INTEGRATION OF MODEL PREDICTIVE CONTROL AND OPTIMIZATION OF PROCESSES

Enabling technology for market driven process operation

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Abstract: This paper discusses changes in the market of chemical processing industries and its consequences for process operation. The problem of continuously declining capital productivity is tackled, which has been faced by the chemical processing industries during the past decades. In the paper a motivation is given on how new technologies in the area of model predictive control and dynamic process optimization can contribute to improve business performance of the chemical processing industries in the changed markets. These new technologies have to support dynamic operation of plants at intended dynamics. Extensions and changes required to technologies that are currently applied in the oil refining industries and in some petrochemical industry applications are discussed. These extensions and changes are necessary to meet the specific requirements of the chemical processing industries.

Keywords: Process Control, Model Based Control, Industry Automation, Plantwide Optimization, Chemical Processing Industry, Process Operations, Capital Productivity, Manufacturing Execution Systems

1. INTRODUCTION

Chemical Processing Industries are currently facing an enormous challenge: Within the next few years they have to realize a significant improvement in their financial performance to remain attractive for capital investors.

Gradual decline of the productivity of invested capital over the past three decades is a main problem of the chemical processing industries. The financial performance of many companies belonging to the Chemical Processing Industries has approached dangerously low levels, which may make it hard to compete with industries that do well like for example the Information and Communication Technology oriented industries.

An interesting parallel can be observed between this situation the Chemical Processing Industries are facing now and the situation of the Consumer Electronics and Automotive Industries about twenty years ago. Consumer Electronics Industries and the Automotive Industries also saw their performance rapidly going down despite extensive reorganisations oriented to reduction of costs. The industries that survived this critical situation and that prosper now, are the ones that completely turned around their way of working from a supply driven approach to a market driven approach. The ones that did not survive are the ones that did not follow in this turnaround.

The solutions created by the Consumer Electronics and Automotive Industries can of course not be copied directly by the processing industries. Market driven operation is far more complex for a processing industry -with its process inertia that spans several decades on a time scale- than in industries that primarily have to focus on logistics and supply chain only.

Chemical Processing Industries are confronted with further complicating factors related to tightening operating constraints imposed upon production sites in terms of required reduction of consumption of energy, raw materials and natural resources at one

hand and in terms of required reduction of ecosphere load at the other hand.
The constraints imposed upon production result in increasing complexity of processes and of their operations. More sophisticated operation support systems will be required to exploit freedom available in process operation (Backx, Bosgra and Marquardt, 1998).

The paper is structured as follows:
Section two of the paper discusses the economic drivers and motivation for improvement of the process control and optimization technologies applied in process operations. An analysis is made of problems faced by industry. A general problem definition is given on the basis of the analysis. Section three gives an overview of developments that have been done and that are currently applied in the areas of model based process control and model based process optimization. Comparison of capabilities of current technologies with the general problem definition results in a functional specification for new technologies.
Section four outlines requirements for the integration of next generation model based control and model based optimization technologies.
A polymer manufacturing case is elaborated in section five as an example. It shows initial results of integrated process control and dynamic optimization techniques.
Section six finally gives some final remarks.

2. ECONOMIC DRIVERS FOR MARKET DRIVEN PROCESS OPERATIONS

To get a clear understanding of the problems process industry is facing, an analysis needs to be made of the way processes are operated today in comparison with market demand and market opportunities. Analysis of the market reveals that most chemical industries are operating in a market that is saturated to a large extent. The market has become global for most suppliers of chemical products and intermediates. Market demand is furthermore showing unpredictable movements with a growing demand for diversification in product specifications.
The Chemical Processing Industries are still largely operating their production facilities in a supply driven mode of operation. This implies that no direct connection exists in most companies between actual market demand and actual production. Products are to a large extent produced cyclically in fixed sequences. Delivery of orders is largely handled from stock of finished products or from intermediates that only require finishing. Recent developments in chemical processing industry show that many of the smaller operating companies have been taken over by larger ones. At this moment two tendencies can be observed within companies operating in this area:

- Companies that try to further reduce operating costs by minimizing the number of different product types produced at a production site and by extending the production of well selected sites using the ‘economy of scale’ principle. These companies focus on minimization of the fixed cost component of the product price and try to drive towards minimization of total costs of the operation. Flexibility is realized by ensuring that sufficient production plants are available to cover the variety in market demand. Due to the limited number of different products per plant relatively short production cycles can be applied, which reduces the amount of finished products that have to be kept in stock to supply the market. Each production site can only produce a limited and a small range of products. This implies that flexibility to respond to actual market demand and especially to changes in market demand are very limited.
- Companies that try to significantly increase their flexibility in producing and processing a wide range of products at their sites and that attempt to move to production at demand. These companies improve their financial performance by minimization of stock, by increase of their flexibility to adapt to market demand, even if new product specifications are requested, by maximization of margins and by reduction of the capital turnaround cycle time related to capital invested in products and intermediates.

The first category of companies produce products clearly at lowest costs initially as they can realize a lean operation with minimum overhead costs and no significant investments in upgrade of their operation support technologies. Longer term it will appear however that the average residence time of products in warehouses will be long in comparison with the average residence time of products in warehouses for the second category of companies due to the remaining lack of flexibility to directly link production to market demand. Also margins will continuously be under extreme pressure for a significant part of the volume produced due to market saturation effects and due to mismatch between market demand and supply from stored products. The average capital turnaround cycle time, although improved due to the limitation of the number of grades produced per plant, will remain poor. This will continue putting pressure on the ultimate business results of these companies.
Companies belonging to the second category are the ones that are setting the scene for turning around the way of working in the Chemical Processing Industries. These companies are doing exactly the same thing as the ultimately successful companies in the Consumer Electronics and Automotive Industries did: Operate production directly driven by market demand to the extent feasible. These companies are facing tough times however as their total production costs, due to their focus on flexibility, initially appear to be higher. They have to make significant investments in adapting their production equipment and instrumentation to enable the flexible operation.

Ultimately, these companies will see their overall performance rapidly improve. These improvements are due to the increase of capital turnaround, the better margins they can realize related to improved flexibility, their ability to better adapt to changing market conditions and their capability to timely deliver at (changing) specifications and varying volumes of product demand. The influence of reduction of the capital turnaround cycle on business performance is showing interesting characteristics. Defining capital productivity (C_{pr}) by:

$$C_{pr} := \frac{M}{K * T_{cycle}} \qquad (2.1)$$

with:

Cpr	-	Capital productivity per year
M	-	Total margin realized per production cycle
K	-	Capital 'consumed' during the production cycle for production and for enabling production
T_{cycle}	-	Length of the production cycle in years

The capital productivity can now be calculated as follows:

$$C_{pr} = \frac{n \cdot T_h \cdot [(V_h - C_{in}) \cdot P - F - F_{eq}]}{n \cdot (T_h + T_w) \cdot (P \cdot C_{in} + F + F_{eq}) \cdot T_{cycle}} + \frac{n \cdot T_o \cdot [(V_w - C_{in}) \cdot P - F - F_{eq}}{n \cdot (T_h + T_w) \cdot (P \cdot C_{in} + F + F_{eq}) \cdot T_{cycle}} \qquad (2.2)$$

with:

P	-	average production rate [kg/hr]
F	-	fixed costs related to operation of the equipment (e.g. salaries, maintenance, overhead, …) [DM/hr]
F_{eq}	-	fixed costs related to depreciation of equipment and interest paid on capital invested in equipment [DM/hr]
V_h	-	market value of high spec product [DM/kg]
V_w	-	market value of wide spec product [DM/kg]
C_{in}	-	variable costs related to input materials, energy costs, etc. [DM/kg]
T_h	-	average run time of a specific grade [hr]
T_w	-	average grade transition time during which time wide spec product is produced [hr]
n	-	number of grades in a total production cycle [-]

Variable	Value	dimension
P	11416	[kg/hr]
F	2750	[DM/hr]
Feq	5900	[DM/hr]
Vh	1.41	[DM/kg]
Vw	0.90	[DM/kg]
Cin	0.56	[DM/kg]
Th	40	[hr]
Tw	8	[hr]
n	1-30	[-]
Tcycle	$n \cdot (T_h + T_w)$	[hr]

Table 2.1 Overview of the assumed values for calculation of the capital productivity

Taking as an example an average size polyethylene production plant this capital productivity can be calculated as a function of the number of product grades produced within a production cycle.

Assuming the conditions given in table 2.1 the capital productivity as a function of the number of product grades in a total production cycle is given in fig. 2.1. The underlying assumption made in this calculation is that production of a total production cycle is stored before it is sold on the average. The capital invested in products is released and the margin is made after a production cycle. In case flexibility is maximally increased to enable production directly on demand, the capital productivity realised is equal to the capital productivity corresponding with a cycle of one grade only as a limit.

In general, capital productivity can be further increased, if flexibility in operation of the plant supports production at market demand due to better margins that can be obtained for the products produced. This further potential for improvement stems from the market mechanism that products that have high demand can be sold at better prices than products that are abound. The average margin improvement due to this market mechanism will easily be a few percent of the market price of the products. The dashed line in fig. 2.1 shows the capital productivity for an assumed additional average margin improvement of only 0.1 percent of the market value of the product due to this mechanism.

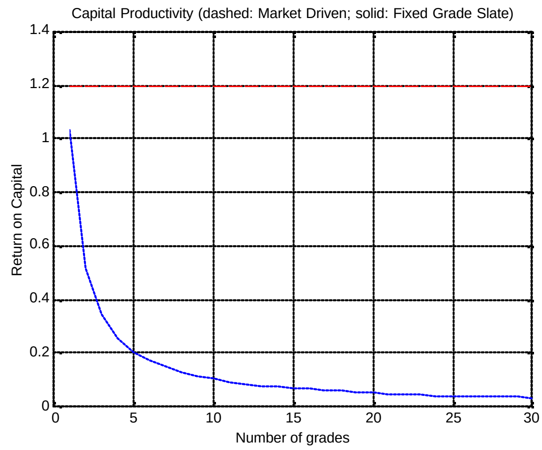

Fig. 2.1 Capital productivity as a function of the number of product grades in a production cycle

As can be seen from this figure, a significant improvement of performance results when the overall cycle time is significantly reduced. Focussing operations on enabling market driven operation of processes opens up this opportunity amongst others. It ultimately ensures that products are almost directly delivered to customers after production so enabling shortest possible capital turnaround and significantly improved capital productivity.

Market driven process operation puts extremely high requirements on predictability and reproducibility in process operation. One needs to be able to produce products at adjustable specifications in predefined, tight time slots and in changing volumes. Flexibility and timing are key parameters that drive performance. Technologies that support such process operation have to provide the functionality to operate processes this way.

The problems faced by process industries to turnover production control from supply driven process operation to market driven process operation may be summarized by the following problem statement:
Given an industrial scale production plant that forms one link in a supply chain, provide the process operation support technologies for this plant that:

- *Enable operation of the plant in such a way that imposed operating constraints related to safety, ecology, plant lifetime and plant economics are always satisfied*
- *Continuously drive the plant towards operating conditions that comply with supply chain optimum operation within a pre-defined, feasible operating envelope for the plant*
- *Operate the plant in accordance with process operating conditions that push for maximization of capital productivity of the company the plant belongs to.*
- *Exploit remaining freedom in plant operation to maximize capital productivity of the plant over plant lifetime*

This problem definition clearly reveals that a set of subproblems needs to be resolved that interfere with one another:

- Optimization of supply chain operation
- Optimization of overall capital productivity of the company the plant is part of
- Window over which the optimization is done together with the weighting applied over this window
- Restricted operating envelope and its resulting limitations to business performance

All freedom available in plant operation must be used for driving the plant continuously to the operating conditions that best comply with a selected balance of mutually conflicting objectives.

3. STATE-OF-THE-ART MODEL BASED PROCESS CONTROL AND OPTIMIZATION TECHNOLOGIES

State-of-the-art technologies that industry currently applies for model predictive control and model based process optimization are not well suited to solve the problems defined in the previous chapter. A more detailed evaluation of the applied technologies is required to reveal the problems with these technologies in solving the problems related to optimal process operation. The main reason for the mismatch between current state-of-the-art operation support technologies and operation requirements related to overall optimization of plant performance in the sense described in chapter 2, basically finds its cause in the focus on (quasi) steady state behaviour in stead of looking for full exploitation of plant dynamics (Koolen, 1994).

Model Predictive Control technology has been widely adopted by process industries in general and by the Oil Refining and Petrochemical industries especially over the past fifteen years to improve results from process operations. This technology has originally been developed by industry for this purpose (Camacho and Bordons, 1995, 1998; Cutler and Ramaker, 1979, 1980; Cutler, 1983; Cutler and Hawkins, 1987; Froisy, 1994; Garcia, 1984; Garcia and Morshedi, 1986; Garcia and Prett, 1986; Garcia, et al., 1988; Garcia, et al., 1989; Grosdidier, et al., 1988; Lebourgeois, 1980; Morshedi, 1986; Peterson, et al., 1989; Prett and Gillette, 1979; Richalet, et al., 1976, 1978; Richalet, 1993; Song and Park, 1993; Zafiriou, 1990). Model Predictive Control technology has evolved from a basic multivariable process control technology (Cutler and Ramaker, 1979; Richalet et al., 1976, 1978) to a technology that enables operation of processes within well defined operating constraints (Allgöwer, et al., 1999; Bequette, 1991; Lee, 1996; Qin and Badgewell, 1997). Essential in model predictive control is the explicit use of a model that can simulate dynamic behavior of the process at a certain operating point. In this respect model predictive control differs from most of the model based control technologies that have been studied in the Academia in the sixties, seventies and eighties. Academic research has been primarily focussing on the use of models for controller design and robustness analysis of control systems only for quite a while (e.g. Alamir and Bornard, 1994; Balakrishnan, et al., 1994; Doyle, et al., 1995; Doyle, 1984; Doyle, et al., 1989; Economou and Morari, 1985; Kalman, 1960; Maciejowski, 1989; Zadeh, 1962). With their initial work on internal model based control Garcia and Morari (1982) made a first step towards bridging academic research in the area of process control and industrial developments in this area. Significant progress has been made in understanding stability and performance of model predictive control systems since the end of the eighties (e.g. Lee and Yu, 1994; Meadows and Rawlings, 1993; Rawlings and Muske, 1993; Rawlings, et al., 1994; Scockaert, et al., 1999; Zheng and Morari, 1994). A lot of results have been obtained on stability, robustness and performance of model predictive control systems since the start of academic research on model predictive control (e.g. Bloemen and Van den Boom, 1999; Clarke and Scattolini, 1991; Eaton, et al. 1989; Eaton and Rawlings, 1990; Economou, et al. 1986; Kwon, 1994; Lee, et al., 1994; Lee and Yu, 1994; Lee, 1996; Mayne and Michalska, 1990; Michalska and Mayne, 1993; Morari, 1988; Morari and Zafiriou, 1989; Nevistić and Morari, 1996; Özgölsen et al., 1993; Patwardhan, et al. 1990; Saint-Donat, et al., 1991;

Soeterboek, 1992; Tan and De Keyser, 1994; Wahlberg, et al., 1993)

The quadratic objective function that is minimized by the latest model predictive control systems has the following generic form:

$$J = \sum_{j=0}^{N} \hat{z}^{T}(k+j\,|\,k)\cdot\Gamma(j)\cdot\hat{z}(k+j\,|\,k) \qquad (3.1)$$

The vector variable $\hat{z}(k+j\,|\,k)$ in this expression is a *linear* function of manipulated variables, controlled variables and/or states of the process. The assumed linear function includes weights on the variables. The objective function J is minimized subject to amplitude and rate of change constraints on manipulated variables, controlled variables and/or states:

$$\begin{aligned} u_{\min} &\le u(k) \le u_{\max} & \forall k \\ \Delta u_{\min} &\le \Delta u(k) \le \Delta u_{\max} & \forall k \\ y_{\min} &\le y(k) \le y_{\max} & \forall k \\ x_{\min} &\le x(k) \le x_{\max} & \forall k \end{aligned} \qquad (3.2)$$

The objective function (3.1) only regards a finite horizon of N samples ahead at each sample interval. Todays most widely applied model predictive control systems approximate this multivariable receding horizon model predictive control problem by solving three consecutive subproblems (Qin and Badgewell, 1997):

- Prediction of the expected future output behavior on the basis of known past inputs, known disturbances and expected future disturbances
- Steady state optimization of an (economic criterion based) objective function (QP or LP)
- Calculation of best future input manipulations by minimizing a quadratic objective function (LQ or constrained QP based optimization)

The model applied within the model predictive control system plays a crucial role: It enables *feedforward* driving of the process to desired operating conditions to compensate for measured and observed disturbances to the extent feasible (cf. fig. 3.1). *Feedback* control is only applied for compensation of inaccuracies in model-based predictions and unmeasured disturbances. The model is explicitly applied twice in the controller:

- for the prediction of future outputs
- and for the calculation of best future input manipulations

The feedforward driving of the process, together with its capabilities to respect operating constraints and to optimize the use of available degrees of freedom in process operation form the strengths of the model predictive control technology.

It is clear that these strengths only apply for process behavior that is covered by the model. The models applied in model predictive control systems are mostly black box type models obtained with process identification techniques.

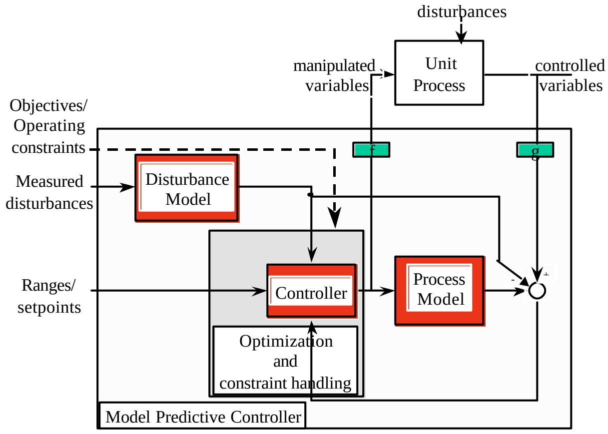

Fig. 3.1 Model Predictive Control system

A lot of research has been done over the past decades to develop reliable multivariable system identification and model reduction techniques that can be applied for process modeling (e.g. Åström and Eykhoff, 1971; Backx, 1987; Backx and Damen, 1992; De Vries, 1994; Eykhoff, 1974; Falkus, 1994; Hakvoort, 1994; Heuberger, 1990; Ho and Kalman, 1966; Ljung, 1987; Moore, 1981; Pernebo and Silverman, 1982; Schrama, 1992; Söderström and Stoica, 1989; Swaanenburg, et al., 1985; Van den Hof et al., 1994; Van Overschee en De Moor, 1993; Van Overschee, 1994; Verhaegen and Dewilde, 1992; Wahlberg and Ljung, 1991; Willems, 1986, 1987; Zeiger and McEwen, 1974; Zhu and Backx, 1993). Despite the extensive research done in this field with reliable process identification techniques as a result, most of the model predictive control systems are still based on the use of rather primitive, limited complexity, non-parametric model types (Finite Step Response models, Finite Impulse Response models), low order transfer function models (First and Second Order transfer function models with time delays) or low order State Space models. The models are mostly linear, discrete time, time invariant models. If non-linearities are included, only *static non-linear describing functions* are applied for input and/or output transformation (Hammerstein, respectively Wiener models).

The complexity limitation results in models that only cover a very small part of all process dynamics that may be applied for control. The dynamic range covered by a Finite Impulse Response/ Finite Step Response model with 60 samples is approximately 1:10 for example. This implies that the largest time constant represented by the model can only be 10 times slower than the smallest time constant. Similarly, a second order transfer function model can only cover two major time constants of the process. The actual process will cover a much broader dynamic range in general. Even a simple distillation column may serve as an example: An industrial column with 50 trays will have a time to steady state that will be in the order of magnitude of 5-6 hours approximately. This same column will show a change in distillate composition in response to a top pressure change well within a minute. The dynamic range of this column, applicable for high performance control, is therefore at least 1:300. This wide dynamic range could be used for control, if the model would cover all these dynamics. Due to the limited bandwidth of the model and due to the fact that the modeling effort focuses on making the model responses accurately match with process behavior for low frequencies, high frequency response characteristics of the process are not covered by the model.

Similarly, the linearity of the system dynamics assumed also restricts the performance that can be achieved by the control system. Deviation from the operating conditions applied for modeling will result in an error between the model and the actual process behavior. This model error needs to be corrected by the feedback loop, which implies that the tuning of the controller needs to be such that stability still will be guaranteed. As a consequence a robustly tuned controller results with its related sluggish responses: It will take relatively long time for the controller to correct for the errors in the prediction. Although the control system will be tuned for robust performance over some operating envelope, this envelope will still be rather small and often not be large enough to include a broad range of different operating points corresponding to the production of different product grades.

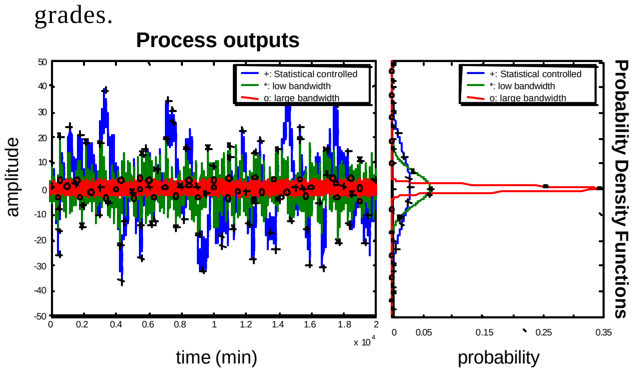

Fig. 3.2 Effect of controller bandwidth on performance

The consequence of applying low complexity/low order, linear, time invariant models inside the model predictive controller is that the controlled process will only have low frequent (quasi steady state) response characteristics. Model mismatch at frequencies higher than about 10 times one over the largest time constant of the model will not permit a significant loop gain at those frequencies. The tuning required for robust performance will prohibit the use of these higher frequency process transfer characteristics for control. As a result performance in terms of enabling extensive reduction of variance and fast transitions between various operating points will be severely restricted. Fig. 3.2 shows the effect of the bandwidth of the control system on reduction of variance. The large bandwidth controller applied for constructing this figure has a bandwidth, which is 30 times larger than the bandwidth of the low bandwidth control system. A significant additional reduction of variance results, which implies both a better compliance with specifications and more freedom to operate closer to the tolerance limit corresponding with minimum cost of operation.

Model predictive control enables predictable and reproducible operation of processes within a given operating envelope on the basis of a linear approximation of dynamic behavior of the process. In addition to the model predictive control techniques *closed loop plant wide optimization* techniques have been developed to operate plants at best economic operating conditions using an approximate model that describes steady state non-linear plant behavior. These closed loop optimization techniques use a first principles based steady state model of the plant for calculation of the operating conditions that will bring best economic performance from plant operation (e.g. Bailey, et al., 1993). Contrary to the optimization done inside the model predictive control system by means of a locally valid linear approximation of plant behavior, a first principles based model is applied that covers non-linearities in plant behavior over a large operating envelope. This model may therefore be applied to look for best operating conditions over a broad operating envelope. The objective function that is optimized has the following generic form:

$$J_1 = F(y(t), u(t), x(t), J) \qquad (3.3)$$

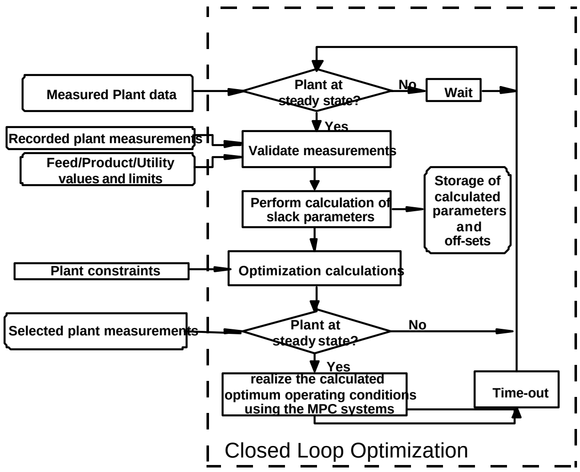

Fig. 3.3 Flow diagram of a closed loop, real time plant optimization system

After detection of steady state conditions by means of statistical analysis of recorded process signals and after reconciliation of the recorded process data, this objective function is optimized in two subsequent steps (cf. fig. 3.3):

- In a first step a selected set of slack parameters J are adjusted to make the model match with the actual recorded plant behavior
- In a subsequent optimization step the operating conditions are determined that maximize plant economics for given market and plant conditions using the adjusted plant model.

To solve these non-linear optimization problems primarily SQP techniques are applied (e.g. Biegler, 1984).

The closed loop optimization system looks at steady state conditions of the plant only, as it does not have any information on plant dynamics. Due to disturbances that continuously influence plant processes, a plant will never really be in steady state. The steady state assumed can only be artificial as a consequence.

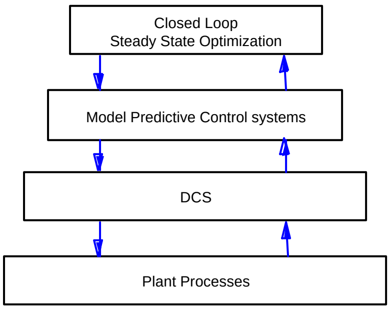

Fig. 3.4 Closed Loop Real-Time Optimizer configuration

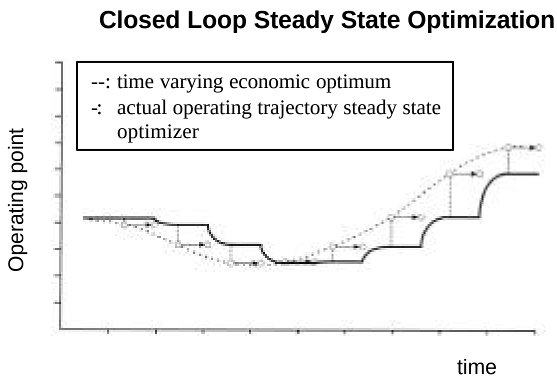

Fig.3.5 Quasi steady state operation of a plant

After optimal operating conditions have been determined by the optimizer, these conditions are to be realized by the model predictive control systems that are supervised by the optimizer (cf. fig. 3.4). The calculated optimum operating conditions of the plant will in the best case follow the true plant optimum with a severe lag (cf fig. 3.5). The calculated optimum furthermore only reflects the conditions at the moment of detection of the steady state. The plant may therefore already be at different operating conditions at the moment the optimum is realized by the underlaying model predictive control systems due to disturbances.
Another problem related to the current state-of-the-art configuration of closed loop real-time optimizers is the potential inconsistency between the models applied for optimization and the models used inside the model predictive control systems. The model predictive controllers use models that essentially are valid in one specific operating point of the process only due to the *linear approximation of process behavior in a single operating point*. The model(s) applied stem(s) from process identification. The optimizer uses a *non-linear steady state model* that is assumed to reflect dominant process mechanisms over the complete operating envelope. Both models will in general be inconsistent at most of the regarded operating envelope.

Looking at the problem statement formulated in section 2 it is clear that the technologies described above don't really solve the problem related to optimal supply driven operation of a plant. *Dynamic optimization techniques* are required to continuously drive the plant to optimal operating conditions. Due to complexity of the full dynamic optimization of a plant, still a separate optimization and control layer will be required for practical feasibility. These two layers will be operating at different overlapping time-scales initially. The control layer needs to exploit the full dynamics of the plant and its freedom in operation for local optimization, whereas the dynamic optimizer needs to continuously push towards (global) optimal operating conditions. Optimization and control need to be fully integrated to prevent inconsistencies between the optimization and control layer. The full integration also has to minimize lag in chasing plant optimal operating conditions.

4. CONSISTENT INTEGRATION OF MODEL BASED CONTROL AND MODEL BASED OPTIMIZATION

Plant optimization and process unit control in general cover a time-scale range from seconds to days. Since separation of time scales is no longer feasible the approaches applied for market driven plant operation are characterized by establishing intentional dynamics in process operations. In contrast to current practice of operating the process as long as possible in a certain stationary mode -at a steady-state operating point, at a certain production schedule with a minimum of planned switches, or with a certain operating process or control system structure- dynamic (or transient) process operations in an encompassing sense must be aimed at in order to accomplish the highest possible responsiveness of the production to market needs. Realization of this goal requires integration along several dimensions :

- integration across the control hierarchy layers, which allows both high performance quality control and flexible transient operation of a process on all time scales,
- integration of the various tasks during process operations such as automatic control and optimization, measurement and estimation as well as operator supervision and corrective action,
- integration of intended control actions over a wide range of process scales ranging from the

microscale (e.g. the kinetic processes on a catalyst surface), the mesoscale (e.g. physical transport phenomena) up to the macroscale (e.g. the processes in the worldwide supply chain)

- integration of process performance diagnosis with the engineering design processes aiming at continuous overall process improvement.

Plant wide *dynamic* optimization is a complex problem. State-of-the-art dynamic optimization techniques (Li and Biegler, 1990; Li, et al., 1990; Støren and Herzberg, 1995) only enable closed loop real-time optimization of plants with very specific characteristics:

- Fastest relevant dynamics for process operation are sufficiently slow in comparison with the simulation speed of the dynamic simulator and with the time required for optimization.
- Sufficiently accurate first principles based and/or empirical dynamic models are available of the plant for closed loop optimization.
- The optimization problem is well conditioned and sufficiently good initial values are available to guarantee convergence to the optimum

The above requirements will only be satisfied for a very limited number of plants. The control relevant dynamics of most processes will be too fast for enabling real-time non-linear closed loop dynamic optimization. To overcome this problem a control and optimization hierarchy has been defined that uses a model based dynamic optimizer for calculating optimum trajectories for all relevant process variables of the plant. Model predictive control systems operating in delta model have to ensure optimal tracking of the optimum trajectories (cf. fig. 4.1). The model predictive control systems are based on process models that are assumed to be fully consistent with the models applied by the dynamic plant optimizer. As the optimizer will generally only be capable of covering low frequency dynamics due to complexity of the full-scale problem, the optimizer only will cover these low frequency dynamics. Computational complexity will highly determine computation time required for optimum trajectory computation (Van der Schot, et al. 1999).
The model predictive control systems need to apply models that are consistent with the model applied for optimum trajectory generation by the plant wide optimizer. This implies that the models applied by the optimizer (M_{opt}) and by the model predictive control systems (M_{MPC}) will need to have equivalent dynamics for low frequencies:

$$M_{opt}(y,x,u,J,f \mid 0 \le f \le f_{opt}) \cong M_{MPC}(y,x,u,J,f \mid 0 \le f \le f_{opt}) \qquad (4.1)$$

The model predictive control system models will in general cover a larger bandwidth than the models applied by the optimizer. The additional bandwidth is used to keep the process as tightly as economically feasible in the low frequency optimum operating condition determined by the optimizer.

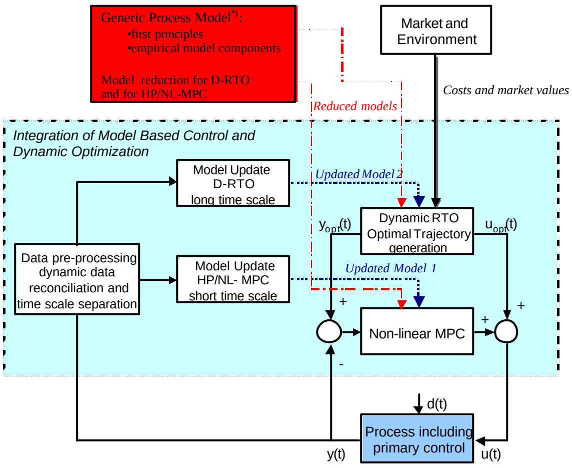

Fig. 4.1 Closed loop dynamic plant optimization

In case the assumption holds that the optimizer drives the process so slowly through its non-linear dynamics, that control relevant dynamics may be considered to be fast in comparison with changes in these dynamics, the model predictive control system may be based on time-varying linear models in stead of time-invariant non-linear models. These time-varying linear models have to represent the local process dynamics observed in the operating point determined by the optimizer:

$$\begin{bmatrix} \Delta x_{k+1} \\ \Delta y_k \end{bmatrix} = M_{MPC}(\Delta x_k, \Delta u_k, J, t \mid t = t_i) \approx \begin{bmatrix} A(t_i) & B(t_i) \\ C(t_i) & D(t_i) \end{bmatrix} \cdot \begin{bmatrix} \Delta x_k \\ \Delta u_k \end{bmatrix} \qquad (4.2)$$

An economically successful production can only be established, if the process can follow changing market conditions at each point in the supply chain. Besides adjustments to changes in the market by adaptation of the operation including closed loop (feedforward and feedback) model based control and optimization, the adaptation to changing conditions must also span the engineering design processes to modify the plant, its control system, or its operation strategy.

The EC funded research project INCOOP is focussing on fundamental development of technologies that enable consistent integration of model based control and model based optimization for intentionally dynamic operation of plants as part of a supply chain.

5. HDPE POLYMER MANUFACTURING CASE

A model based optimization and control system for a fluidized bed gas phase polymerization reactor (cf. fig. 5.1) is used as an example to demonstrate some aspects of the concepts discussed in section 4. The optimizer is used for calculating optimum transition trajectories. The delta mode model predictive control system is applied to closely track these optimum (transition) trajectories.

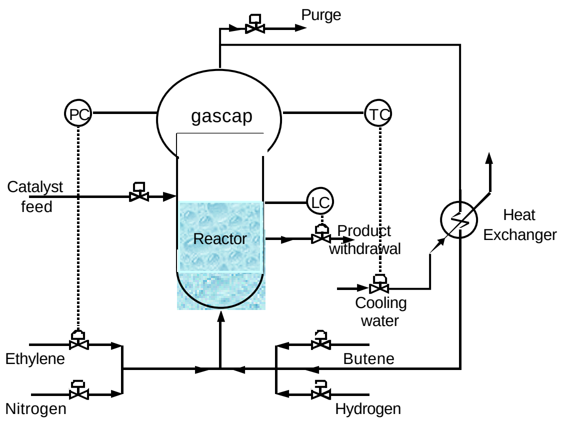

Fig. 5.1 Gas phase polymerisation reactor

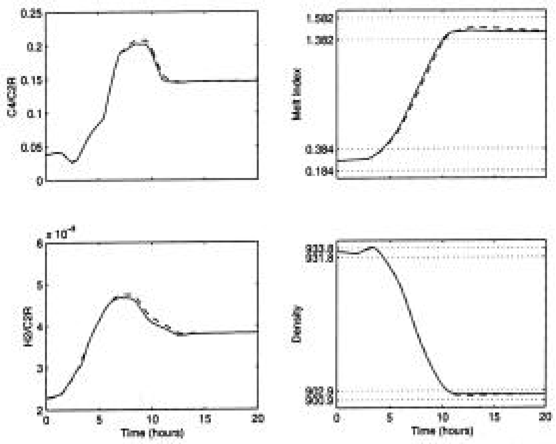

Fig. 5.2 Intended trajectory (dashed line) and actual controlled transition behaviour under external disturbances (solid line)

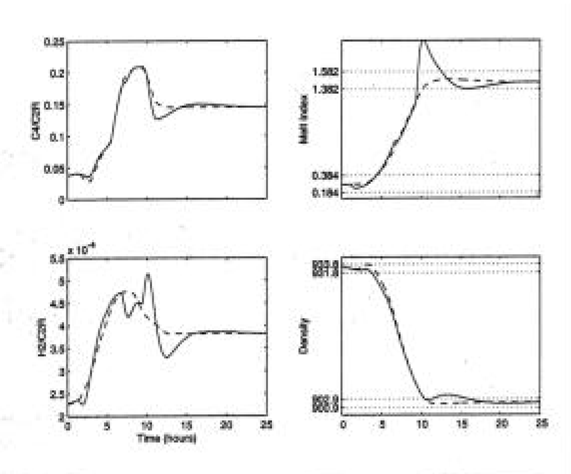

Fig. 5.3 Grade transition with severe disturbances (dashed: intended trajectory; solid: actual controlled response of the process)

The model predictive control system simultaneously manipulates Monomer/Co-monomer ratio, Hydrogen/Monomer ratio, Catalyst flow, Gascap Pressure and Bed Temperature. It controls Density, Melt Index and Production Rate by using the full bandwidth applicable for control. Direct or inferential measurements of the controlled variables are needed for this purpose especially for those variables that cannot be measured on-line over this full bandwidth.
The controller calculates required control actions on the basis of the inferred measurements. The soft sensors are calibrated by means of the real measured process values. State estimation techniques are applied for this purpose. This functionality enables robust operation of the control system at various sample rates of Melt Index and Density measurements.
The control system includes linearizing functions to cover large, non-linear operating ranges of the process with sufficient accuracy (Van der Schot, 1998). It is designed for robust control of relevant polymer properties over a broad operating range of the process.
Figure 5.2 and 5.3 show some results of a grade change subject to a variety of external disturbances acting on the process. Despite severe disturbances the grade transition is performed well.

6. CONCLUDING REMARKS

Changing market conditions enforce chemical processing industries to better utilize process capabilities. Process operation needs to be closer tied with market demand to improve capital productivity. Currently applied state-of-the-art model predictive control and model based optimization techniques have been analyzed for their capabilities to solve the problems related to intentional dynamic operation of plants in accordance with continuously changing market demand. Shortcomings have been revealed related to close tracking of optimum operating conditions. Optimum transition control is not supported by these techniques. They only regard (quasi) steady state operating conditions; relevant plant dynamics are not used for performance improvement.
New concepts have been discussed that enable exploitation of plant dynamics for performance optimization. Consistency between model-based optimization and model-based control is crucial for high performance in plant operation. Intential dynamic operation of a plant opens opportunities for significant improvement of plant economics and capital productivity. Market driven operation of plants may become feasible, if plant and process designs support it.

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