Chapter 3

Methodology I: a drifting optimum

Non bis in idem

3.1 Introduction

The goal of an optimal process operation is to maximise profit. In the very ideal case, a perfect dynamic model of the process exists, the initial state s_{ini} at the beginning of the operation is exactly known and the process is not disturbed during a given time horizon. Then, the associated optimal trajectories for the operational degrees of freedom can be determined entirely off-line through the solution of an optimal control problem (*P1*):

$$\max_{x(t),t_{end}} \quad \Phi(s,x,p,t_{ini},t_{end}) \tag{3.1}$$

subject to:

$$\varphi(\frac{ds}{dt},s,x,p,t) = 0 \tag{3.2}$$

$$\gamma(s,x,p,t) \leq 0 \tag{3.3}$$

$$t \in [t_{ini},t_{end}]$$
$$s(t_{ini}) = s_{ini}$$

In this formulation, s denotes the system state with initial conditions s_{ini}, $x(t)$ the free operational variables as a function of time t, and p given parameters. φ contains the differential-algebraic process model, while the constraints are encapsulated in γ. Φ denotes an economic objective function to be maximised on the time horizon $[t_{ini},t_{end}]$ of the process operation. In principle, problem *P1* can be solved by standard techniques for dynamic optimisation to determine an optimal x and, optionally, the final time of the operation, t_{end}.

The fact that the assumptions stated above are not fulfilled prevents an off-line solution of the problem *P1* from being sufficient in any practical application (Kadam et al., 2002). This is mainly due to:

- Model uncertainty (obtaining a reliable dynamic model for optimisation purposes still being impossible in most of the cases of practical interest) and. . .
- that in general, external disturbances exist and they future values are unknown functions of time, besides. . .
- the initial conditions are usually unknown.
- Moreover, despite the reasons given that became a rigorous statement of *P1* meaningless, current numerical techniques are not able to solve the optimal control problem for industrial-size applications involving large models sufficiently fast on the sample frequency.

The strategy used in RTO for continuous processes, consists in assuming that during a given and relatively long period of time, the disturbances values will remain constant (since $t_{end} \approx \infty$). Then, if this time horizon is long enough to allow the process to *reach and keep* the steady-state, the transient terms in the model can be neglected without loss of accuracy, so that a new problem (*P2*) can be stated using only the steady state analogy for *P1*:

$$\max_{x} \quad OF(x,p) \tag{3.4}$$

subject to:

$$f(x,p) = 0 \tag{3.5}$$

$$g(x,p) \leq 0 \tag{3.6}$$

In correspondence with φ, γ and Φ, f contains the algebraic process model equations (steady state), g encapsulates the algebraic constraints and OF the objective function. In such a way that the use of the RTO procedure explained in section 2.1 (page 19) is a practical approach for actually reaching *P1* objectives by solving *P2*. The repetitive execution of the RTO procedure with a suitable time interval (given that this time interval is relatively long), allows to update the models and disturbance values so that the hypothetical optimum of *P1* is eventually approximated.

3.2 Methodology

The challenge is then to solve the problem *P1* in a efficient way. As explained in chapter 1 the main motivation for on-line optimisation is the variability of the conditions. Such variability is originated by the disturbances that significantly affect the process economy. It has been mentioned that there are on the one hand ***internal disturbances*** given by intrinsic changes in unit conditions, mainly process degradation and, on the other hand, there are ***external disturbances*** carried by material and energy streams that enters in the process (besides the information flows, as are the economical parameters). The current chapter addresses the problem of the required set-points changes to track the variability originated by the disturbances (both, internal and external). The next one is particularly dedicated to the discrete decision problems that arise when there is a significant process degradation. Although the underlying idea for both methodologies is the same, a separated explanation results convenient.

3.2.1 The RTE concept

Real Time Evolution is next introduced as an alternative to current RTO systems. The key idea is to obtain a continuous adjustment of set-point values, according to current disturbance measurements,[1]present operating conditions and a steady state model.

An analogy is used to illustrate the proposed methodology. Consider a dog, and his master. The dog position represents the current set-points of the plant, his master position represents the plant optimal operating conditions and the distance between the dog and his master represents how far the set-points (*sp*) are from their steady state optima. Solid lines are the master trajectory, and dashed lines the dog trajectory. The dog objective is to be always close to his master, wherever he is. Thus, a rational dog A (figure 3.1) following the RTO scheme will remain motionless until he acknowledges the position of his master. Hence, the dog activity sequence will be: wait for the master to stop, determine his position, and then if allowed go to this position. This activity scheme results in periodical discrete movements, and has the drawbacks mentioned in the previous chapters (what if the master never stops, what if the master starts to move while the dog is going towards him, what if the dog can not identify his master position, what if the master goes too far…).

Another dog (dog B) has the behaviour shown in figure 3.2. This dog does not wait for his master to be still. Instead, this dog corrects every few seconds his position according to the current position of his master. This behaviour will lead to the dashed line trajectory. By this analogy one means that in the proposed strategy, the system's set-points are improved periodically regardless of a steady state situation.

In summary, the main differences between both dogs behaviour are:

- Dog B does not seek optimisation, he only improves his trajectory in such a way that in the long run[2]his position is the "steady state" optimum.
- Dog B does not wait for his owner to be still to attempt improvement, but he is continuously improving.

[1] As explained earlier, the term disturbance also includes economical disturbances, for instance a change in product price.

[2] It will be shown that it is not so long.

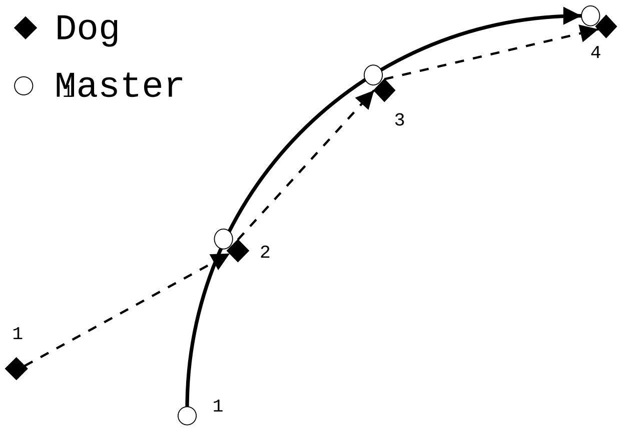

Figure 3.1: Dog A behaviour (RTO)

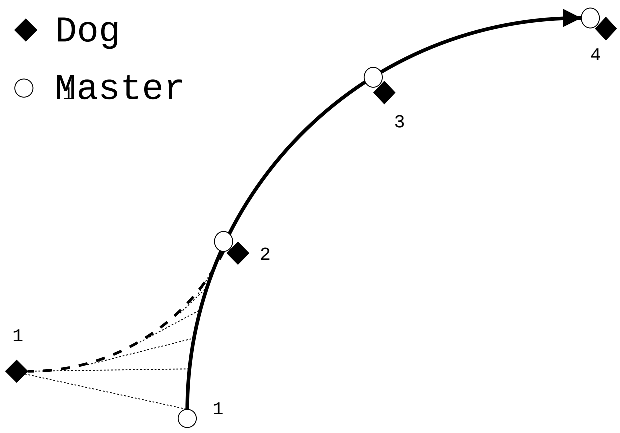

Figure 3.2: Dog B behaviour (RTE)

Table 3.1: Functional sequences for RTO and RTE

RTO		**RTE**	
Data Acquisition		Data Acquisition	
Data Pre-processing		Data Pre-processing	
if steady	*if unsteady*	*if steady*	*if unsteady*
Data Validation	-	Data Validation	-
Model Updating	-	Model Updating	-
Optimisation†	-	-	Improvement‡
Check Steadyness	-	-	-
Implementation	-	-	Implementation

† Optimal set-point values.
‡ Best small set-point changes.

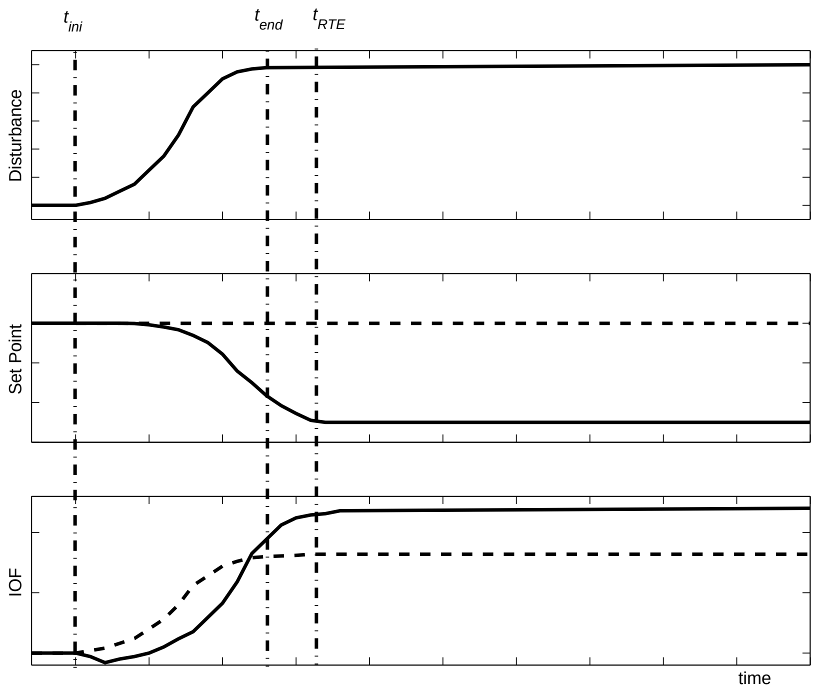

Figure 3.3: Qualitative results of applying an RTE system (solid lines) compared with no optimising system (dashed lines)

This kind of approach is called Real Time Evolution (RTE) instead of RTO. Table 3.1 summarises the main aspects of both systems methodology. The steady state information is used by RTE only for data reconciliation and model updating, while the core of the system is the recursive improvement, which does not need the process to be at steady state.

Qualitative results of such philosophy are shown in figure 3.3. Immediately after the disturbance begins (t_{ini}), RTE will slightly move the set-point towards a better objective function value at the corresponding steady state. In this way, RTE will be continuously improving and after the disturbance ceases (t_{end}) RTE reaches the optimal set-points for the new conditions (t_{RTE}).

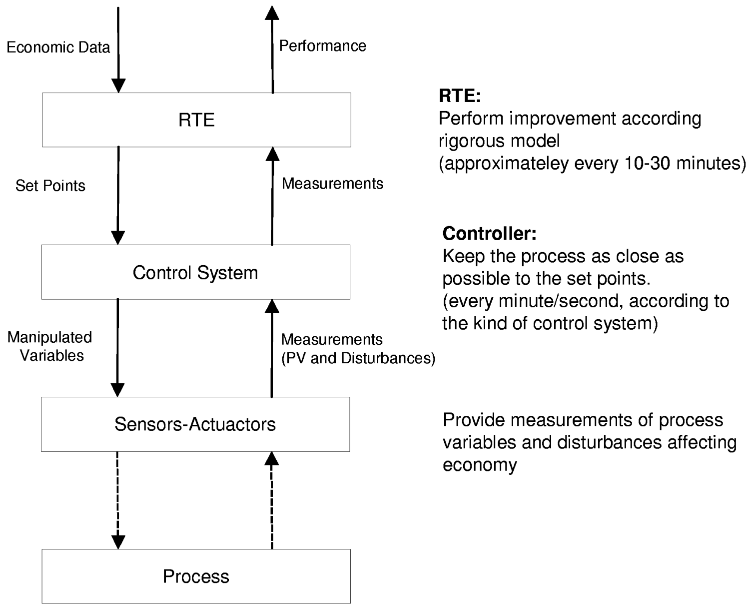

Figure 3.4: RTE structure and information flows (*pv*: process variables)

Regarding the information exchange with the control system, there is a subtle difference between RTO and RTE. An RTO system uses process measurements to produce set-points. By contrast, during the transient period, RTE uses disturbance measurements and current set-points to update set-point values (figure 3.4). Advances in instrumentation, decreasing sensor prices and also soft sensor techniques are making readily available disturbance measurements (Harold and Ogunnaike, 2000) and hence the application of this approach.

In order to understand how RTE works, the next section describes in more detail its components.

3.2.2 The RTE components

There are four main aspects to consider in RTE: the improvement algorithm, the exploration neighbourhood, the time between two successive RTE calculations (δt), and the model used.

The *improvement algorithm* is any procedure used to obtain a better plant operating conditions located inside the current operating point neighbourhood. For example, figure 3.5 shows the current decision variables values $[x(1), x(2)]$ which define the current operating point at steady state. This figure also shows four possible steady state conditions located at the neighbourhood of the current one $[x(1) \pm \delta x(1), x(2) \pm \delta x(2)]$. A steady state model is used to predict the corresponding objective function values at the five points, and then the best one is selected. In this way, the corresponding set-points are determined and sent to the control system.

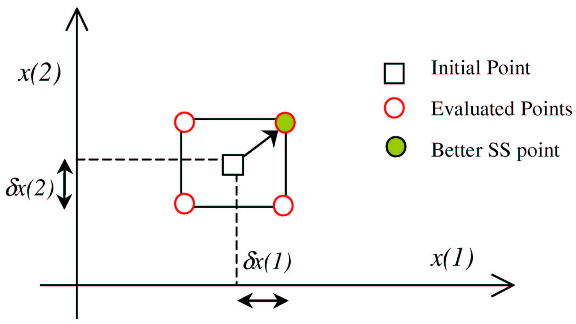

Figure 3.5: Direct search as improvement algorithm

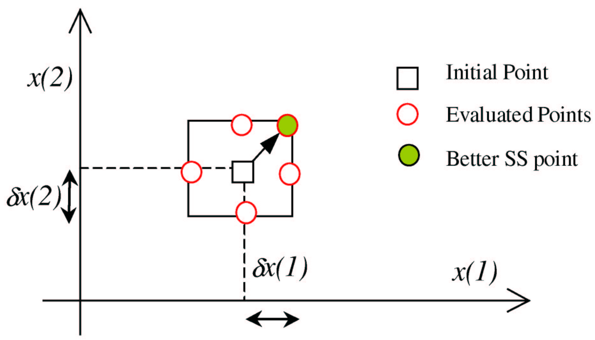

Figure 3.6: Linear approximation as improvement algorithm

Another possibility is to approximate the objective function (linearly for instance) with the values obtained from the model at properly chosen points. Once the approximated objective function is obtained, the best point can be selected (figure 3.6).[3]The selection of the improvement algorithm becomes more important as the number of decision variables increases, because the number of points evaluated at each RTE step will determine the algorithm computing time. In the same way that for the RTO case, the optimisation method strongly affects the algorithm calculation time. Furthermore, given the improvement algorithm's simplicity, it is very easy to deal with constraints (absolute and relative bounds in set-points values, undesirable conditions, etc.) because infeasible points may be readily discarded. This is really significant because for RTO, any additional constraint included in the optimisation problem means computational cost and / or lost of robustness, which may not be affordable in a real time environment.

The next issue is concerned with the RTE *neighbourhood* definition. Although there are many possible ways to define a neighbourhood, in this work it was defined by the maximum

[3]An algorithm that has provided good results consists in the application of direct search, where the angle of the square (for the two dimensional case, as shown in figure 3.5) is randomly selected at every RTE execution.

changes allowed for the decision variables values at each RTE step (δx). Bounds for such changes are given by the capability of the control system and the desired optimisation accuracy. Thus, minimum changes are bounded by sensor accuracy and controller precision, while the maximum change is given by the accuracy allowed. In this work, changes of about 1-3 % the variation range of the process variables have proved to give good performance, and consequently can be taken as preliminary heuristic values. It should be pointed out, that bounds in the implementation of set-point changes rates can be implicitly taken into account in the definition of the neighbourhood.

An additional degree of freedom in an RTE system is the *time between successive RTE executions*, δt. A very high δt won't likely improve plant operation. However, δt should be large enough to allow calculation improvement. As a preliminary approximation, a δt value of about 1-7% of the process residence time has been used in this work, producing satisfactory results. However, this parameter must be in accordance to the disturbances frequency, as will be explained in chapter 6.

Finally, the last main component of the RTE system is the *steady state model*. Opposite to direct search procedures (section 1.2.1.2, page 5) is a model based improvement procedure. One may think that when the plant is far from the optimum operating point there is no need for an exact model. Under such circumstances, the model needs only to reflect tendencies, giving a chance of using simplified models. However, the quality of the system trajectory always depends on the model accuracy, and considering that the improvement algorithm is no hard time consuming, the use of a rigorous model will always lead to better results.

All the above components must be tested and analysed prior to implementation in the plant. This tuning may be achieved using dynamic simulation, because the RTE system needs to be adapted to the process complexity, process dynamics, disturbance rate and frequency. However, it should be noted that there is no reason for keeping these parameters constant. It is also possible to change strategically and on-line the parameter values. Besides, in order to reduce gradually the available degrees of freedom, a hierarchical structure of RTE layers can be also used, by selecting appropriate parameters (frequency, changes allowed, etc.).

The proposed approach can be seen as a variant of the *EVOP* strategy (Box and Draper, 1969). The differences are mainly that:

- RTE relies in a model rather than experimenting over the plant: that means not spending time, money and safety in non-profitable trial moves.
- Steady state is not waited: adequate tuning of RTE parameters allows the system to follow a pseudo steady state behaviour and hence producing better economical performance even under continuous disturbances.

3.2.3 Mathematical interpretation

The point x_1 represents a hypothetical current plant status (steady state), and under the same conditions, the optimal point (respect to $IOF(x)$, and also at steady state) will be x_{opt}. Figure 3.7 represents this situation showing besides a contour chart for $IOF(x)$, where $x = [x(1), x(2)]$.

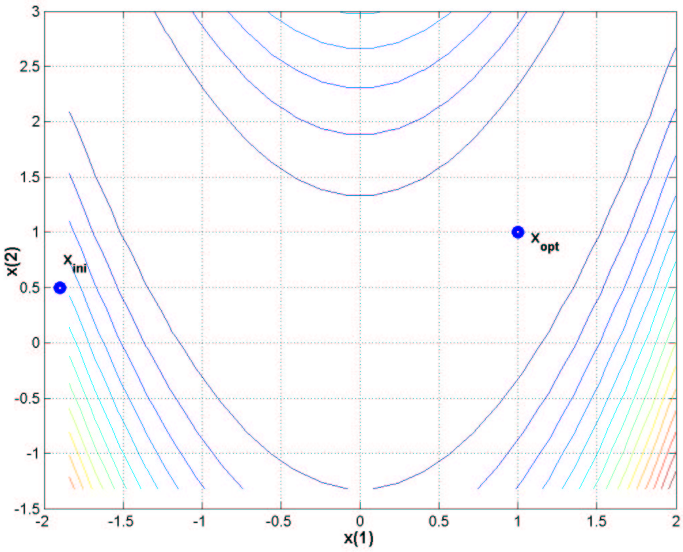

Figure 3.7: A hypothetical initial situation

If the conditions are kept constant, the challenge is to lead the plant to this new point with the best possible transition, using a steady state model. Many different ways are possible, to mention:

- One alternative is to directly implement the new set-points (x_{opt} point) and wait the plant to reach this optimal steady state. However, the dynamic transition will be not negligible and the transition cost should be considered in order to represent the trade off between the benefits finally obtained and the costs associated to the transition itself.
- Ramp the previous set-points in order to make the transition smoother. This will diminish the losses in control performance and then lead to a cheaper transition, but clearly sub-optimal.
- Make a time partition (N equal time intervals, where a generic time interval is denoted by k), and then find the best trajectory in the economical sense. Assume the transition is slow and smooth enough to consider that the system evolves as successive steady states and therefore, the influence of punctual system dynamics can be neglected. This requires to force N to have an arbitrary big value and besides avoid brusque changes between the values at interval k and $k+1$. Under such situation, it makes sense to state the following problem *P3*:

$$\max_{x_k \forall k} \quad MOF(x) = \frac{1}{N}\sum_{k=1}^{N} IOF(x_k, p) \tag{3.7}$$

subject to:

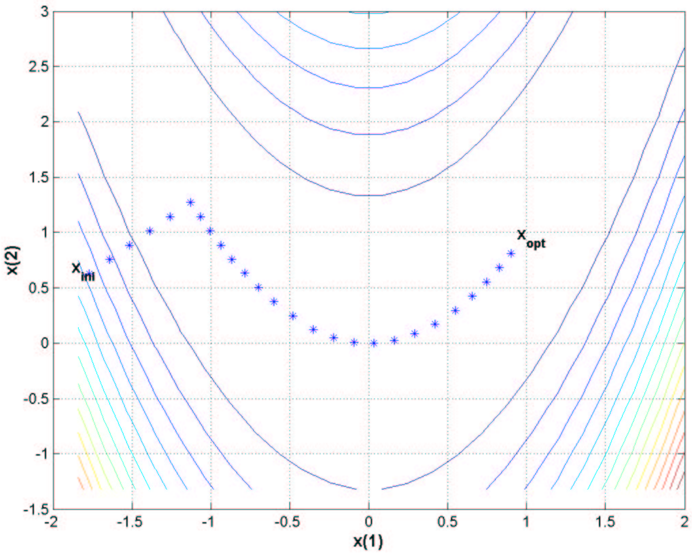

Figure 3.8: Solution to the problem P3

$$g(x_k, p) \leq 0 \quad k = 1, \ldots, N \tag{3.8}$$

$$|x_{k+1} - x_k| \leq \delta x \quad k = 1, \ldots, N-1 \tag{3.9}$$

where:

MOF: Mean Objective Function.

IOF: Instantaneous (punctual) Objective Function.

g: any additional steady state constraint.

k: interval number (from 1 to N).

δx: maximum allowed difference between consecutive points.

N: a big integer number.

p: any model parameter.

The equality constraints (f, equation 3.5) have been deliberately omitted to indicate that now x designs the decision variables in the reduced space. The solution to $P3$ results in a trajectory, that is to say $x_1, x_2, \ldots, x_N$ like the one shown in figure 3.8.

Even when the problem seems difficult because the objective function and constraints may be non-linear, a very simple procedure can be used for obtaining the optimal solution with an acceptable accuracy. Consider for instance the simplest vectorial case of $x = [x(1)\ x(2)]$, a suitable procedure (*A1*) will be the one given by the algorithm 1.

Algorithm 1 *(A1)*

```
Initialisation
k = 1
Make x_k ← x_ini
Main Loop
Do
    Evaluate IOF and get every vertex of current point
     neighbourhood ([x(1) ± δx(1), x(2) ± δx(2)]).
    Make x_{k+1} equal to that being feasible (g ≤ 0)
     have the best value of the objective function.
    k ← k + 1
Loop Until x_k ≈ x_opt
Make x_k ← x_opt for remaining k's
```

Therefore, given x_{ini},N,δx and p, the previous procedure leads with an acceptable accuracy to the same trajectory of figure 3.8.

Additionally, it should be considered that in the industrial environment the point x_{opt} changes continuously as a consequence of disturbances (i.e. changes in some values in p). Therefore the previous hypothetical situation is actually repeated at each time interval. In order to deal with that, it is possible to apply a receding horizon strategy. That is to say, at each time interval, *P3* is solved using the proposed procedure *A1*. Then, only the point x_k for $k = 2$ of the solution obtained is actually implemented. The remaining points are "overwritten" during the trajectory optimisation corresponding to its next period.

On the other hand, it can be seen that changes in x_{opt} only affect the termination of *A1* but not to the initial set of points. Therefore, the global procedure (*A2*) for a moving x_{opt} is given by the algorithm 2.

It should be noted that *A2* is an endless algorithm. Besides, it is clear that *A2* is totally equivalent to the proposed RTE approach. Nevertheless, its main limitation is that in order to be optimal, a very smooth enough plant operation is required to be considered as a successive steady state points, which is an objective rather than a hypothesis. On the other hand, if the changes are too small (or N too big) the procedure will not be able to track an optimum that moves too fast. Fortunately, δx and the time between k interval (δt, associated also to N) are adjustable parameters. Therefore, a proper selection of such parameters may allow a suitable satisfaction of the main assumption and to track acceptably the moving optimum.

The extension of the explained procedure to n-dimensional array is straightforward. The problem is that the number of vertexes increases exponentially with the number of variables. In cases with many variables, a proper design of experiments will reduce substantially the required

Algorithm 2 *(A2)*

```
Initialisation
k = 1
Make x_k ← x_current
Main Loop
Do
    Evaluate IOF and g at every vertex of current point
     neighbourhood ([x(1) ± δx(1), x(2) ± δx(2)]).
    Make x_{k+1} equal to that being feasible (g ≤ 0)
      have the best value of the objective function.
    k ← k + 1
Loop
```

effort.

As it can be seen, there may be no need for an explicit optimisation on-line. The interesting fact is that just a continuous evolution, which is substantially less computationally expensive, seems to lead to better economical results than the previous alternatives.[4] Next section will test such proposal in some examples to gain insight into the capabilities and limitations of the proposed strategy.

3.3 Validation studies

The integration of RT systems (RTO or RTE) may be tested using a dynamic model describing the plant. Figure 3.9 illustrates the scheme of the prototype used in this thesis work for validating a RT system and also for the corresponding parameter tuning. A dynamic first principles model is used to emulate "on line" data, which are consequently validated, filtered and reconciled.

The RT system includes the following components:

- The Steady State detector, used for model updating.
- The Steady State process model, and its corresponding economic model.
- The Solver, that for RTO is an optimisation algorithm, while for RTE is an improvement algorithm.
- The implementation block that sends the generated set-points to the plant, if they are acceptable.

Within this framework, two scenarios are presented. First the Williams-Otto reactor benchmark (for details see appendix B, page 189) is used for RT implementation. After that, a second scenario is presented, which consists of a pilot plant (PROCEL) at UPC, where the system is being implemented.

[4] The simplicity of the procedure make the uncertainty management affordable. For illustration purposes, appendix A (185) describes a conventional way of treatment of uncertainty using the RTE algorithm.

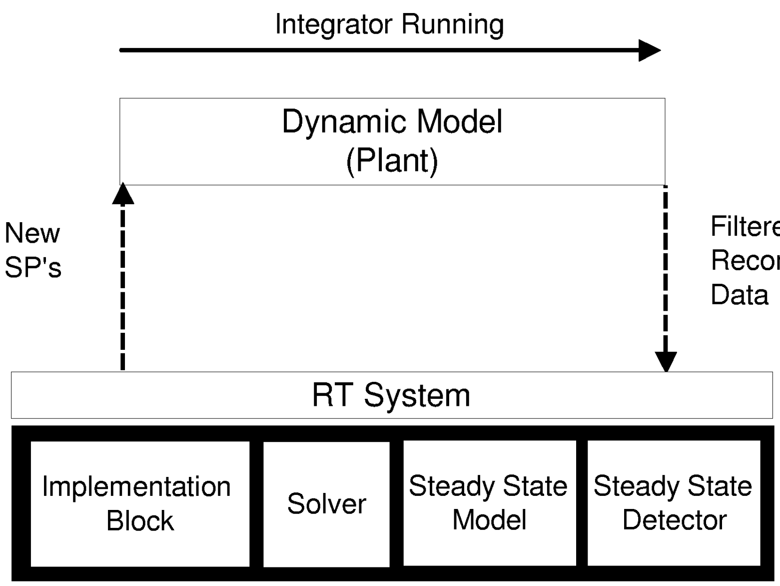

Figure 3.9: Scheme of the validation prototype

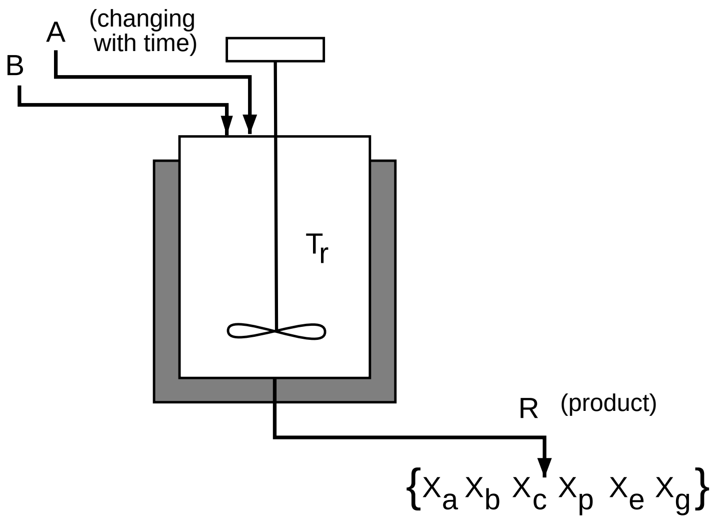

Figure 3.10: Williams-Otto Reactor

3.3.1 Scenario I: Williams-Otto reactor

The Williams-Otto Reactor is shown in figure 3.10 (Williams and Otto, 1960). A jacketed CSTR operating at temperature T_r is fed with reactants A and B, so that a six component outlet stream (R) is obtained when the following reactions occur:

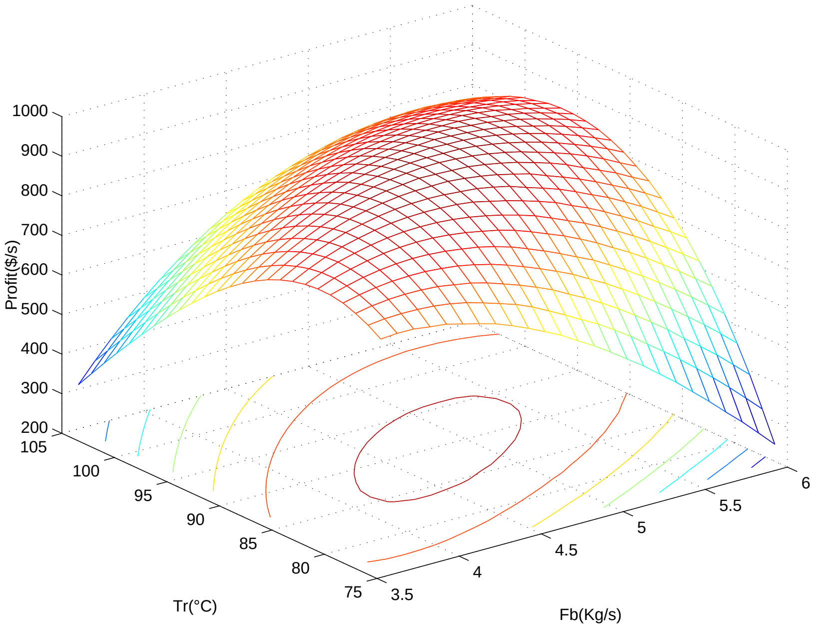

Figure 3.11: Objective function shape (steady state) for the Williams-Otto reactor scenario ($F_a = 1.83\,kg/s$)

$$
\begin{array}{rl}
A+B \rightarrow C & k_1 = 1.660 \cdot 10^6 \cdot e^{\left(\frac{-6667}{T_r+273}\right)} \\
C+B \rightarrow P+E & k_2 = 7.211 \cdot 10^8 \cdot e^{\left(\frac{-8333}{T_r+273}\right)} \\
P+C \rightarrow G & k_3 = 2.675 \cdot 10^{12} \cdot e^{\left(\frac{-1111}{T_r+273}\right)}
\end{array}
$$

The objective is to maximise the IOF, the corresponding profit which is given by the following equation (figure 3.11):

$$Profit = 5554\,F_r X_p + 125.9\,F_r X_e - 370.3\,F_a - 555.4\,F_b \qquad (3.10)$$

where the X_i are the mass fractions of the corresponding components. The main disturbance is the flow of stream A, F_a. The decision variables (and also set-points) are the reactor temperature, T_r and the flow of stream B, F_b.

For this operating condition ($F_a = 1.83\,kg/s$), the optimum operating point corresponds to: $F_b = 4.89\,kg/s$ and $T_r = 89.7\,^oC$, and the function is clearly convex. Once both models are developed (dynamic and steady state), the system's performance can be tested. For this scenario, the implementation has been made using Matlab, in its Simulink environment. For the sake of simplicity, perfect control is assumed for the two experiments considered. A step and a wave in F_a were simulated and the corresponding RTO and RTE responses analysed, as is following explained.

3.3.1.1 Experiment I: step in F_a

Starting from the optimum operating conditions, a step is simulated in F_a (from $F_a = 1.83\,kg/s$ to $F_a = 1.7\,kg/s$ at $t = 300\,s$). The RTO system will react after steady state detection, while the RTE is tuned to actuate every $4\,s$. The RTE parameters were steps of $0.2\,^oC$ for T_r and $0.02\,kg/s$ for F_b, and direct search as improvement algorithm.

RTO response: Temporal values of F_a, T_r, F_b and the instantaneous objective function (IOF) using the RTO system are shown in the figure 3.12.

It can be seen that at a time near to $t = 1500\,s$ (about 3.5 times the reactor residence time), the RTO system implements the optimal set-points ($T_r = 89.7\,^oC$ and $F_b = 4.98\,kg/s$). The delay is mainly due to the steady state detection and also to the time consumed by the subsequent optimisation procedure. The system was considered steady when the variation of the variables was less than $7.2\,\%/h$. The IOF against time chart in figure 3.12-d clearly reflects this behaviour and the improvement reached thanks to the RTO system (area under the curve).

It is interesting to look at how sudden changes in set-points affect the IOF. First, the decrease in F_b and T_r is translated in an instantaneous decrement in IOF. This is because F_r is immediately reduced and therefore the produced quantity too. However, after the CSTR stabilisation time, the composition at the reactor output greatly compensates such IOF temporary decrement by an increased production quality.

RTE response: Temporal values of F_a, T_r, F_b and the instantaneous objective function (IOF) using the RTE system are shown in the figure 3.13.

It can be seen that the RTE system does not wait for the steady state, but immediately reacts and changes set-points. The evolution of both decision variables is to proceed step by step to their optimum values. In the case of T_r, RTE tries at first to increment its value, but later changes the direction towards the final optimum value. This means that RTE will let T_r increase until a good enough product quality can be guaranteed according to the new F_a and F_b values, and only thereafter T_r will be allowed to reach its optimum value.

Figure 3.13-d shows comparative results of RTO, RTE and no optimising action, with IOF as performance criterion. For both RTO and RTE final IOF approximates to $898\,\$/s$, while taking no action leads to $891\,\$/s$. It can be seen, that after the process comes to a true steady state, the IOF value for RTO eventually approximates to that of RTE as the time goes.

However, RTO and RTE should not be compared on the basis of final IOF values but rather regarding the cumulative profit produced. Thus, a more meaningful comparative plot (figure 3.14) is obtained using the mean objective function (MOF), which contemplates the history of the process and is defined as:

$$MOF(t) = \frac{\int_{t_0}^{t} IOF(\theta)d\theta}{(t - t_0)} \tag{3.11}$$

where t represents the current time and t_0 is a reference instant.

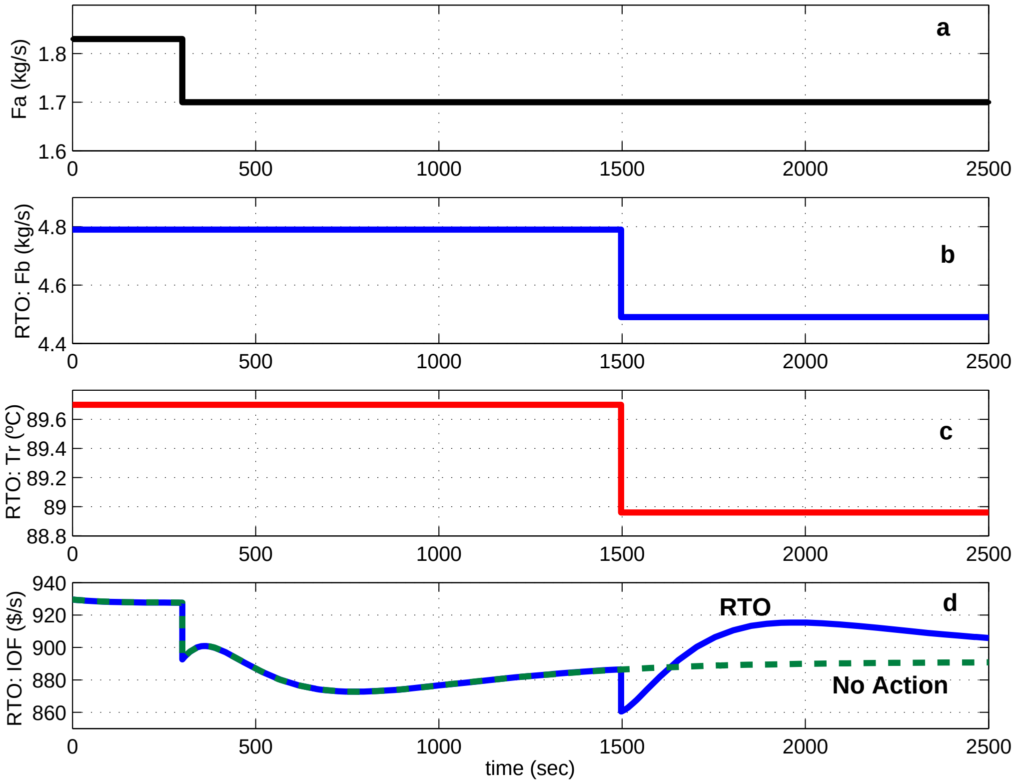

Figure 3.12: a- Step disturbance in F_a at $t = 300\,s$. b- and c- RTO response over the set-points (F_b and T_r). d- Instantaneous Objective Function (IOF) with (solid) and without (dashed) RTO

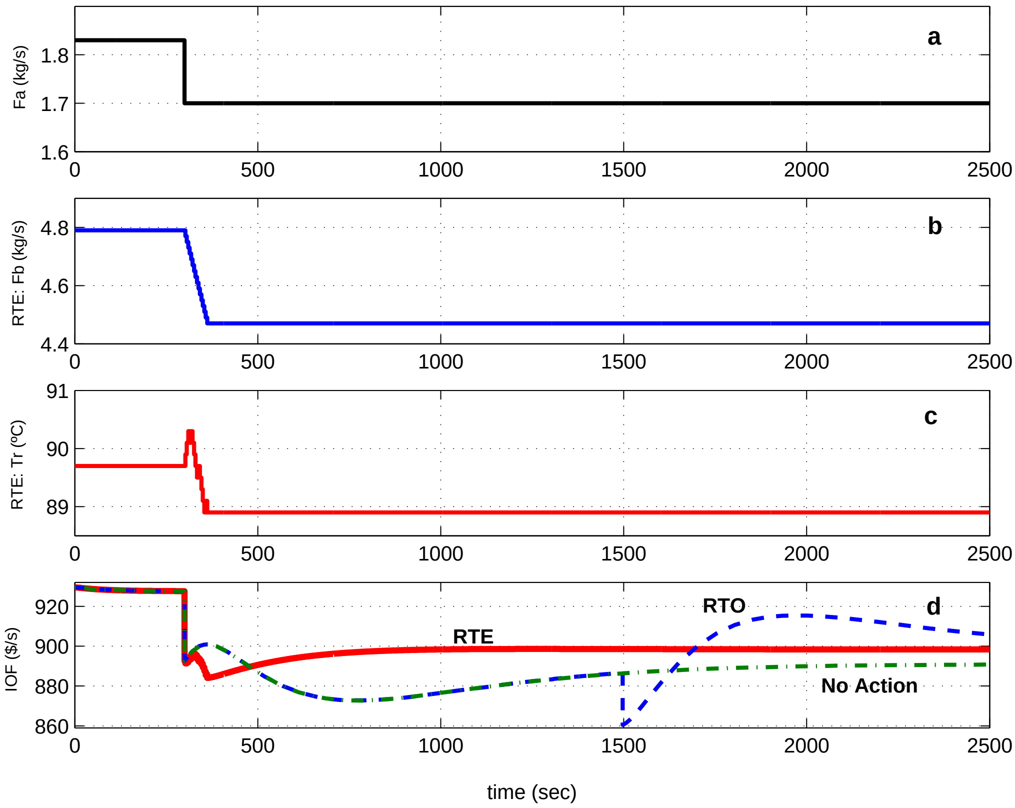

Figure 3.13: a- Step disturbance in F_a at $t = 300\,s$. b- and c- RTE response over the set-points (F_b and T_r). d- IOF with RTE (solid), with RTO (dashed) and no action (dot dashed)

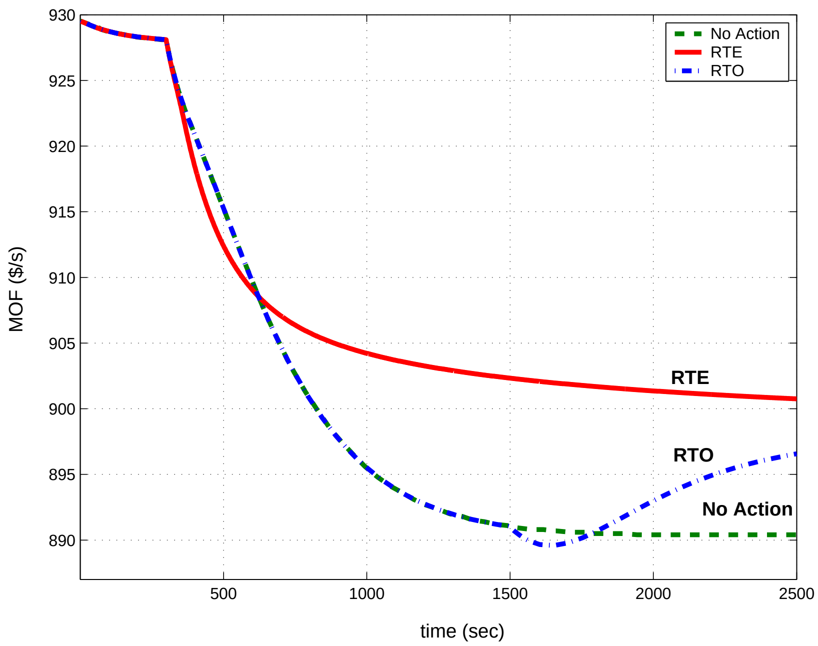

Figure 3.14: *MOF* profile comparison between RTO (dot dashed), RTE (solid) and no RT system (dashed) using $t_0 = 0\,s$

A deeper analysis of this chart reveals that during a few seconds the *MOF* values for RTO and RTE systems are lower than those for no optimising action. This happens because RTO and RTE systems are based on steady state models, which only guarantee long-term improvement, when the steady state is achieved. Certainly, for the step disturbance case, both RTO and RTE reach steady state and thus the same *IOF* and *MOF* final values are expected when time tends to infinity. However, disturbances can arrive at any time, rather than infinity. Given that RTE produces faster improvement of *MOF* (and more generally, the associated set-points) than RTO, the latter should always lead to better overall performance if further disturbances occur (i. e. at $t = 2000\,s$). This fact suggests testing the RTE performance when the disturbance consists in a continuous change, which is the subject of the following experiment.

3.3.1.2 Experiment II: wave in F_a

Starting from the optimum operating conditions, a wave was simulated in the feed flow (from $F_a = 1.83\,kg/s$ to $F_a = 1.83\,kg/s - 0.13 \cdot sin\,(t/6000)\;\; kg/s$. Figure 3.15-a represents the disturbance shape.

In this case, the RTO system could do nothing because steady state will never be achieved. Otherwise, RTE produced the results shown in 3.15-b and 3.15-c. RTE parameters were the same as in the previous experiment.

It was made clear that RTE is able to make on-line adjustment of set-points to improve process performance, thus adapting the plant performance to the changing external conditions. For

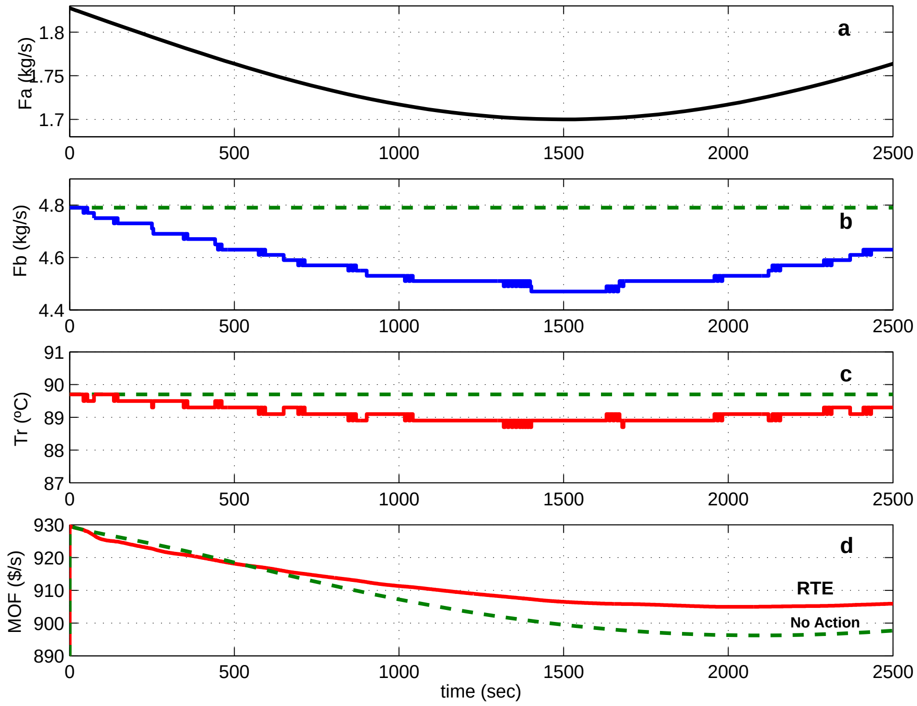

Figure 3.15: a-Wave disturbance in F_a at $t = 300\,s$. b- and c- RTE response over the set-points (F_b and T_r). d- MOF with RTE (solid) and no action (dashed)

the wave disturbance (F_a) a wave-like response is obtained for set-points, T_r and F_b, as well as for MOF.

Regarding performance, it should be noted that in both experiments (step and wave disturbances) the MOF obtained when using RTE follows closely the shape shown by the process without optimisation but shifted up and left.

3.3.2 Scenario II: PROCEL

The following scenario consists in a real pilot plant (PROCEL at UPC). Here, perfect control is not assumed, as it was in the previous example.

The plant flowsheet is shown in figure 3.16. The stream 1 is fed to a vessel (Tank) provided with level and temperature controllers. The Tank output is preheated (E-1), heated (E-2) and finally cooled (E-3), being heat exchanger E-1 used for heat recovery. The vessel V is only used to hold the heating utility (water). The process could be regarded as a pasteurisation operation. The fluid to be pasteurised is at first stored, and later suddenly heated and cooled.

The objective function to be maximised is profit, defined as the difference between sales revenues and production costs, including a penalty for poor quality. Temperature gives the raw material quality, while the product quality depends on process history: residence time in vessel and temperatures in tank, streams 7 and 9 (see figure 3.16).

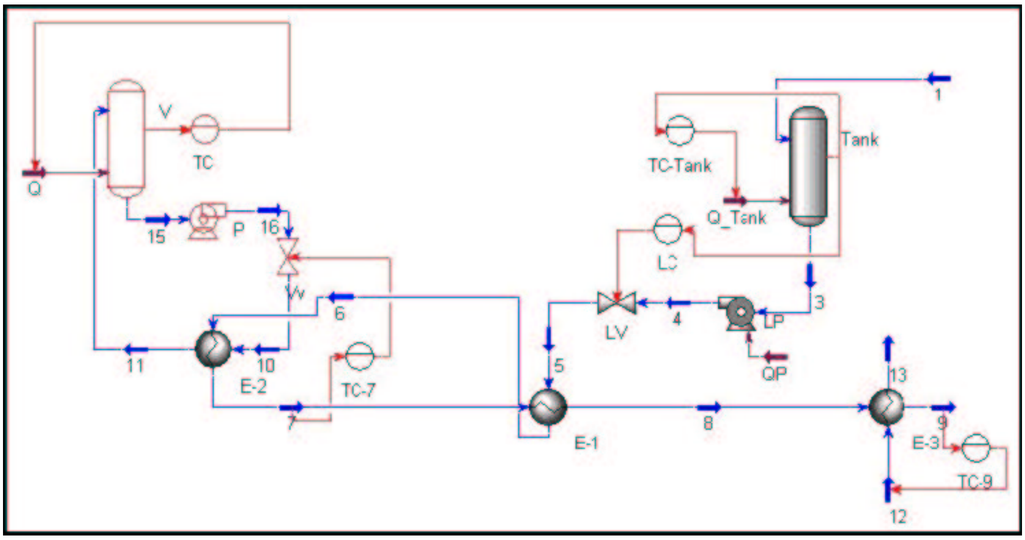

Figure 3.16: PROCEL flowsheet (continuous configuration)

The decision variables are the operating conditions, that is to say, the set-points of controllers:

1. Tank temperature (TC-Tank, PI controller).
2. Tank level (LC-Tank, PI controller).
3. Stream 7 temperature (TC-7, PI controller).
4. Output stream temperature (TC-9, PI controller).

And finally, the disturbances are:

1. Quantity (flow) of raw material (stream 1).
2. Quality (temperature) of raw material (stream 1).
3. Prices and costs (of product, raw material, heating, cooling, etc.)

Raw material flow affects the residence time in the Tank, and hence influences the product quality. Raw material temperature affects the raw material cost and also dictates the recommended temperature in Tank (for highest quality). The influence of prices and costs on the objective function is straightforward.

The steady state and dynamic models were developed using HYSYS.Plant.[5] In order to send "on line" data to the RT system, the DCS interface of HYSYS was used. Again two experiments were carried out, corresponding to a step and wave disturbance. The starting point for both examples is given in table 3.2 and corresponds to the optimal operation for a given set of external conditions.

[5]The models used are publicly available at http://tqg.upc.es/procel

Table 3.2: Initial conditions for scenario II

External conditions	
Stream 1 flow (F-1)	60 kg/h
Stream 1 Temperature (T-1)	20 ^{o}C
Set Point Values	
TC-Tank	45^{o}C
LC-Tank	50 %
TC-7	86^{o}C
TC-9	48^{o}C

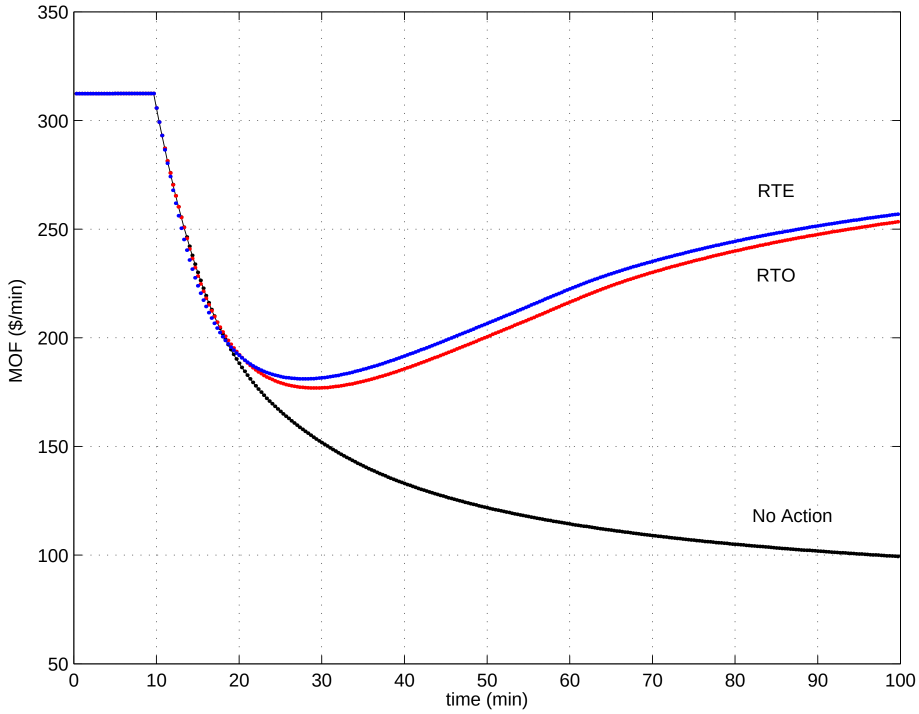

Figure 3.17: *MOF* for RTE, RTO and no action after a step disturbance

3.3.2.1 Experiment I: step disturbance

The disturbance was simulated at time $t = 10\,min$ and consisted of a step in the inlet stream temperature, from $20\,^{o}C$ to $13\,^{o}C$. The RTE parameters used were calculated every minute and step changes of $0.5\,^{o}C$ were considered for temperatures. A direct search method was used in the improvement algorithm.

Comparative results in figure 3.17 show the effect on *MOF* when no action is taken and when using the RTO and RTE systems. The *MOF* value will naturally decrease, but appropriate corrective actions from both, RTO and RTE systems attain better performance than doing nothing.

The calculation time spent in the optimisation was not taken into consideration, but even

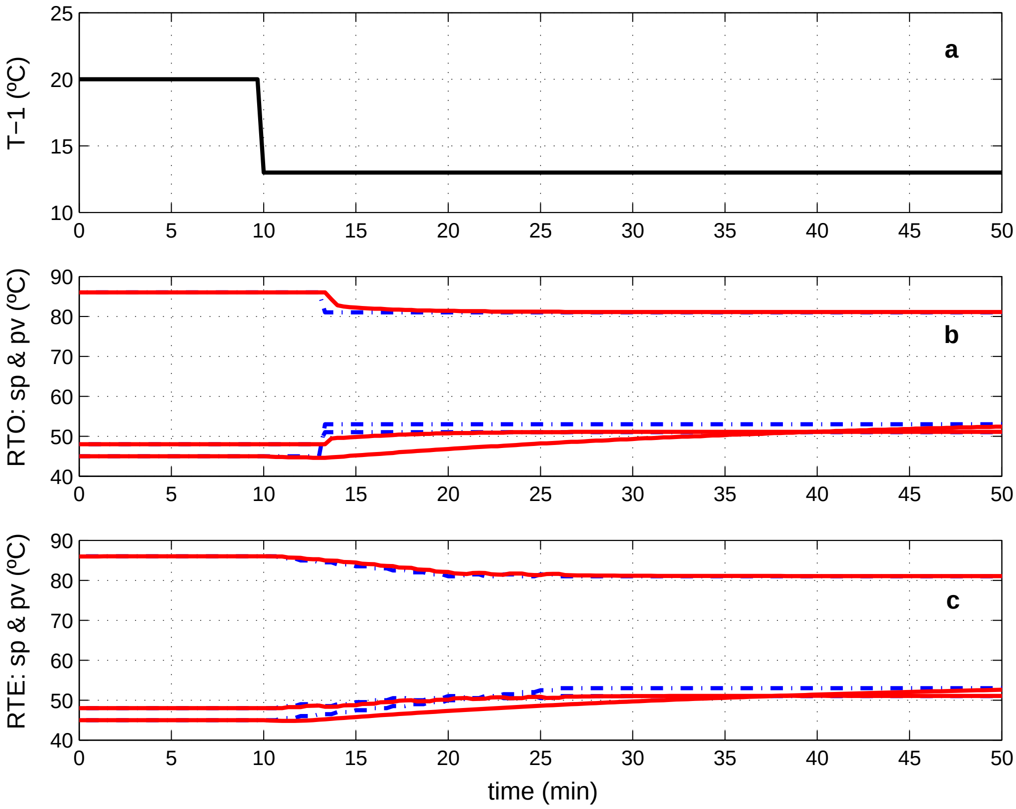

Figure 3.18: a- Disturbance. b- and c- Set-points (dashed line) and their corresponding process variables (solid line) for RTO and RTE

so, the RTE performance is slightly better than RTO. The difference between both curves is (mainly) due to the time required to achieve the steady state which is in this case small because the damping effect of the Tank.

As mentioned before, a key issue to choose this scenario is to relax the hypothesis of perfect control. Therefore, besides the objective function value, it is also relevant to consider the operating conditions behaviour in both cases. Figure 3.18 shows process temperature profiles (set-points and process variables). It can be seen that the differences between both, set-points (*sp*) and process variables (*pv*) are not significant when RTO is used (figure 3.18-b). The same chart for the RTE approach (figure 3.18-c) shows an even smaller difference. This result is obvious if one considers that the changes in RTE are smoother than in RTO, allowing the control system to keep the process variables values almost equal to the set-point values. Therefore, it can be thought that poor controller tuning should have a more significant impact when using RTO than RTE.

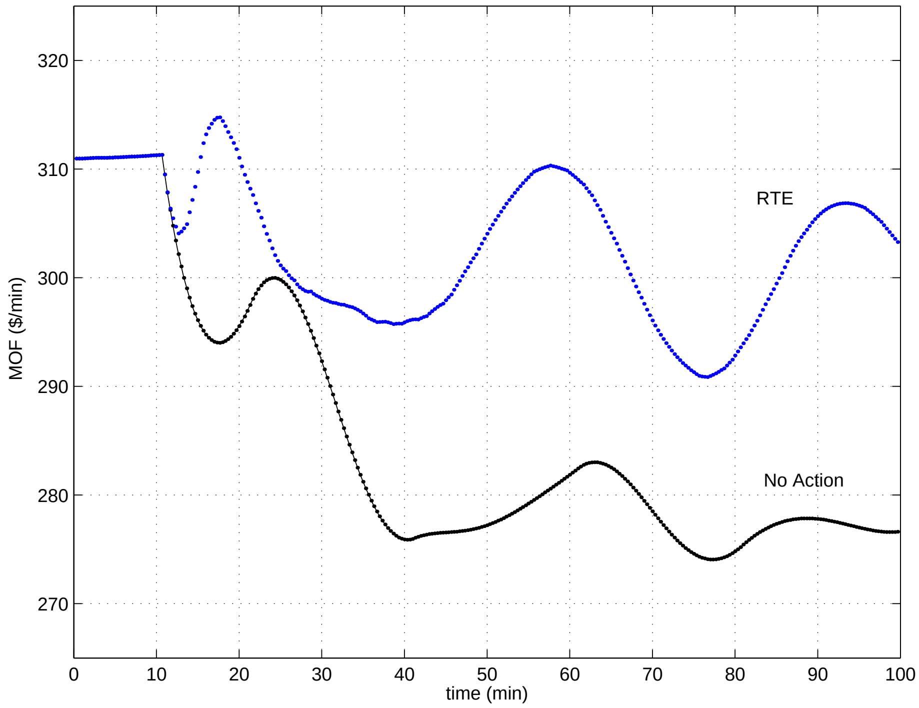

Figure 3.19: *MOF* for RTE after sinusoidal disturbances

3.3.2.2 Experiment II: wave disturbance

The disturbance was simulated at time $t = 10\,min$ and consisted of a sine wave at the inlet stream temperature and flow. The amplitudes were $8\,kg/h$ for flow and $6\,^oC$ for temperature, with a $30\,min$ period for the flow and $40\,min$ period for temperature. RTE parameters were the same as in the previous experiment.

Again in this case, since there is no steady state, RTO can do nothing, while RTE produces the *MOF* shown in figure 3.19. RTE results show a significant economic improvement, and the shape of both curves (flow and temperature) is clearly similar which indicates a close follow-up of the process behaviour. It can be seen that the *MOF* amplitude in both cases is decreasing as a result of the damping effect of integration (see *MOF* definition, equation 3.11) which should result in limiting values for *MOF* when time tends to infinity. Furthermore, since corrective actions are obtained along time, smooth plant behaviour is observed and negligible differences between process variables and set-points are obtained (figure 3.20).

This example enhances RTE and RTO differences and illustrates a more realistic situation (true steady state uses to be difficult to reach in practice). A key point of the proposed method is the use of a steady state model improves the process performance, even though the steady state could not be reached. This is mainly owed to that the evolution of many systems (specially those found in the chemical industry) may be described as successive steady states (pseudo steady states). This situation poses the additional issue of data reconciliation and subsequent model

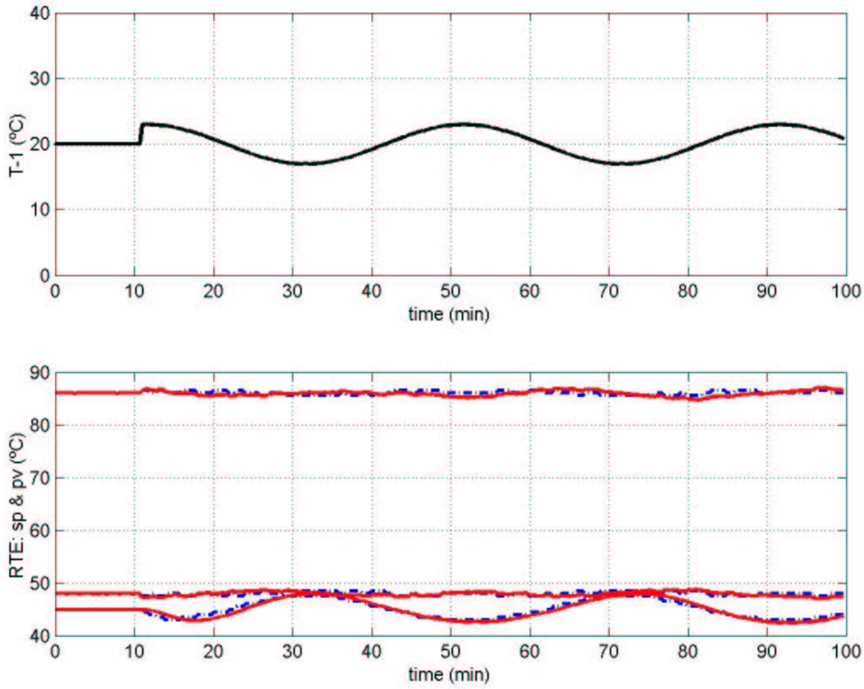

Figure 3.20: a- Sine wave disturbance in stream 1 temperature. b- Set-points and their corresponding process variables for RTE

updating required by both RTO and RTE (table 3.1). When steady state is not achieved, current dynamic data reconciliation techniques could be used to obtain instant reliable data. Furthermore, models could be periodically updated using average values and heuristic procedures.

3.4 Conclusions

This chapter presented a revision of the philosophy behind on-line optimisation objectives. As a result, a new methodology has been proposed, and the concept of Real Time Evolution (RTE) has been developed as an alternative to classical RTO systems. Tests carried out of the RTE system show the adequacy of the RTE structure to keep the plant at the optimum operating conditions when disturbance information is available.

Once correctly tuned, the RTE system will produce a successive improvement of plant performance, making the plant evolve continuously toward the objectives set. Although RTE requires more time than RTO to reach optimum operating conditions, it improves plant performance immediately after disturbances occur, thus resulting in an overall faster and smoother system, which is able to deal even with continuous changes. The algorithms involved in RTE (improvement) are simpler and faster than those used by RTO (optimisation); this allows the intensive use of the available rigorous process model with little computational effort. Finally, results show that the RTE strategy is less affected than RTO when using a poor controller performance.