Chapter 10

Nonlinear control of industrial processes

Babatunde A. Ogunnaike

Abstract

As a result of increased customer demand for consistent attainment of high product quality, coupled with increasingly stringent safety and environmental regulations, and intensified global competition, the current drive in the chemical and allied industries has been towards more efficient utilisation of existing assets (especially capacity and energy) rather than new capital expenditure. The result is that a growing number of industrial processes must now operate under conditions that emphasise their inherent nonlinearities. Nonlinear control is thus becoming more important in industrial practice. This chapter assesses the current status of nonlinear control applications in the chemical industry, discusses some of the most pertinent issues of, and barriers to, practical implementation, and presents an actual industrial application to illustrate the main points.

10.1 Introduction

It is well known that virtually all processes of practical importance exhibit some degree of nonlinear behaviour. Nevertheless, the vast majority of well-established controller design techniques are for linear systems. Such techniques typically work well in practice for processes that exhibit only mildly nonlinear dynamic behaviour. More recently, increasingly stringent requirements on product quality and energy utilisation, as well as on safety and environmental responsibility, demand that a growing number of industrial processes operate in such a manner as to emphasise their inherent nonlinearity even more. There is therefore increased industrial and academic interest in the development and implementation of controllers that will be effective when process nonlinearities cannot be ignored without serious consequences.

The growing interest of the process control community in nonlinear control is reflected in several reviews of currently used techniques (see, for example, References 1–4). To be sure, many significant theoretical and practical issues remain unresolved; nevertheless, the impact of the available theory on industrial practice is becoming more noticeable. First, observe that it has become standard industrial practice to use certain simple nonlinear elements to improve performance in some control loops – for example, square root correction in flow control (see Reference 5). But beyond such simple applications, there is a growing number of more complex nonlinear control applications that have appeared in the open literature – for example, see Reference 6, model based control of an industrial extruder; Reference 7, generic model control of an industrial blast furnace; Reference 8, geometric nonlinear model-based control of a binary distillation column; Reference 9, geometric nonlinear control of an industrial CO_2 adsorption/desorption pilot plant process; References 10 and 11, nonlinear control of industrial pH processes; Reference 12, nonlinear model predictive control of an industrial packed-bed reactor; Reference 13, nonlinear model predictive control for economic optimisation and control of gas processing plants. For a more recent overview of nonlinear model predictive control applications, see Reference 14.

However, while the number of industrial applications of nonlinear control is growing, a careful consideration of the current opportunities *vis-à-vis* the currently available theory indicates that such applications are, in fact, not as widespread as they could be. This chapter has a twofold overall objective:

1. to discuss the issues involved in implementing nonlinear control in industry: assessing the current status (the problems and challenges) and identifying the means by which the impact of nonlinear control on industrial practice can be improved
2. to use an industrial case study (a) to demonstrate the potential impact of nonlinear control, appropriately applied; and (b) to illustrate the main issues involved in successful industrial implementations of nonlinear control.

10.2 Applying nonlinear control to industrial processes

A significant proportion of the demands placed on the typical industrial production facility translates into one, or more, of the following:

1. the need to increase capacity (to meet overall market demands)
2. the need to improve product quality (to meet individual customer demands)
3. the need to reduce environmental emissions (to meet safety and environmental regulatory demands).

Traditionally, it has been customary to adopt the 'capital expenditure' approach in solving these problems: for example, building new production facilities to handle the 'capacity problem'; adding blending facilities to handle the 'quality problem' and redesigning and retrofitting processing units to handle the 'environmental problem'. More recently, however, increasing global competition has dictated the current trend towards finding alternative solutions requiring little or no capital expenditure. This almost invariably implies seeking effective control solutions first, wherever possible. But when most processes are operated under the conditions dictated by these stringent market, customer and environmental demands, the tendency is for the inherent process nonlinearities to become more pronounced – making it more difficult to obtain acceptable solutions from traditional linear controller design techniques. The prevailing global economic conditions thus continue to create opportunities for the application of nonlinear control techniques.

Given the current potential for nonlinear control to contribute significantly to industrial productivity, we now consider the issues that must be addressed for such potential to be realised fully.

10.2.1 *Quantitative needs assessment*

It is widely accepted that only about 10–20 per cent of industrial control problems require the application of so-called 'advanced control'. It is also accepted that processes in which such problems are encountered account for close to 80 per cent of the revenue. Of the industrial control problems in need of advanced control applications, there is now an increasing realisation that a certain proportion cannot be solved effectively by linear techniques, which constitute the bulk of the most widely applied of these advanced techniques. However, the application of nonlinear techniques requires incrementally greater investments in implementation effort and costs, and such costs must therefore be economically justifiable. Thus, being able to answer the following questions as objectively as possible will increase the impact of nonlinear control in industrial practice:

1. For which problem is the application of nonlinear control critical to the achievement of the desired operational objectives (and which of the available tools is most appropriate for the specific application)?
2. How does the cost of implementation compare to the potential benefits to be derived from the application?

For many of the documented applications of nonlinear control, these questions were relatively straightforward to answer. When the process nonlinearity is obvious, and severe enough (as with the application soon to be discussed), the need for nonlinear control is usually clear. By the same token, if a critical process is virtually inoperable with linear controllers, it will be relatively straightforward to quantify the benefit of nonlinear control. The vast, virtually untapped – and currently difficult to quantify – potential for nonlinear control lies with the class of problems for which linear control methods are applicable, but for which nonlinear methods will result in significant process performance improvements. In this regard, observe that theoretical tools for quantifying the degree of process interaction (and process conditioning) have been useful in assessing the applicability of multivariable control and have thereby promoted industrial application. Similar tools for measuring the degree of process nonlinearity could conceivably play a commensurate role in promoting the industrial application of nonlinear control methods.

10.2.2 Technological and implementation issues

There are a few major factors that currently prevent the widespread use of nonlinear control, even in the cases where the need is obvious, and the potential benefit is known to be substantial:

1. *Control technology*: The typical analytical tools required for rigorous nonlinear systems analysis and controller design still remain largely inaccessible to all but a few researchers concerned with such problems. Naturally, these techniques tend to be more complicated and less transparent and 'intuitive' than the linear techniques.
2. *Model development*: Virtually all high performance controllers are model based; and nonlinear controllers in general require nonlinear process models. Developing linear process models can be difficult enough in practice; developing nonlinear models is several orders of magnitude more difficult.
3. *Implementation*: Most nonlinear controller design techniques give rise to complex controllers that often require unique, specialised software and hardware resources for real-time implementation.

These issues arise primarily because of the intrinsic characteristics of nonlinear systems. First, because nonlinearity is an intrinsically more complex phenomenon to analyse than linearity, nonlinear systems are understandably more difficult to analyse, and nonlinear controllers more difficult to design; by extension, nonlinear control technology will therefore not be as widely accessible as its linear counterpart.

Second, because of all the nice properties enjoyed by linear systems (additivity, homogeneity, superposition, *etc.*) linear model development is relatively straightforward, in concept, if sometimes tedious in practice. The literature on linear model identification from empirical plant data in particular, is vast, and essentially complete; and industrial practice of linear empirical modelling is reasonably well developed. When the desired process model is to be nonlinear, however, many additional issues immediately arise by virtue of this departure from linearity, the most important of which has to do with what modelling approach to adopt: the theoretical (or first-principles) approach, the empirical approach or the 'hybrid' approach.

The first-principles approach is often not employed because it requires a significant amount of process knowledge which may not always be available; when such knowledge is available, the resulting model may simply be too difficult to be useful for controller design purposes. The empirical approach has the advantage of depending strictly on data, but it requires an *a priori* choice of model structure (itself a very difficult task); in addition it requires a very careful design of the input sequence to be used for the identification (see, for example, Reference 15). An increasingly promising approach is the so-called 'grey-box' or hybrid approach in which basic first-principles information is augmented with empirical data, thereby taking advantage of the benefits of each approach. For some sample hybrid modelling applications, see, for example, References 16–19.

Finally, by definition, and intrinsically, nonlinear systems tend to defy classification: they are all characterised by the property they lack – linearity. Each nonlinear control application thus tends to be unique and specialised, making it difficult to employ any generalised approach, or tools or implementation platforms.

Taken together, all the foregoing factors argue strongly for the development of commercial nonlinear control packages in the same spirit as those available for (linear) model predictive control (MPC). Observe that, even though (i) linear MPC analysis and design techniques, obviously less complicated than nonlinear techniques, are still complicated enough compared to classical methods, and (ii) linear model development for MPC applications is still not a trivial task, commercial packages such as DMC and IDCOM (see Reference 20, Chapter 27, for a summary of other commercial MPC packages) have made the implementation of this technology much more widely accessible than would otherwise be possible.

Despite the obvious difficulties regarding 'standardisation' of model forms and design techniques, Continental Controls, Inc. has commercialised one nonlinear control package – MVC – with the claim that it could potentially do for nonlinear control what IDCOM and DMC did for linear model predictive control. One of the reported applications of this technology may be found in Reference 13. (See also Reference 14.)

In the next section we discuss the development and on-line performance of a nonlinear control system for an industrial process, to illustrate how the problems noted above – control technology, modelling and control system implementation – were addressed in this specific case.

10.3 Model predictive control of a spent acid recovery converter

10.3.1 The process

The process in question is the 'spent acid recovery' converter shown schematically in Figure 10.1. It consists of a series arrangement of four vanadium pentoxide fixed-bed reactors used to convert a cold feed of sulphur dioxide, (SO_2), oxygen, (O_2) and some inerts into SO_3. Because the reaction is highly exothermic, interstage

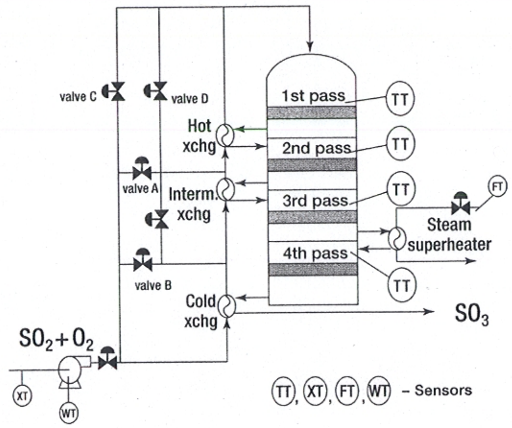

Figure 10.1 Spent acid recovery converter

cooling is provided primarily via heat exchange with the incoming cold feed, except between stages 3 and 4, where cooling is achieved via heat transfer to steam in a superheated steam generator.

10.3.2 Process operation objectives

Safe, reliable and economic process operation requires close regulation of the inlet temperatures of the first, second and third stages. In general, there is an 'optimum' inlet temperature for each stage (or pass) that will give rise to optimum conversion. These desired target values are determined by 'gas strength' (SO_2 concentration), production rate and the conversion achieved in the preceding passes. In addition, these temperatures must not fall below 410° (otherwise the reaction will be quenched) or rise above 600° (otherwise the catalyst active life will be shortened considerably).

Frequent fluctuations in feed conditions – the blower speed, gas strength (SO_2 concentration) and O_2 concentration – constitute the main obstacles to smooth process operation. Primarily to minimise yield losses, and to comply with strict environmental regulations on SO_2 emissions, these persistent disturbances must be rejected effectively and quickly. Ineffective process control has been responsible for low conversions, and low conversions result in both high SO_2 emission rates and high yield losses.

The indicated network of pipings, baffles and valves A, B and C provide the means for controlling the inlet temperatures through by-pass feeding of cold reactants. (For reasons that will soon become clear, only the valve openings – or

'valve loadings' – for valves A, B and C are available for manipulation; the valve loading of valve D is not.) For example, observe that increasing by-pass flow through valve C will reduce the first pass inlet temperature.

The dynamic characteristics induced by the network of valves can be quite complex. First, observe that the valves merely redistribute the feed, sending a portion directly as cold feed, and the rest through the various heat exchangers. A change in a single valve loading therefore affects not just the feed flow rate through that valve; it also affects the flow rate through all the other valves. These manipulated variables are therefore not entirely independent. Observe therefore that only three of the four valves can be manipulated independently. Next, consider, for the purpose of illustration, the effect of an increase in the valve C loading. The initial direct response will be a decrease in the first pass inlet temperature (as a result of increased cold feed bypass to this stage); but because the increased by-pass through valve C causes a concurrent decrease in the amount of cold feed distributed to the interstage heat exchangers, this action also results in an increase in the second and third pass inlet temperatures. This otherwise 'normal' process interaction is then complicated by secondary effects resulting from the fact that a reduction in the first pass inlet temperature ultimately causes a reduction in the exit temperature, which in turn causes a reduction in the inlet and outlet temperatures in the succeeding stages. The reduced temperature in all the stages then produces a tertiary effect in which the amount of the first stage feed preheating provided by the three interstage heat-exchangers is reduced, further reducing the first pass inlet temperature. This now starts another round of inlet temperature reductions with the potential for open-loop instability induced by the progressive cooling, and the possibility of quenching the reaction outright. Finally, as a result of the nonlinearity induced by the chemical reaction kinetics and the heat exchanger characteristics, a 'mirror image' decrease in the valve C loading will not give rise to a precise, 'mirror image' reverse net effect in inlet temperatures. To keep the process away from potentially unstable operating regimes, a lower constraint of 30 per cent is imposed on the valve loadings; the upper constraint of 100 per cent is physical.

The overall process objective may therefore be stated as follows:

> In the face of persistent process disturbances, control the inlet temperature for each of the first three passes to their respective prespecified desired target values, maintaining them between the operating constraints of 410°C, and 600°C at all times, with the loadings for valves A, B, and C constrained to lie between 30 and 100 per cent.

10.3.3 A control perspective of the process

The process variables may be categorised as follows:

- Output (controlled) variables:
  1. first pass inlet temperature

2. second pass inlet temperature
3. third pass inlet temperature.

- Input (manipulated) variables:
  1. valve A loading
  2. valve B loading
  3. valve C loading.

- Disturbance variables:
  1. SO_2 concentration
  2. O_2 concentration
  3. blower speed
  4. valve D loading.

As summarised above, the main control problems are caused by persistent disturbances, strong interactions among the process variables, constraints on both the input and output variables, and the process nonlinearities due to the reaction kinetics, heat transfer characteristics and the flow distribution network. The specific objective of the application is to develop an effective control system for this process, but the broader objective in this section is to use this specific application to illustrate various aspects of how nonlinear control can be applied on an industrial process.

10.3.4 Overall control strategy

The multivariable nature of the process, along with the process operating constraints, make this an ideal candidate for model predictive control (MPC); however, the severity of the process nonlinearities argues strongly for the application of nonlinear MPC instead of the more popular standard, linear version. The most important implications of this decision are as follows: technologically, this boils down – in principle – to obtaining a reasonable, nonlinear process model and a reliable nonlinear optimisation routine for performing the optimisation that lies at the heart of MPC. In practice, however, unlike with linear MPC, few theoretical results are available to guide the choice of critical design parameters such as the prediction horizon, the control move horizon and the various weights in the objective function. The nonlinear optimisation will thus have to be carried out with extra care. Also, unlike with linear MPC, no standard commercial packages were available at the time of this application (1991/92).

At the heart of the nonlinear model predictive control technique is the nonlinear process model, and based on the following three main points, the decision was made to obtain this model via input/output data correlation:

1. Not enough is known about certain critical details of the process to generate a first-principles model having sufficient integrity.

2. Even if the required fundamental process knowledge were available, the resulting first-principles model will be far too complicated for on-line optimisation-based control. Observe that, at the very least, such a model will consist of a combination of individual models for each subprocess making up the overall process: a gas distribution network model; a heat transfer model for the four heat exchangers; and a kinetic model for the four fixed-bed catalytic reactors. Each contributing model could conceivably consist of a system of several, coupled nonlinear partial differential equations, and the overall combination will clearly be far too complex for controller design.
3. From a process control perspective, the process is a 3×3 process with four disturbances; this process dimensionality is actually not so high as to render empirical modelling prohibitively time-consuming.

The issue of model structure selection in empirical nonlinear modelling is not trivial, and many factors influence each individual choice (see, for example, References 15 and 21). For this particular application, a recurrent neural network representation was chosen because of the flexibility of the neural network paradigm in general for representing arbitrary nonlinear input/output maps; the recurrent structure (as opposed to the standard feed-forward structure) was chosen in particular for improved long range prediction (see Reference 12), a critical requirement for model predictive control.

The overall control strategy is therefore to represent the process dynamics with a recurrent neural network, and to use this in a model predictive control framework in conjunction with a nonlinear optimiser. This control structure is shown in Figure 10.2.

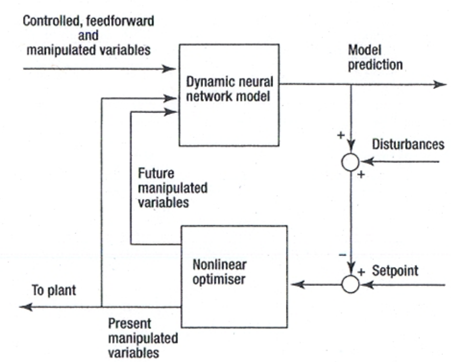

Figure 10.2 Control strategy

10.3.5 Process model development

A systematic procedure for nonlinear empirical model development involves the following steps [15]:

1. model structure selection
2. model identification (input sequence design; data collection and preconditioning; model parameter estimation)
3. model validation.

In this specific application, the selected model structure – a recurrent neural network – and the reasons for the choice have been presented. The next step – actual identification of the neural network model for the spent acid recovery converter – involves making decisions about the input sequences to be used for the model identification, implementing these input changes, collecting the sets of process response data, and analysing the collected input/output data sets.

The theoretical issues concerning input sequence design for nonlinear model identification remain largely unresolved (see, for example, Reference 15); much of what is done in practice is influenced mostly by sensible, but vague heuristics. For example, it is generally recommended that the magnitude of the inputs must be such that the desired region of operation is 'adequately covered' and that the 'frequency content' must be such that those aspects of the process that must be captured in the model are 'adequately excited'. Such heuristics and available theoretical results immediately rule out the typical inputs employed in industrial practice for linear model identification, i.e. single steps, single pulses and the PRBS; but there is as yet no comprehensive theory regarding 'optimum' input sequences for general nonlinear model identification.

In this specific case, therefore, the decision was to employ six-level, pseudo-random sequences (as opposed to the binary, i.e. two-level, sequences employed for linear systems) that span the 'normal' input range. From process operation data, and process knowledge, this 'normal' range was determined to be 30–80 per cent valve loadings. Because the 'dominant time constant' for the process is known to be approximately 40 min, the duration of each 'step change' in the sequence was fixed at 5 min, at the end of which the valve loading was switched to a different randomly drawn level. The total duration for each input sequence was fixed at 12 h.

Figure 10.3 shows the valve A loading input sequence and Figure 10.4 shows the observed responses in the first, second and third pass inlet temperatures, respectively. Similar responses were obtained from similar input changes in valves B and C.

Each process data set acquired during the plant tests was partitioned into two: one part for model development (the 'training set') and the other for model validation (the 'validation set'). The backpropagation-through-time algorithm was used to obtain the seven-input, three-output recurrent NN model from the plant data in the 'training set'. The final NN model architecture consisted of three layers and four nodes in the hidden layer, with unit time-delayed output feedback connections

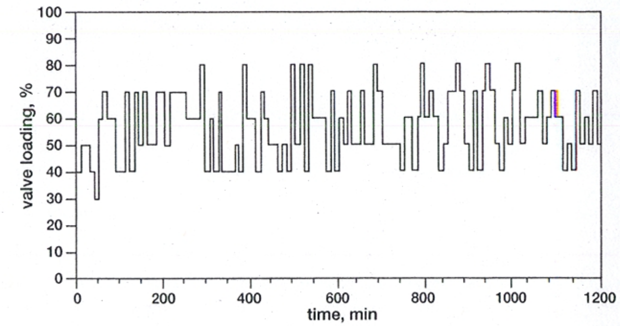

Figure 10.3 Identification input sequence for valve A loading

to the input layer. For additional details about the model development, see Reference 12. The performance of the resulting model is illustrated in Figure 10.5, where the long range, pure prediction of the first pass inlet temperature is compared with corresponding validation data. Comparable performance was observed from the other parts of the model.

10.3.6 Control system design and implementation

Conceptually, the nonlinear model predictive controller was implemented as shown in Figure 10.2: the NN model provided the long-range prediction, and 'ADS', a

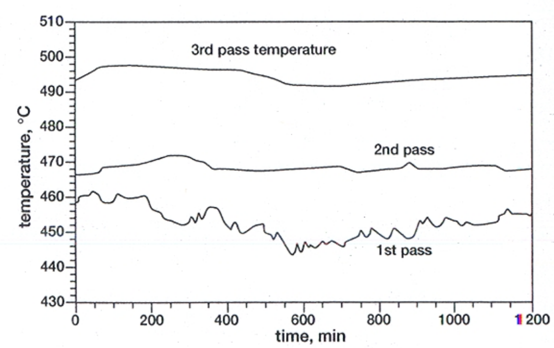

Figure 10.4 Temperature responses to changes in valve A loading

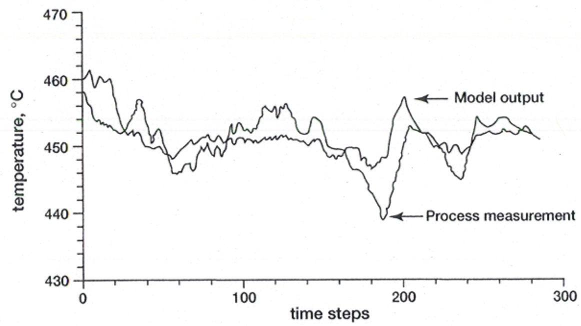

Figure 10.5 First pass inlet temperature prediction and validation data

public domain nonlinear optimisation routine (obtained from the Naval Postgraduate School in Monterey, CA) was used to determine optimal control action sequences. The model prediction and control sequence horizon lengths were chosen to be 20 and 5, respectively, with $\Delta t = 10\,\text{min}$. Additional details about the optimisation routine are available in Reference 12.

The actual implemetation of this nonlinear MPC scheme requires a few additional hardware and software considerations. Process operation data were collected and archived by a PDP 11/85 host computer interfaced to a dedicated DCS (distributed control system) through vendor-supplied software running on a MicroVAX system. The NN process model and the optimiser were deployed within an in-house expert system shell on the same MicroVAX computer. Apart from providing a convenient environment for integrating all the Fortran routines used to execute the modelling and the optimisation functions of the nonlinear MPC scheme, the expert system also performed two additional relatively simple, but critical, tasks: (i) it determined when it was time to execute the controller; and (ii) it checked the availability and validity of process data, and the 'reasonableness' of the computed control action.

At each control cycle, the desired setpoints computed for the valve loadings were sent from the expert system (in the microVAX) to the host computer; this was then communicated to the DCS, from where it was implemented on the actual process. The implementation hardware/software architecture is shown in Figure 10.6.

10.3.7 Control system performance

Figures 10.7–10.9 are representative of the actual closed-loop performance of the control system. Figure 10.7 shows the process output variables over a 24 h period during which the process was subject to the disturbances indicated in Figure 10.8.

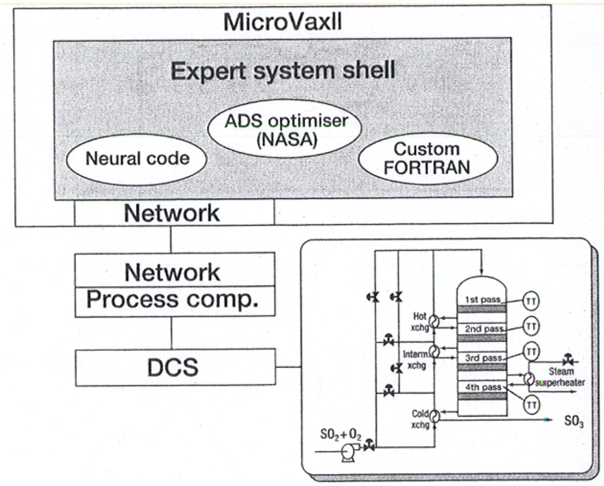

Figure 10.6 Control system implementation architecture

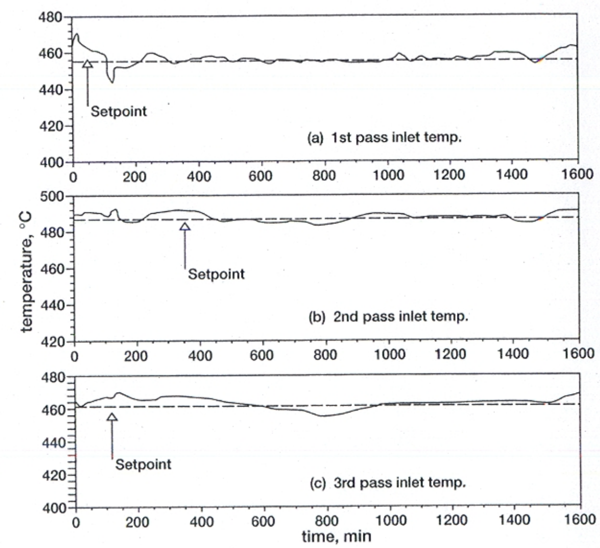

Figure 10.7 Closed-loop temperature responses

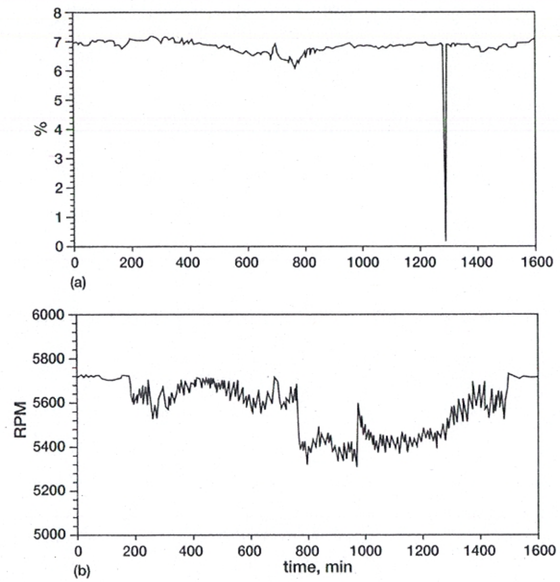

Figure 10.8 Process disturbances during closed-loop operation: (a) SO_2 concentration (b) blower speed

Between $t = 500$ and $t = 900$, the SO_2 concentration dropped by more than 15 per cent – by process operation standards, a significant feed disturbance; the indicated change in the blower speed (related to the process throughput) is also significant. In responding to these disturbances, the control scheme successfully maintained the inlet temperatures close to their respective desired setpoints, as shown in Figure 10.7, by implementing the control action sequences shown in Figure 10.9.

Compared with standard process operation prior to the implementation of this controller (not shown) the controller performed remarkably well. Observe that the 30–100 per cent constraint range was enforced for each of the valves during the entire period. The SO_2 concentration 'spike' that occurred at $t = 1300$ was due to the daily scheduled analyser calibration; observe, however, that such a clearly anomalous measurement did not affect the controller performance. This illustrates the effectiveness of the expert system in checking and validating process measurements before they are used in computing corrective control action. For additional details on the performance of the controller and a comparison to conventional control approaches, see Reference 12.

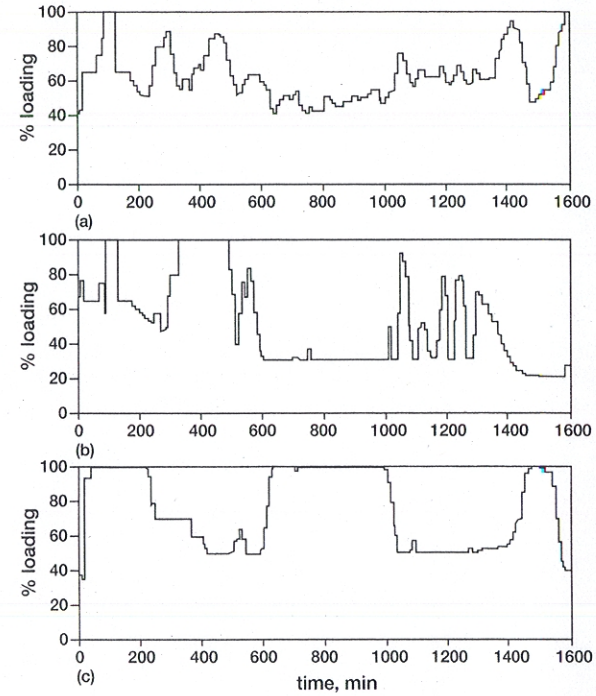

Figure 10.9 Implemented control actions: (a) valve A; (b) valve B; (c) valve C

10.4 Summary and conclusions

We have presented here one perspective of the 'many-sided' issues involved in the industrial application of nonlinear control, using the 'spent acid recovery' process as an illustrative case study of the successful design and implementation of one such industrial nonlinear control system.

Clearly, nonlinear control is becoming ever more relevant to industrial practice; the key issue now is essentially one of how best to identify and capture the stake presented by the ever-increasing demands on process operation. In this regard, by making the inevitable comparison with (linear) model predictive control and what has been primarily responsible for the significant impact it has had on industrial practice to date, it is not difficult to arrive at the following conclusion: the commercialisation of nonlinear control packages similar in spirit to those available for linear MPC will significantly increase the impact of nonlinear control on industrial practice. There are several obstacles to the widespread development and application of such packages; some of the most important have been noted. Nevertheless, that one such package is in fact already available is an encouraging sign that the potential exists for a significant increase in the application of nonlinear control techniques on many more actual industrial cases.

10.5 Acknowledgment

This chapter is based in part on an earlier paper jointly written with Ray Wright of The Dow Company, and presented at the 5th international conference on *Chemical process control* (CPC V) in January 1996. Ray's contributions are gratefully acknowledged.

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