible. This multi-component distillation column has fifteen stages and is fed by two streams consisting of a mixture of light hydrocarbons. Firstly, the column has been simulated in Hysys.Plant® in steady state mode. This will

be the steady state model for the RTE algorithm. Secondly, the necessary modifications have been made in order to build the dynamic simulation including the control mechanism (Table 1) given by Figure 2. This dynamic simulation will be used as the real plant to be online optimized.

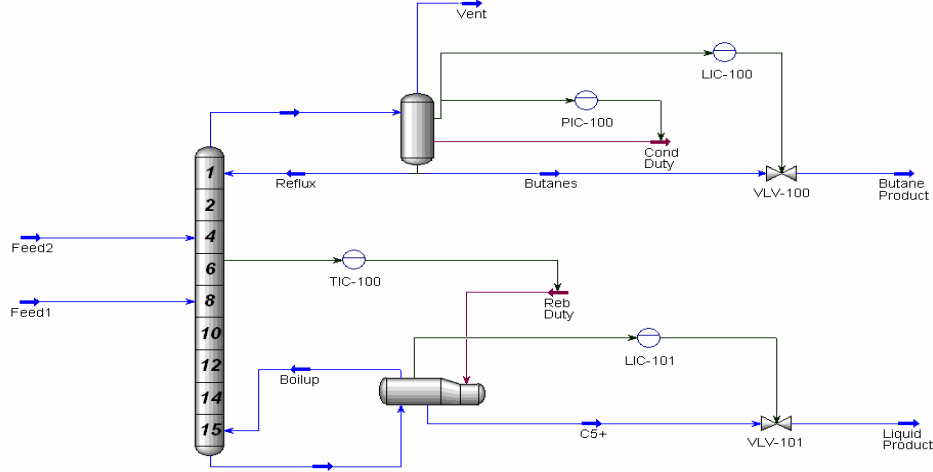


Figure 2. Debutanizer Flowsheet

Table 1. Parameters for the PI controllers

Controller	LIC-100	LIC-101	PIC-100	TIC-100
Kc	1.80	2.00	2.00	5.00
Ti, min	10.00	10.00	2.00	20.00

An objective function IOF (instant objective function) has been proposed in order to evaluate the plant performance at every moment:

$$\text{IOF}(t) = (\text{Amount of C4 \& lighter in Butane Product}) \cdot (\text{Price of Butane Product}) + (\text{Amount of C5+ in Liquid Product}) \cdot (\text{Price of Liquid Product}) - (\text{Flow of Feed1}) \cdot (\text{Price of Feed1}) - (\text{Flow of Feed2}) \cdot (\text{Price of Feed2}) - (\text{Condenser Heat Duty}) \cdot (\text{Price of Condenser Heat}) - (\text{Reboiler Heat Duty}) \cdot (\text{Price of Reboiler Heat}), \text{ m.u./time} \quad (1)$$

Table 2. Prices of the feed and product streams

Feed1, m.u./ kg	Feed2, m.u./ kg	Butane P., m.u./ kg	Liquid P., m.u./ kg	Cond. Heat, m.u./ kW	Reb.Heat, m.u./ kW
2.00	2.00	3.00	3.00	0.00009	0.0005

As RTO and RTE are not comparable in terms of an instant objective function, a mean objective function is employed taking into account the accumulative produced profit:

$$\text{MOF}(t) = \frac{\int_{t_0}^t \text{IOF}(t) dt}{(t - t_0)}, \text{ m.u./time} \quad (2)$$

6. Results

A case study is considered for which the decision variables are the set points of one of the controllers (6th stage temperature) and the reflux rate of the column. RTE requires a parameter tuning depending on the studied scenario. In this case, a maximum allowed change in set points of 0.3% around the old value and 50 seconds between consecutive executions have been considered showing satisfactory results.

In a first situation, a step rise (+20%) in the mass flow of Feed1 is diagnosed and automatically the RTE optimization is activated. While RTE reacts immediately against this disturbance, RTO has to wait until steady state is reached. This faster RTE response is translated in a better value of the mean objective function compared to those obtained by RTO. Figure 3 shows RTO has reacted later (11000 seconds approx.), losing benefits during the transition to steady state.

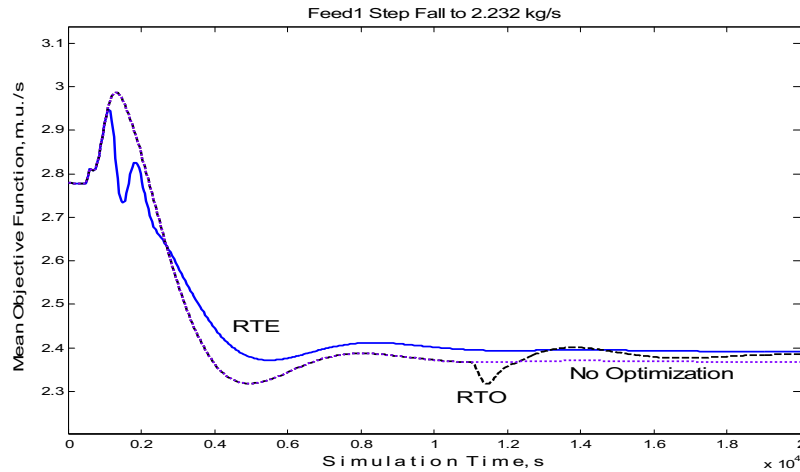


Figure 3. Mean Objective Function for a step disturbance in the Feed1 temperature

In case of a continuous disturbance arises in the mass flow of Feed1 (-0.0002 kg/s), the optimization by RTO shown in Figure 4 is not possible since the plant never reaches a steady state. This RTO's weak point is where RTE shows better performance, since for these situations RTO may not be applied. Therefore, the obtained results with RTE can be only compared when no optimization is carried out. Figure 4 shows the instant objective function for this case while Figure 5 represents the mean objective function for the simulation time considered.

In this distillation column, an example of possible fault is a fall of 20% in the mass flow of Feed2. When the supervisory control diagnoses this fault, a message advises the operator to check the valves involved. In addition, the supervisory control will perform a protocol consisting of a by-pass of the feed flows and an operation change to total reflux until the break-down is mended.

7. Conclusions and Future Work

A supervisory control based in a fault diagnosis system integrated to the RTE algorithm has been implemented for a debutanizer column. Further work will be orientated to

adapt the fault diagnosis system to the new conditions of the plant after an optimization, since current FDS is only prepared to detect disturbances from the base normal operation. It will be also possible to modify critical parameters from the optimization model obtaining for each case diagnosed a more accurate model.

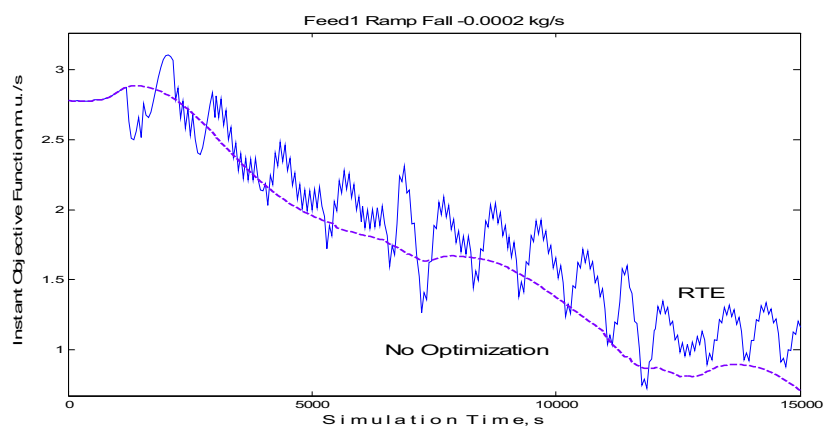


Figure 4. Instant Objective Function for a continuous disturbance in the Feed1 temperature

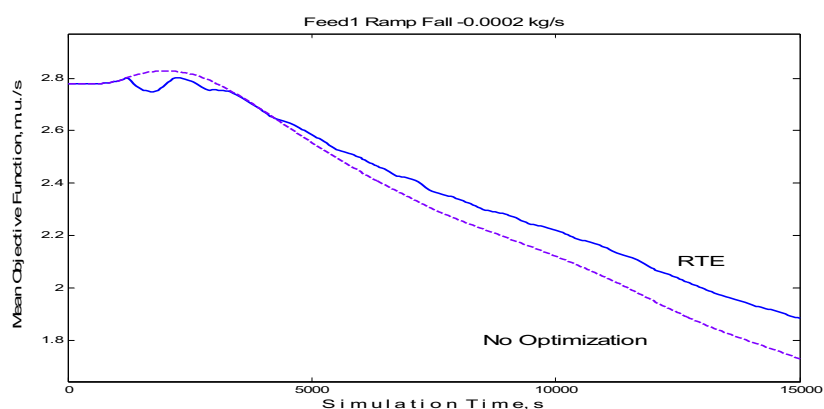


Figure 5. Mean Objective Function for a continuous disturbance in the Feed1 temperature

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