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Implementation of linear and nonlinear optimal control techniques in a CO_2 absorption/desorption plant

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Abstract

A large-scale CO_2 Absorption/Desorption pilot plant has been used to investigate the feasibility of applying a Nonlinear Model Predictive Control technique - Receding Horizon Optimal Control (RHC) - and to investigate the performance of such algorithms when applied to a real system where mismatch between plant and model is always present. The performance, stability and robustness of the nonlinear algorithm are compared to those of a standard linear technique, Dynamic Matrix Control (DMC) applied to the same system. The critical nature of the various components of the RHC (model, estimator of unmeasured states and parameters, optimisation algorithm) has also been assessed. Moreover, the differences in performance of the algorithms in both simulations and experimental studies has been explored.

Results showed that both the linear and nonlinear optimal control algorithms performed extremely well in simulation studies and were able to achieve excellent control while minimising the overall cost. Implementation of the algorithms on the real plant, however, showed that good performance was critically dependent upon reducing the plant/model mismatch. This was especially true in the case of the nonlinear RHC algorithm. A problem which had to be resolved in on-line experimental implementation is the trade-off between improved model accuracy and computation time for both modelling and optimisation.

Keywords: absorption/desorption; optimal control; model predictive control; dynamic matrix control

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INTRODUCTION

It is well known that the great majority of chemical processes are inherently nonlinear in nature. In spite of this fact, many processes are still controlled by linear classical controllers. Furthermore, the most successful advanced control techniques applied in the chemical industry nowadays (such as Dynamic Matrix Control, DMC) are based upon **linear** predictive controllers. The main reason for the popularity of the linear methods lies in their simplicity and the existence of more rigorous stability and performance proofs. Also the computational requirements of linear methods are more modest, both in terms of hardware and computation time. These factors make linear methods highly convenient for on-line implementation. Nonetheless, the performance of a linear system technique in a highly nonlinear chemical process may be limited. The requirement of better control techniques for this cases has stirred the academic world to work on the subject. As a consequence, much theoretical work has been published about nonlinear control of chemical processes in the last 15 years (Bequette, 1991).

Several reasons though, have limited the use of nonlinear predictive controllers in industrial implementation. These include the large investment required in modelling studies and the uncertainty posed by the inevitable mismatch between the plant and the model representing it. Another hindrance in applying nonlinear optimal control strategies on real plants is the computational time necessary to solve the optimal control problem on-line. The computational time is often too long for real time applications, when compared to the sampling time and the dominant time constant of the process.

The main goal of this experimental project is the application of a Nonlinear Model Predictive Control technique - Receding Horizon Optimal Control (RHC) - and the investigation of the performance of such algorithms when applied to a real system where mismatch between plant and model is always present. It has been shown theoretically that, under restricted conditions, the RHC approach guarantees plant stabilisation (Mayne and Michelska, 1990). However, in the presence of plant/model mismatch, no such guarantee of stability is provided.

The performance, stability and robustness of the nonlinear algorithm is compared to a standard linear technique, Dynamic Matrix Control (DMC) applied to the same system. The critical nature of the various components of the RHC (model, estimator of unmeasured states and parameters, optimisation algorithm) is assessed. Moreover, the difference in performance of the algorithms between simulation and experimental studies is explored.

EXPERIMENTAL SYSTEM

The CO_2 absorption/desorption plant at Imperial College consists of 2 columns of diameter 25 cm and height 9 m. The feed to the plant is a mixture of up to 5% carbon dioxide in nitrogen. Carbon dioxide is absorbed counter-currently in a monoethanolamine (MEA) solution (15 wt% MEA). Nearly pure nitrogen (traces to 1000 ppm CO_2) leaves the top of the packed absorption column. The MEA solution carrying the absorbed CO_2 is sent to a desorption column with 18 sieve trays and a steam-heated reboiler, where the CO_2 is removed and the MEA solution is regenerated. The regenerated solution is sent back to the absorber in a closed loop.

Typical disturbances include the feed gas flow rate and composition. The control objective is expressed in terms of the CO_2 concentration in the sweetened gas, the residual CO_2 concentration in the regenerated liquid solution, and the operating costs of the plant. The primary manipulable controls are the liquid circulation rate and the power (steam) used to regenerate the absorbent liquid in the desorber. It was demonstrated that other possible controls (operating temperature and pressure) were less effective in achieving the desired objectives.

The plant is served by a PC-based computing system, which is used for logging and for regulatory control purposes. The computer is linked to a SPARC workstation which can run programmes simultaneously, so that on-line control algorithms and strategies, simulation, estimation, and optimisation can be performed.

PROCESS MODEL

A lumped parameter model of the absorption desorption system was developed (Disli, 1996) based upon conservation equations, rates of mass transfer and chemical reaction and physical and chemical equilibrium relationships. Experimental evidence confirmed that the absorption process was controlled by the rate of mass transfer with chemical reaction. By contrast, it was reasonable to assume that the desorption process involved an instantaneous reverse reaction and was controlled by the rate of physical desorption.

Disli's (1996) lumped parameter (mixing cell) model of the absorption column expressed the overall process dynamics as a system of differential algebraic equations (DAE). The approach taken limits the number of discrete mixed cells in order to make computation time sufficiently small for on-line control purposes. Each cell of the model is of fixed volume and is made up of two phases: a liquid and gas phase. A number of simplifying assumptions are made, but these have been justified based upon off-line steady-state and dynamic experiments carried out on the plant. These assumptions are described in detail by Rotava (1997) and lead to a model which consists of a set of approximately 300 nonlinear mixed DAE's; these were solved within the gPROMS environment.

A key issue in both the simulations and the experimental studies was to ensure that any control policy remained within the constraint bounds for stable operation of the plant, as determined by separate experiments.

RESULTS

Simulation and experimental studies were carried out for both regulatory and servo control for both the linear (DMC) and nonlinear (RHC) model predictive controllers.

The DMC Controller:

The implementation of the linear DMC algorithm required the identification of a suitable model. This was done experimentally by off-line perturbation of the operation of the pilot plant. The manipulated variables were constrained by an operational region, as well as by maximum and minimum values to avoid valve saturation. It was not possible to identify a single linear model which would serve adequately throughout the region of operation. It was found that an adequate description of the feasible operating space of the plant required at least two separate linear models because of variations of the hydrodynamic behaviour at low and high flow rates. A reasonable compromise led to the division of the feasible region into 2 zones as indicated in Figure 1.

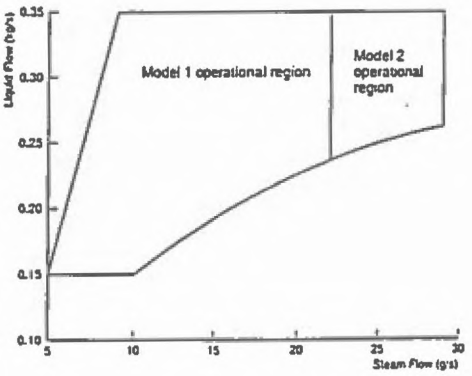


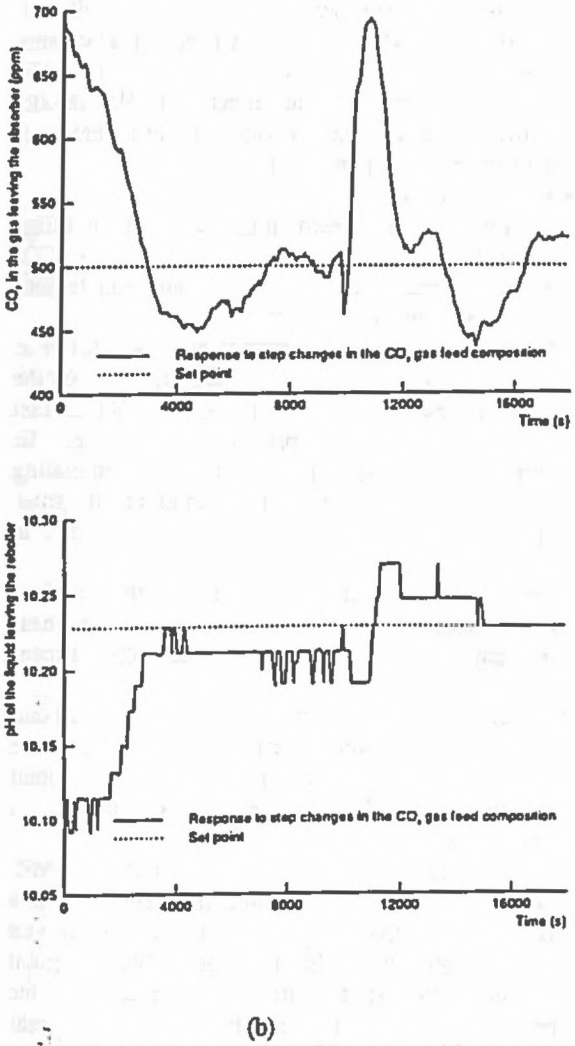
Figure 1. The stable operating region of the plant, and the zones in which linear models were identified.

A typical experimental result of the linear controller is shown in Figure 2 for an initial approach to the set point and the response to a step change in the CO_2 feed composition at a time, t=10000 s. The objective function included weighting of both the gas and liquid phase CO_2 compositions and penalised excessive use of energy in the form of steam and liquid circulation. Despite the presence of mismatch, the controller is successful in controlling both variables of interest with little or no offset. Surprisingly, the shape of the experimental results bears little resemblance to that of the corresponding runs (not shown) carried out on the simulated plant (see Rotava, 1997), although the controller performed well in both cases.

The Nonlinear RHC Controller

The process model was described by a DAE set of 263 equations with 27 differential variables. The implementation of the nonlinear RHC algorithm required the estimation of some unmeasured states and parameters which had to be obtained on-line using recursive estimators or observers. Simulations carried out with an Extended Kalman Filter showed that it was unable to function within the constraints of real-time computation for this large a set of equations; a simple closed-loop observer was used in those cases.

(a)

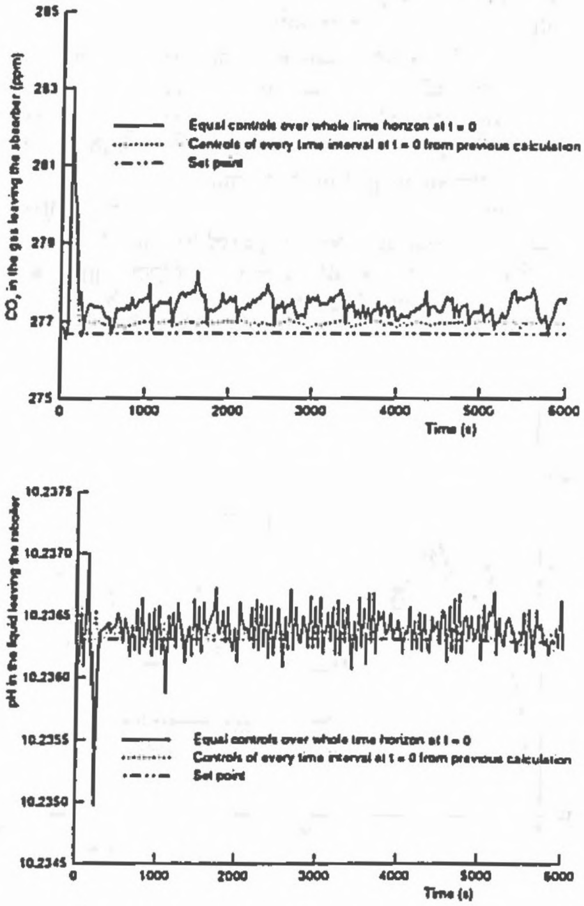


(b)

Figure 2. DMC control of CO_2 compositions: servo control at t=0 and response to a feed disturbance at t=10000; composition of (a) gas (b) liquid

The simulation of the nonlinear RHC without model mismatch and with no concern for real time implementation produced remarkably good results (not shown here), as predicted by nonlinear control theory (Mayne and Michelska, 1990). However, when plant/model mismatch was introduced into the simulation studies, the RHC performance decreased significantly. Implementation of RHC under these conditions led to instability when the mismatch was large, although increasing the optimisation horizon reduced (but did not eliminate) the problem. Other factors which improved the performance included the estimation of parameters to compensate for the mismatch and the use of a fairly tight end-point constraint within the optimal control calculations. A typical result is shown in Figure 3 and confirms that the controller can be made to perform well in simulations if one takes steps to minimise the effects of plant/ model mismatch.

(a)



(b)

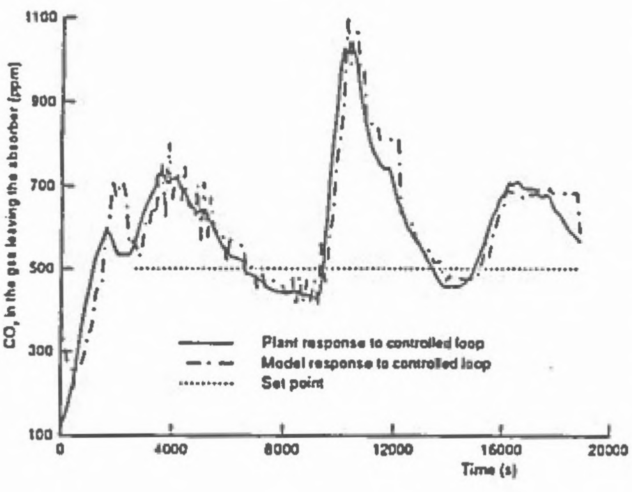
Figure 3. Simulation studies on the non-linear RHC in the face of imposed plant/model mismatch and a feed disturbance at t=100; composition of (a) gas (b) liquid

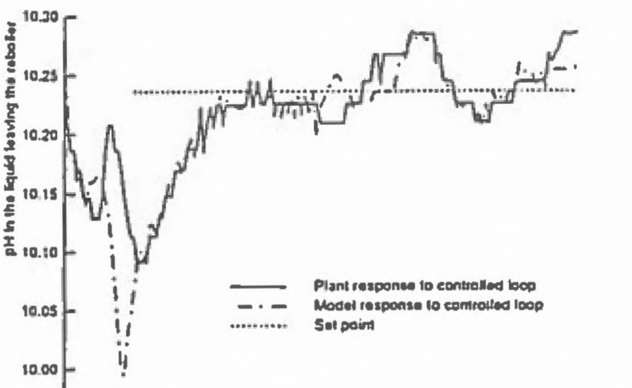
Experimental tests on the nonlinear RHC in the pilot plant inevitably included a certain degree of mismatch which was difficult to quantify. Nevertheless, its behaviour in on-line operation reproduced some of the features observed in simulations with imposed plant/model mismatch. However, in the experimental studies, it was not possible to employ sophisticated estimation methods because of the long computation time required; instead, much simpler observers had to be used and these did not always compensate fully for the mismatch. Similarly, the optimisation calculation which had to be carried out at each interval also required a substantial computation time, especially when the state and control constraints were active. Clearly, there was a question of trade-off here since the RHC algorithm utilises only the first step in the calculated optimal control policy at each interval. To what extent should the optimal control calculations be allowed to converge to their true optimum values before the first step of the control is implemented?

The imposition of tight end-point constraints were very important as a way of keeping the process stable and closer to the set point (Bell, 1997). If they were left very wide, the controlled variable could drift around the set points with a wide oscillation. The presence of the constraints did not avoid the off-set but helped to keep it small. An alternative approach is the use of the Dual-mode Receding Horizon Controller (Kershenbaum et al., 1993; Mayne, 1995) which replaces the nonlinear controller with a linear one in the vicinity of the setpoint.

A typical experimental result is shown in Figure 4. Here, the controller was required to bring the system to its set point initially and then respond to a large disturbance in the feed composition at t=10000 s.

(a)





(b)

Figure 4. The on-line nonlinear RHC at start-up and subject to a large change in the feed composition at t=10000; composition of (a) gas (b) liquid

Some of the difficulties which we encountered in the implementation of the nonlinear RHC could have been eliminated if it had been restricted to a supervisory layer of control, generating set point profiles for linear controllers, like DMC, to implement. In such an application, the optimisation technique could be used on-line but with a lower frequency of execution and hence, a much longer computation time available for estimation of unmeasured states and convergence of the optimal control calculation.

In summary, the experimental implementation of on-line nonlinear control was valuable because it allowed one to establish which are the key factors in any future development: the optimisation calculation must be efficient and robust; the effects of plant/model mismatch must be reduced within the available real-time window for computation.

CONCLUSIONS

As a result of the present implementation of linear control (DMC) and nonlinear RHC in the CO_2 absorption-desorption pilot plant, some conclusions can be drawn and are given below.

The extent of plant/model mismatch is a key factor in the success or failure of the implementation of the Nonlinear Receding Horizon Control. Simulation results show that if mismatch is reduced, the nonlinear control algorithm is effective in eliminating off-set. Nevertheless, the experimental results show that mismatch elimination is not easy to achieve in real time.

Experiments have also shown that if the required computation time is sufficiently small, the nonlinear RHC can follow set points and reject disturbances faster than the linear controller.

Experiments have confirmed that use of end-point constraints gives added stability to the nonlinear RHC. In addition, the presence of end-point constraints in the optimisation calculation is important in order to minimise off-set.

Linear Model Predictive Control, specifically DMC, was very reliable in controlling the plant. It has a remarkable ability of reliably handling servo and regulator problems. On the other hand, if plant conditions are different from those present in the identification step, the performance of the Linear Controller is poorer. This effect can be compensated for by dividing the operating region into several zones with different identified linear models.

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