## Chapter 1

# Introduction, Motivation and Objectives

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### **1.1** An introductory view

There is a long tradition in the process industries of using fundamental knowledge captured in the form of mathematical models to aid plant operations (Perkins, 1998; Balchen, 1999). As confidence in the ability to develop adequate representations of plant behaviour has grown, combined with the ever increasing availability of low cost high powered computing, there has been a trend to make process models available on-line, and to use them to made real-time decisions related to plant operations.

In this thesis, one particular class of on-line modelling applications is addressed, where a process model is used as the basis for on-line optimisation of plant operation. Such functionality does not work in isolation, and is one of the elements of a very complex structure used for the operation of modern chemical plants. Thus, before continuing with on-line optimisation, next section briefly summarises its operational context.

### **1.1.1** The context: plants operational hierarchy

Bernard (1966) already stated that the most practical way to develop a control system is by examining and controlling the process at increasing levels of scope until the process objectives are met by the hierarchy of control layers. How are these layers determined, and what are their tasks? Gijsbrechts (1985) reviews practical and theoretical results in the field of hierarchy. The physical, operational and functional structure of the plant determines the structure of the control hierarchy.

A plant is physically divided in a number of units, in which distinct chemical operations are carried out (e.g.: a catalytic cracker, an extraction column, a heat exchanger). Units are grouped in sections marked by some stage of important intermediary products (e.g. sulphuric acid production, ammonia production, etc.), and these sections are grouped in separate plants. A flow control loop, for instance, generally uses only local information (information from the same unit as the controlled flow). The set-point of this flow controller could be, however, determined by an optimiser considering the global plant behaviour. The flow controller belongs to a much lower level than the optimiser.

Bernard (1966) suggests four levels. In the first level, conventional loop control maintains plant set-points of variables such as flow, temperature, pressure and liquid levels employing relatively simple control schemes. The second level maintains plant heat and material balance, and compensates for important interaction phenomena. The same author includes "unconventional feedback schemes employing non-linear, logic, or sampled data concepts" in this second control level. The author refers to techniques that are now well known, such as adaptive control, internal model control, minimum variance control, dead time compensation, certain applications of artificial intelligence, and many others. The third level buffers the lower two levels and the optimiser, which is located on the fourth level, by changing the plant operating point as dictated by the optimiser. This level could include techniques such as Model Predictive Control (MPC). An important task of such a level is to satisfy constraints.

More recent works (e.g. Coombes et al. (1983); Lasdon and Baker (1986); Jang et al. (1987)) will often group the first three levels by Bernard (1966) together in one single level. This single level will then have the task of enforcing the process control set-point on the plant while keeping certain constraints satisfied. Bernard and Howard (1970) even add a "zero level" to the four levels of Bernard (1966). That zero level contains procedures for safe emergency shut down and system failure warnings. Later, this zero level is expanded with the "safety reflexes" of the process, also called "security control". These control mechanisms contain early reactions to specific disturbances to stop the process from going into an emergency status.

The fourth level of Bernard (1966), or equivalently the second level of Coombes et al. (1983), determines the best operating condition of the plant in an optimisation based way. On top of the optimisation level, Bernard (1966) suggests that other levels may be added, but no details concerning the task or scope of higher levels are listed. It is clear that these higher levels have to provide instructions to the plant optimiser. Coombes et al. (1983) refer to this level above the optimisation level as the production scheduling and production control level. The task of this level is to maximise company or division capacity utilisation while spreading the production activity over the smallest possible number of unit processes.

In order to summarise these ideas, figure 1.1 (Edgar et al., 2001) shows the relevant levels for the process industries in the optimisation hierarchy for business manufacturing. The information sources for the plant decision hierarchy for operations are the enterprise data, consisting of commercial and financial information, and plant data, usually containing the values of a large number of process variables. Such data and the models used are of major significance since they

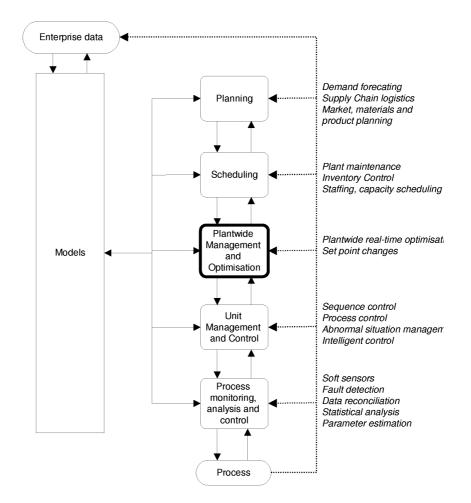


Figure 1.1: The sequential and functional decision hierarchy for plant operations

are the basements of all the decisions made.

### **1.2** Continual improvement

Regarding the automatisation of the decision of the previous structure, decades of industrial experience have demonstrated the particular success of process control in maintain selected variables around their desired values. In general, process control is very effective when the desired operation point has been determined from prior analysis and the control system has sufficient time to respond to disturbances (i.e. the feedback dynamics are fast compared with the disturbance dynamics).

While process control is required for regulating some process variables, the application of these methods may be not appropriate for all important variables. In some situations, the best operating conditions change, and a fixed control design may not respond properly to these changes. In other situations, continuous feedback compensations can be too aggressive, leading to excessive variation in the controlled variable. There are roughly two approaches for continually improving plant operation: Statistical Process Control (SPC) and Optimisation. Most volume manufacturing processes are monitored for their location and variability at multiple steps in the manufacturing process using SPC techniques. Measured data are collected and plotted on trend, or control charts to provide an indication of whether or not the process is behaving in a stable manner and will meet product performance requirements. Both, SPC and Optimisation involve very different technologies to address a unique objective. Next section will focus in optimisation, since is this thesis subject.

### 1.2.1 Optimisation

A control design procedure adjusts manipulated variables to achieve good dynamic performance, which is measured by the variability in the key variables and the difference with their desired levels. Often, the number of manipulated variables exceeds the number of controlled variables. In these situations, safe operation and good product qualities can be achieved by manipulating selected process inputs that gives the best control performance, and some manipulated variables can be maintained at arbitrary, constant values within an acceptable range. Alternatively, the excess manipulated variables can be adjusted to increase profit; these excess manipulated variables are refereed optimisation variables.

For relatively complex but common situations, the strategy of adjusting the excess variables is not so straightforward to determine, and may change frequently. One may face such situations using any of the approaches described in the following subsections (Marlin, 1995).

#### 1.2.1.1 Good control design

The first step when designing optimising control, once regulatory controls have been designed, is an analysis to determine the proper strategy for set the optimisation variables values. This analysis uses models of the process or plant data to answer two significant questions:

- *Do incentives exist for optimisation?* In some situations the profit will not vary significantly as the values of the excess manipulated variables change, so that the latter can be maintained to constant values selected for convenient operation.
- *Is the optimal strategy constant and simple?* When the profit is sensitive to the optimisation variables, the response of these variables to external changes, disturbances, and set-point changes (if relevant) should be evaluated. In some cases, the optimal response to these external changes:

- Is nearly the same for the same for all expected operating conditions and economics, and:
- Can be implemented via straightforward real-time calculations of the control strategy.

When the answer to both questions is yes, a control strategy can be designed to approximate the best performance (Skogestad and Halvorsen, 1998; Larsson et al., 2001). Such approach to approximate optimal operation is appropriate when the control calculation needs not change with time. In contrast, there are other approaches that can respond to changes in plant performance by using process measurements in the calculation of profit, at the cost of much greater complexity. They are:

- direct search and...
- · model based on-line optimisation

which are next described.

### 1.2.1.2 Direct search

This approach can be used when incentives exist for adjusting the optimisation variables, but the strategy for optimisation cannot be implemented in a straightforward way, such as constraint pushing or ratio control, and accurate models are not available. In these situations, a very simple, locally accurate model of the process is determined empirically from the plant data. This model is used to determine the direction in which changes in the manipulated variables will increase profit. The plant operating conditions are then changed by a small amount in this direction, and a new, updated model is evaluated. The direction for optimisation is determined again from plant data in an iterative way.

This iterative approach has been used for many years to study plant behavior and determine improved operating conditions. When the experiments are time consuming and expensive, effort must be made to reduce the duration of the study; then only few experiments are performed and careful statistical evaluations are used to determine whether further improvement is likely and, if so, which direction is the best. Infrequent application of this concept in studies or "campaigns" is usually termed evolutionary operation (*EVOP*), a term coined by Box and Draper (1969), who provided procedures, guidelines, and statistical tests for this periodic approach. While the periodic approach minimizes disturbances to the plant resulting from its designed experiments, it cannot track the best operation when it changes frequently.

The *EVOP* approach requires the plant to achieve steady state between trial executions for measured values to represent profit properly. Thus, the minimum execution period must be long enough for the process to achieve steady state. This fact is a strong drawback when dealing with systems with slow dynamics and many manipulated variables.

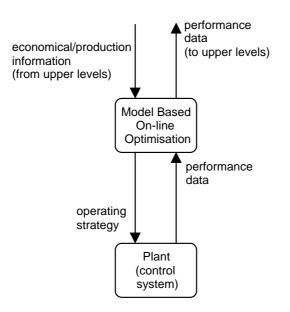


Figure 1.2: The general idea of on-line optimisation

### 1.2.1.3 Model based optimisation

It corresponds to the most complex and powerful approach. The arrangement is illustrated in figure 1.2. In the most general sense, information on the status of the plant is gathered, and used to assess the consistency of current conditions with the assumptions built into the mathematical representation. Where appropriate, adjustments are made to the model to reflect the latest situation. Armed with an up-to-date mathematical representation, and information on current operational requirements, parameters and objectives (coming from the upper level of the control hierarchy), an "on-line" decision-making problem is solved to determine the best operating strategy for the plant. If appropriate, this strategy is implemented. The plant and operational requirements are monitored to detect changes that might necessitate a re-determination of the best operating strategy, and the cycle is repeated at appropriate intervals.

As explained before (section 1.1.1, page 1), in a general sense such a system makes part of an *expert supervisory system* which performs an important number of functionalities, including for instance Fault Diagnosis, Data Mining, Gross Error Detection and Advanced Control, between others.

Undoubtedly, the main protagonists of the model based on-line optimisation system are the *disturbances*, which continuously shift the optimum in such a way that a periodical optimisation is needed. It is of upmost importance to distinguish the term disturbance in this context from the typically associated with the control system. For the purposes of an on-line optimisation system, a disturbance is a non manipulated variable whose value significantly affect the optimum location. According to the way the corresponding variable is associated to the system under consideration, the nature of such disturbances may be categorised as:

- *external*: typical examples of this kind of disturbances are given by changes in feed or utilities conditions/availability, desired product rates and specifications, between others.
- *internal:* commonly caused by some degradation mechanisms present in plant equipment. Examples are given by catalyst deactivation, decreasing efficiencies, fouling and scaling in heat transfer units, etc. Its rate of change is likely to be lower in order of magnitude with respect to the external disturbances.

Although it does not influence substantially the underlying idea, it is worth mentioning that the system is said to operate in a "closed-loop" fashion if the results of optimisation are automatically applied over the plant, otherwise, if the operator is consulted prior implementation, the system is said to operate "open-loop".

Additionally, although is not strictly correct, the on-line optimisation methodology is generally termed Real Time Optimisation (RTO). Hence, for the sake of clarity, the RTO term will be only applied to the currently adopted methodology for on-line optimisation of continuous processes.

### **1.3** Current scope of on-line optimisation in the chemical industry

The idea of on-line optimisation is quite general, but there are some procedural differences in the specific variants according the way the corresponding processes operates, that is to say, in a batch or continuous environment. Following, is given the current relative relevance in every area.

### **1.3.1** Batch processes

There have been two different research and applications areas concerned with the on-line optimisation of batch processes, which are briefly summarised next.

# **1.3.1.1** On-line optimisation of temporal profiles of operational variables for a single process unit

This kind of problem corresponds to the on-line solution of the so studied "optimal control problem" in the literature, this is to say, the optimisation of temporal profiles of key variables for process units. Some recent works that study this problem are those of Dimitratos et al. (1989); Filippi-Bossy et al. (1989); Cuthrell and Biegler (1989); Lee et al. (1997); Krothapally and Palanki (1997); Ishikawa et al. (1997) and Guay et al. (2001) between others. Although the problem is quite complex, the solution techniques involved are today relatively well known.

The main limitation for the application of on-line optimisation concepts are firstly, the difficulty of obtaining and validating acceptable dynamic models (either first principles based or empirical). Secondly, in order to know the state of the process significantly more information is required than that one for the case of continuous processes (Jazwinski, 1970). Unfortunately, discontinuous processes do rarely count with the desirable set of sensors to obtain a minimum quantity (and quality, i.e. because the significant delay in compositions measurements) of on-line information to properly perform optimisation in an on-line way. Furthermore, the optimisation problem complexity may not lead to the minimum acceptable robustness for an on-line implementation (Biegler, 1990, 1992).

An additional and not less important factor is that in batch processes, relatively low production-rate processes are usually involved, therefore, the benefits obtained may poorly justify the implementation of the technology. A subset of this kind of processes corresponds to sectors that incorporate a high added value to the products like fine chemicals or certain kind of plastics. The typical approach in this case is to introduce in the process tight quality controls in raw materials. Therefore, the reduction of variability may became not significant, and on-line optimisation looses one of its main motivations.

Additionally, it should be noted that the typical disturbances for this kind of process are usually of high frequency and low economic impact. Consequently, they seem to be more related to the unit control rather than to its optimisation. This would explain the increasing application of advanced process control techniques, specially non-linear variants of MPC, to deal with their operation (see for instance Qin and Badgwell (1998)).

#### 1.3.1.2 On-line scheduling of batch plants operation

Another important issue in model based optimisation of batch operations concerns planning and scheduling. In the chemical-processing context, production planning and scheduling collectively refers to the procedures and processes of allocating equipment over time to execute the chemical and physical-processing tasks required for manufacturing chemical products.

Usually, the production planning component is directed at goal setting and aggregate allocation decision over long time scale (months, quarters or year). Scheduling focuses on shorter time scale allocation, timing and sequencing decisions required to execute the plan on the plant floor. It is recognised that scheduling can be performed over different time scales from planning a campaign of runs, to developing a master schedule for a given campaign, to modifying the master scheduling to respond to changes and unexpected perturbations which inevitably arise as the schedule is executed (Reklaitis, 1995). From this point of view, the scheduling problem is a rescheduling problem (also termed reactive scheduling) without initial perturbations (Puigjaner, 2001).<sup>1</sup>

Thus, the second possible approach of on-line optimisation of batch plants corresponds to "on-line scheduling". It is a very interesting application field because of the following reasons:

• Models involved in planning and scheduling are simple and relatively easy to obtain.

<sup>&</sup>lt;sup>1</sup>Some authors have, to some extention, simultaneously addressed both the trajectories and scheduling optimisation (Romero et al., 2003).

- Techniques used for the scheduling problems have arrived to an acceptable degree of development.
- The standardisation of terminology, software and in certain degree hardware opens the doors to a high degree of batch plants automation.
- Significant presence of disturbances and uncertainty.

Some years ago, the main challenges of this field were rather practical than theoretical. Specifically, there was a major need of agreement of the co-ordinate way an on-line scheduler should interact with the procedural control. Furthermore, even there has been not consensus in the nomenclature. Nowadays, thanks to the standardisation (The Instrumentation System and Automation Society, 1995, 1999), the remaining step is to wait the industrial performance and acceptance of these systems.

### **1.3.2** Continuous processes

The most common use of on-line optimisation undoubtedly corresponds to this category of processes. This is mainly owed to the fact that the steady state models involved are simpler and easier to develop and validate. Besides, a reduced quantity of measurements allows to identify the current state of the process. Furthermore, continuous processes have commonly high production rates, then small relative improvements in the process efficiency originates significant economic earnings.

# **1.4** Current approach to on-line optimisation of continuous processes

Current industrial applications of model-based real-time optimisation (RTO) address complex plants. The following are the plant features which favor the application of RTO:

- Adjustable optimisation variables remain after higher priority objectives (safety, quality, production rate, etc.) have been achieved.
- Significant profit changes occur as values of the optimisation variables are changed.
- Disturbances occur frequently enough for real-time adjustments to be required.
- Determining the proper values for the optimisation variables is too complex to be achieved by selecting from several standard operating procedures.

There is a fair amount of published evidence supporting the conclusion that a successful RTO application delivers about 3% of the value added by the plant in economic benefits (Cutler and Perry, 1983; Lauks et al., 1992). It should be borne in mind that published applications to date

cover a very narrow spectrum of the full range of manufacturing plants employed in the process industries, e. g. large scale continuous plants in the petroleum and petrochemical sectors. The benefits figure quoted above is at best only typical of plants for that spectrum.

It appears that the cost of engineering of an on line optimisation system is most easily justified with current technology when the cash flows associated with large-scale operation are available. Since these operations are typically continuous, the focus of on-line applications has usually been on the optimisation of steady-state conditions. This has the benefit of greatly simplifying the modelling task associated with RTO, but raises other issues associated with model validation, and the validity of such assumption.

The components of the current generation of RTO systems based on steady-state models are enumerated below, where a typical optimisation cycle is defined (Van Wijk and Pope, 1992):

- 1. Check that plant is at steady-state.
- 2. Assemble plant measurement data for input to the optimisation system.
- 3. Check input data and ignore or adjust wrong values.
- 4. Match the optimisation model to current plant operating conditions. Calculate model parameters (e.g. heat transfer coefficients, pressure drops) according current measurement values.
- 5. Check the current status of all control loops to determine the degrees of freedom available for optimisation.
- 6. Optimise and determine a new set of operating targets.
- 7. Check new operating targets prior to implementation.
- 8. If the plant remains at the same steady state, implement automatically all validated targets.

The cycle is repeated after a suitable time interval, chosen to be sufficiently long to give a reasonable opportunity for the plant to settle to the new steady state determined by the optimiser.

In the procedure defined above, steps 1 to 3 are concerned with ensuring that a valid set of plant operating data is assembled to enable matching of the optimisation model to current conditions. Thus, since the model is typically based on the assumption of steady state, the plant status is assessed to check the validity of this assumption. The techniques employed to do this are straightforward, being based on the analysis of trends in key measurements. However, as with many aspects of RTO implementation, there is an art in the design of these tests. If the requirements are made too stringent, then many opportunities to apply the optimiser will be missed. On the other hand, the use of data sets representing operation inconsistent with the assumption of steady-state built into the model has some dangers.

The identification and removal of measurement values containing gross errors (step 3) is an important prelude to fitting the model to the current plant condition. A combination of checks

based on knowledge of the status of plant elements (e.g. equipment or instruments off-line or known to be malfunctioning), and more formal statistical tests based on assumed distributions of measurements and/or redundancy in the data set, is employed to exclude unreliable information (Crowe, 1996).

Parameter calculation at step 4 may be implemented using statistically-based parameter estimation techniques. It is also feasible to combine gross error detection with simultaneous parameter estimation. Alternatively, local calculations for process units where sufficient measurements are available may be employed. For example, a heat transfer coefficient for a heat exchanger may be determined from local measurements of flow rates and inlet and outlet temperatures.

Having established a mathematical representation of the current plant status that is consistent with available information, an optimisation problem is set up and solved (steps 5 and 6). The problem may be represented as:

Maximise an economical objective function:

$$\begin{array}{l}
\max \quad OF(x,p) \\
x
\end{array} \tag{1.1}$$

subject to:

$$f(x,p) = 0 \tag{1.2}$$

$$g(x,p) \le 0 \tag{1.3}$$

In this formulation, p represents the model parameters estimated from plant data, and x includes all remaining model variables. Equation (1.2) is the collection of equality constraints representing the mathematical model of the process. Typically, the dimensions of x and of f are large (of order 10 to 1000 in current applications). The difference between these two dimensions corresponds to the number of optimisation degrees of freedom. This number is typically in the range 1 to 100. The inequality constraints, the equations 1.3, play a significant role in the problem formulation, since it is quite common for the solution to the optimisation problem to be at least partly constrained. Since the position of the optimum may be determined by a subset of these inequalities which are active at the solution, it is then important that the model contains as accurate a representation of these constraints as possible.

Advances in technology to handle large scale non-linear programming problems have enabled the direct solution of the problem above, based on an "open" or equation-based representation of the plant model (equation 1.2). While this will tend probably to be the most commonly used approach in industrial applications, implementations based on sequential-modular modelling technology, or on hybrid approaches have also been successful (Lauks et al., 1992).

Having solved the optimisation problem, the results are reviewed to decide whether they should be implemented on the plant. Again, a variety of approaches is available ranging from allowing the plant operators to review the recommendations from the RTO systems (Van Wijk

and Pope, 1992) to formal statistical tests (Miletic and Marlin, 1996).

### 1.4.1 Benefits

The main benefit from on-line optimisation is improving the economic performance in terms of increasing the plant's profit and reducing pollutant emissions, which is the immediate benefit called on-line benefit. However other indirect benefits are perhaps more significant. The detailed operation information generated from on-line optimisation provides a better understanding of the processes; and thus, this can be used to de-bottleneck the process and to improve operating difficulties. Also, abnormal measurement information obtained from gross error detection can help instrument and process engineers to trouble shoot the plant instrument errors. Parameter estimation is very useful for process engineers to evaluate the equipment conditions and to identify the decreasing efficiencies and problem sources. Furthermore, the detailed process simulation from on-line optimisation can be used for process monitoring and serves as a training tool for new operators to obtain the first hand operating experience. In addition, this rigorous process model can be used for process maintenance, advanced process control, process design and facility planning, and process monitoring.

It is worth distinguishing between advanced control from optimisation benefits. One area of long-standing confusion is the relative benefit to be gained from advanced control approaches versus optimisation. Sometimes, a simple off-line analysis allows determining the potential active constraints (if any) for manipulating a single variable. Then, the control system must evaluate which constraint is most limiting at any given point in time and operate as close as possible to this constraint. Perhaps, a simple constraint controller utilising a PID algorithm will suffice. If more variables are present, the constraints will have a more complicated surface. However, it may be possible again to perform an off-line analysis to identify at which set of constraints the optimum lies, and to implement a standard MPC to hold the plant at such intersection. Again, there will be no benefit for on-line optimisation. It should be then noted that the optimum vertex might change, or possibly the optimum even lie always at a constraint vertex. In such case, the on-line optimisation benefits will be present.

### 1.4.2 Weak points

Although the public bibliography is very positive, it should be noted that only the successful applications are commonly reported. Most of the publicly reported industrial applications have in common that are extremely vague in detail, very optimistic with the results, and too often the papers' authors pertain to the company responsible for the implementation of the on-line optimisation system. Unfortunately, this is not very good, because somehow reduces the scientific credibility of the technology (Cutler and Perry, 1983; Latour, 1998; Sorensen and Cutler, 1998). The majority of the benefits reported could be attributed just to the improvement in the control level (because most of them use an Advanced Process Control, APC, layer) rather than the optimisation one, or even worse, just to the better understanding of the process (White, 1997).

Indeed, industrial implementations of advanced control are becoming commonplace, while only a very small fraction of such kind of projects include the RTO layer as well, what indicates that something is not so good.

The important thing is that after four decades (Eckman and Lefkowitz, 1956; Crowther et al., 1961; Kuehn and Davidson, 1961) there has been a progressive improvement in the on-line optimisation methodology, but the same initial weakness or more generally speaking some common causes of poor performance still remain, as industry practitioners have reported (Friedman, 1995; White, 1998). The is an agreement about the most significant causes:

- 1. *There is not on-line optimisation problem to be solved* (i.e. disturbance frequency too low, lack of degrees of freedom, etc.) and therefore the optimiser solution does not change with time. This is a possible situation if the conditions for performing on-line optimisation are overlooked or not well understood. The result can be poor initial specification of the system. Changes in the plant or business environment may cause this optimisation irrelevancy.
- 2. Disturbance frequency too high and/or the steady state wait, corresponds to the converse problem. In reality, disturbances affecting the economy come in all the time and no unit is ever at the steady state. How then can be created a set of measurement that is in phase enough and would not mislead the optimiser? The response has been heavy filtering and too long waiting. The system is most of the time idle. This fact make very difficult to catch up with day-night cycle and normal whether changes, being the optimiser out of phase. This is one of the points that most restricts the applicability of on-line optimisation system.
- 3. Inadequate optimisation robustness. The solver does not find a solution, or takes too long to find it. The optimisation problem can involve from a couple to several decision variables and the models (constraints) can be a simple correlation or a huge equation system. Although the optimisation techniques are now able to deal with that fact in an off-line way, the RTO system works on-line. The possibility of optimiser to fail must be reduced to practically zero, and the solution is required as fast as possible. Poor design of an on-line optimiser can contribute to its demise. The answer has been to use simplified models that although improve the optimisation performance, may lead to an economical pitfall.
- 4. No on-line model updating or more generally plant-model mismatch. No practical model of a plant, no matter how rigorous, can provide an accurate long-term projection of the plant's response through its normal evolution. Typically, optimisation projects are implemented with equipment design data and plant tests that are used to fit initial model parameters to actual responses. However, the plant response changes with time. Catalysts age or are replaced, exchangers foul, trace impurities change. The prediction from the model and the actual plant response begin to diverge. Thus, those systems that lack auto-calibration procedures using actual plant data to regularly update the model's parameters will fail.

- 5. No compensation for process instrumentation: if the optimiser calculates the set-points targets and at least one of them cannot be implemented (because saturation or out of service actuator or a manual change in the result), the result will be an unsatisfactory sub-optimal solution. What should be done then? The optimisation system must recognise that these problems will occur and be able to function perhaps in a degraded mode, when they happen. Some mechanism must also be provided to recognise and compensate for invalid process measurements.
- 6. Lack of information or too much uncertainty. A possible situation is that the measurements are not enough to perform a reliable optimisation using nominal conditions for unobservable variables. Therefore, before the implementation of an on-line optimisation, a careful analysis about the degree of current redundancy needs to be performed. Furthermore, its likely that a re-engineering of the sensors location is going to be required to improve the redundancy and the uncertainty associated to the measurements.
- 7. Incorrect pricing and economical information. In many cases, it makes sense to try to optimise individual units rather than the whole plant section. For this effort to succeed, methods for intermediate products economy are required. Arguments about the correct feed and product process to use for unit optimisers have existed since the very first systems were installed. Although shadow prices from planning give approximated values, special effort is needed to properly quantify economically the plant streams. When available, market prices use to be the best choice. Elsewhere, long-term planning prices frequently updated are also convenient. For such strategy to succeed is to keep the planning and the on-line optimisation model as consistent as possible.
- 8. Not enough maintenance and support to the on-line system. While concentrated effort may go into defining an on-line optimisation project and its initial implementation, the same attention is often not given to long-term maintenance and support requirements. There is a failure to recognise that the business and technical environment will change and that the optimiser must be changed to compensate. Changes may be associated to the production objectives, quality specifications, or even a new product or raw material. Furthermore, the addition and removal of different lines, vessels, etc. seldom takes place. What is even more frequent is related to the continuous evolving hardware and software environment.
- 9. The applicability and research efforts have been focused mostly in continuous process operation. Very little attention has been paid to on-line optimisation possibilities in environments somehow different that a huge petroleum refinery. Although it is true that some applications start to move to other areas, the attention is still mainly focussed to the continuous operating way, without considering significant aspects as are catalysts regeneration, heat exchangers cleaning and so on.
- 10. Finally, other significant aspect to consider is the *software design*. It should be designed to facilitate non-expert use and to as user friendly as possible. Besides, it should ease making

changes to the problem set-up and reduce the manpower requirements

Most of the previous causes of poor performance are owed to human factors rather than the technology by itself. Some of the weakness can be avoided just by properly obtaining information, as well a measurement of the uncertainty associated (points 6 and 7). Others can be solved using better models and therefore correspond to the modelling area rather than the optimisation procedure. The key issues are given by the points 2, 3, 9 and 10 and constitute the motivation for this thesis work.

### **1.5** Thesis objectives and scope

### 1.5.1 Objectives

Having shortly described the context and the main functionality of the on-line optimisation technology, the goals of this thesis are now introduced. The main objective of the thesis is to contribute to the improvement of the current technology in the field of on-line process optimisation. Therefore, the strategy for the research will seek the following targets:

- Develop a system consistent with the process dynamics.
- Develop a system able to deal with higher frequency disturbances.
- Develop a system as much independent as possible of sophisticated control layers.
- Develop a system simple enough to be applied in any kind of process despite its size.
- Develop a system that make an intensive use of what is available, as for example the information generated during model updating.
- Open new possibilities for on-line optimisation.

These objectives are directed to overcome the weak points of the current status before presented. Any improvement in the area will likely contribute to the use of the technology, and therefore should lead to the benefits of on-line optimisation, summarised also in the previous section.

### 1.5.2 Scope

This thesis work is dedicated to continuous process, which have received most of the attention by the academic research. Besides, it is also extended to semi-continuous process with decaying performance, where the operation becomes cyclic. The present work is not focused in process particularities, trying to afford the problems as generally as possible, in order not to impose tight limits to the results applicability. However, a particular attention will be paid to the contribution simplicity, because it is a wish of the author not to restrict the potential application to processes that already count with a high technology control system (Sivasubramanian and Penrod, 1990).

### **1.6** Thesis outline

This thesis is structured as follows. Chapter 2 consists in a literature review that addresses to some extension the most significant issues around the on-line optimisation functionality. After that, chapter 3 and chapter 4 introduce two strongly related methodologies for on-line optimisation, which are based in the same underlying strategy. The first one (in chapter 3) focuses in tracking drifting optima, under the combined effect of internal and external disturbances. On the other hand, a parallel methodology is explained in 4, conceived for processes that presents decaying performance, which require discrete decisions about the maintenence actions to be performed. Both chapters include a first part, rather theoretical, and a second part devoted to the validation over typical benchmarks. The explanation of the combined use of the proposed methodologies is given at the end of chapter 4. Then, chapter 5 describes the application of such methodologies over two existing industrial scenarios. After that, chapter 6 addresses a set of issues related to the implementation such as dynamics aspects and software considerations. Finally, chapter 7 draws conclusions and summarises the thesis contribution. Figure 1.3 represents schematically the explained sequence, indicating as well the degree of theory and practice associated to every chapter.

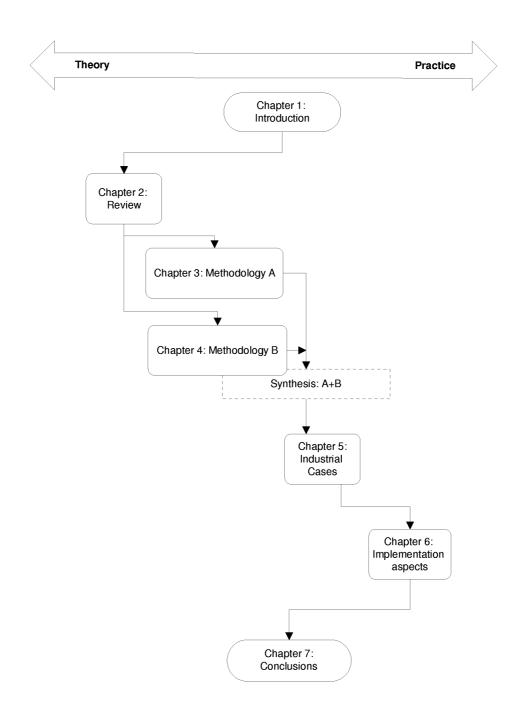


Figure 1.3: Thesis outline

Chapter 1. Introduction, Motivation and Objectives