Directionality and Nonlinearity - Challenges in Process Control

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Foreword

This thesis has been written at the Process Control Laboratory at the Faculty of Chemical Engineering at Åbo Akademi University. Part of the thesis was written during the author's stay as a visiting researcher at the Intelligent Control Laboratory at the Department of Electrical and Electronic Systems Engineering at the Graduate School of Information Science and Electrical Engineering at Kyushu University in Fukuoka, Japan. Overall, the work was carried out during the years 1993-1994 and 1999-2003.

It has been a painful delivery, indeed. So, in effect, all people I know have more or less contributed to it. Especially I wish to express my sincere gratitude to my mentors, foremost my father Professor Kurt Waller and my supervisor Professor Hannu Toivonen. Their encouragement, support and truly intelligent comments have been invaluable to me.

Furthermore I wish to thank my colleagues, co-authors and friends; Dr. Matias Waller, Dr. Jari Böling, Dr. Rasmus Nyström, Dr. Mats Sågfors and Bernt Åkesson in Finland. Also I wish to express my sincere gratitude to my friends and colleagues in Japan; Professor Kotaro Hirasawa, Professor Junichi Murata and Professor Jinglu Hu and the rest of the great people at the Intelligent Control Lab at Kyushu University. I also wish to express my gratitude to my colleagues at Åbo Akademi University and at Swedish polytechnic for their encouragement and support.

Also I thank my financial contributors - see the acknowledgements in the papers. Especially I wish to thank Svenska Tekniska Vetenskapsakademien i Finland for making it possible for me to perform the latter part of the research presented in this thesis.

I wish to thank my mother Ann-Christin Waller for her support and for helping me with the language. Last, but surely not least, I want to thank my wife Dr. Nari Lee and my lovely daughter Jerin.

Abstract

The use of the concepts of directionality and ill-conditionedness is investigated. A lack of consistent terminology is detected, and some clarifications to the terminology are suggested. Robustness issues with respect to directionality are discussed. Control structures in the form of decoupling are discussed, and a more general formulation for dynamic decoupling is formulated. Process nonlinearity, especially in the form of operating region dependent dynamics, is tackled by the use of a nonlinear input/output model of quasi-ARMAX type. The model is applied in the model predictive control framework for control of nonlinear processes, with a pH-process as a case-study. The nonlinear controller is also reformulated for the multivariable case, and applied to control of an ill-conditioned, nonlinear distillation column. The computational demand of the model predictive control formulation is addressed by studying methods to approximate the behaviour of model-predictive controllers by the use of neural networks as function approximators. Also, as a means to decrease the online computational demands, a neurodynamic programming formulation is investigated in the sense that the future cost-to-go function is calculated by use of offline MPC calculations and then approximated.

List of Publications

This thesis consists of an introductory part and the following papers, referred to by their roman numerals.

I Defining Directionality: Use of Directionality Measures with Respect to Scaling, Jonas B. Waller and Kurt V. Waller, Ind. Eng. Chem. Res., *34*, 1244-1252, **1995**.

II Decoupling Revisited, Matias Waller, Jonas B. Waller and Kurt V. Waller, Ind. Eng. Chem. Res., *42*, 4575-4577, **2003**.

III Nonlinear Model Predictive Control Utilizing a Neuro-Fuzzy Predictor, Jonas B. Waller, Jinglu Hu and Kotaro Hirasawa, Proceedings of IEEE Conference on Systems, Man and Cybernetics, Nashville, USA, **2000**.

IV A Neuro-Fuzzy Model Predictive Controller Applied to a pH-neutralization Process, Jonas B. Waller and Hannu T. Toivonen, Proceedings of IFAC World Congress on Automatic Control, Barcelona, Spain, **2002**.

V Multivariable Nonlinear MPC of an Ill-conditioned Distillation Column, Jonas B. Waller and Jari M. Böling, Submitted to J. Proc. Cont., **2003**.

VI Value Function and Policy Approximation for Nonlinear Control of a pH-neutralization Process, Jonas B. Waller and Hannu T. Toivonen, **2003**.

VII Neural Network Approximation of a Nonlinear Model Predictive Controller Applied to a pH Neutralization Process, Bernt M. Åkesson, Hannu T. Toivonen, Jonas B. Waller and Rasmus H. Nyström, Submitted to Comp. Chem. Eng., **2002**.

Contents

Chapter 1

Introduction

Feedback control deals with the specific task of controlling outputs by means of feedback of measurements (or estimates thereof) to the inputs of the process. The system under control can be from various fields. A schoolteacher changing his methods of teaching based on the success or failure of his earlier teaching methods and a fisherman changing the types of lure he uses based on experience to catch the biggest pikes are examples of control problems relying on the intelligence of a human as the controller. On the other hand, controlling the indoor temperature by means of measurements from a thermometer or controlling the water level in a tank are simple tasks easily implemented by means of automatic control.

Technological evolution has led to an increased ability to perform automatic control. As the field of possible areas of application for automatic control grows, so does the need for more advanced methods for control. In fields such as ecology, climatology or economics, there is an obvious need (or at least potential) to apply advanced control, but at the same time the complexity of the systems at hand is so large that control in such fields is extremely challenging (Kelly, 1994). The potential gain of effective control is great, but the price to pay for mistakes is equally great.

Process control is mainly focused on controlling variables such as pressure, level, flow, temperature and concentration in the process industries. However, the methodologies and principles are the same as in all control fields. In process control, the situation of the field is roughly comparable to the field of control engineering in large, however Balchen (1999) points out that process control has lagged behind other areas in implementing control theory. Process control saw some early successes during the evolution of the field of automatic control. The development of the PID controller and the Ziegler-Nichols tuning methods and guidelines (Ziegler and Nichols, 1942) have had an enormous impact on the field. Ninety five percent of the controllers implemented in the process industries are of PID-type (Åström and Hägglund, 1995; Chidambaram and See, 2002). These early successes might also have made it more difficult for other approaches to gain acceptance in process control.

However, as the demands increase and the available methods of implementing controllers expand, so do the possibilities of improving process control (Åström and McAvoy, 1992). What precisely the greatest challenges will be or where the greatest improvements can be achieved is impossible to predict. However, we can note that Takatsu, Itoh and Araki (1998) in a study on industrial process control in Japan, list process interaction as one of the main difficulties and consider time delays and the effect of disturbances as other important challenges. Also nonlinearity, although to a lesser extent, is considered an important challenge to deal with in process control. It is also impossible to predict which methods hold the largest potential for improving process control. However, as the computational capabilities of controllers increase, it is reasonable to assume that this increased capability can be used for improved control and that it will have a significant impact on the field over a foreseeable future (Åström and McAvoy, 1992; Rauch, 1998; Balchen, 1999). Areas benefiting from this increased capability are, e.g. computational intelligence and online optimisations (including the model predictive control formulation). From another point-of-view, it can be argued that the increased complexity of systems under control will lead to a situation where it is (or will be) virtually impossible to achieve feasible control (Kelly, 1994), and thus the ambition to implement advanced control algorithms on certain problems is futile.

The field of what is today referred to as "intelligent" control (control based on soft computing) has had a strong influence on process control since the early 1990s (Åström and McAvoy, 1992; Hussain, 1999). Although the scientific community has been active and there have been commercial successes of these intelligent control methods, the dominating controller in the process industries is still by far the PID-controller (Chidambaram and See, 2002). This stands in contrast to the fact that methods with a high rate of very satisfied users, according to Takatsu et al. (1998), include computational intelligence methods and MPC formulations whereas modern control methods and advanced PID controllers have a much lower rate of very satisfied users.

It is therefore clear that the field of process control is at an active stage where influences from traditional control methods are being mixed with influences from soft computing fields including fuzzy systems, neural networks and also computation-intensive optimisation routines. The possibility to combine these earlier control methods (including the conventional wisdom of the process control engineers) with fields that have grown out of a fusion of cognitive sciences, mathematics and computer sciences, i.e. computational intelligence or soft computing in an environment allowing for computation-intensive implementations, is thus an important over-all goal within the field. More specifically, it should be a goal to combine these approaches to tackle the big challenges in process control, e.g. interaction and nonlinearity.

The possibility to merge the conventional intelligence of process control with the emerging artificial intelligence into a truly intelligent, effective and successful control formulation is thus the ultimate challenge. With the words of Lao Tzu (as quoted in Kelly (1994)):

> *"Intelligent control appears as uncontrol or freedom.*
> *And for that reason it is genuinely intelligent control.*
> *Unintelligent control appears as external domination.*
> *And for that reason it is really unintelligent control.*
> *Intelligent control exerts influence without appearing to do so.*
> *Unintelligent control tries to influence by making a show of force."*

This thesis addresses a few issues of interest in the field of advanced control in the process control field. The issues discussed concern both the traditional control field and fields where traditional approaches and computational intelligence approaches merge. The difficulties focused upon are directionality and nonlinearity, and a few methods concerned with the analysis and control of such difficulties are discussed.

Chapter 2

Multivariable processes

2.1 Interaction

Processes which are multivariable in nature, i.e. processes where the variables to control and the variables available to manipulate cannot be separated into independent loops where one input only would affect one output, constitute a major source of difficulty in process control (McAvoy, 1983; Shinskey, 1984; Balchen and Mummé, 1988; Seborg, Edgar and Mellichamp, 1989; Luyben, 1992; Skogestad and Postlethwaite, 1996). Multivariable processes, for the term to have significance, thus show a certain degree of interaction, i.e. one control loop affects other loops in some way. As this interaction increases, so do the potential control problems.

Multivariable processes in industrial and other applications are often of higher order, where there are many, possibly tens or hundreds, of control loops interacting (Skogestad and Postlethwaite, 1996). However, as the difficulty of the theory of multivariable control increases as the dimension increases, theoretical studies have mainly, at least in the process control field, focused on systems with two interacting loops, referred to as 2×2 systems.

Linear multivariable systems are such that all input-output relationships can be described by linear differential equations plus time delays. As the linear systems exhibit the same behaviour in all operating regions, the analysis might as well be based on descriptions of variables as deviations around operating regions, and thus, e.g. a 2×2 system can in continuous time be described by transfer functions of the type

$$\mathbf{y} = \mathbf{G}\mathbf{u} \tag{2.1}$$

$$\begin{pmatrix} y_1 \\ y_2 \end{pmatrix} = \begin{pmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{pmatrix} \begin{pmatrix} u_1 \\ u_2 \end{pmatrix} \tag{2.2}$$

where the outputs are denoted y_i and the inputs u_j. The transfer function between input j and output i is denoted g_{ij}. As mentioned, the interaction in the control loop strongly affects the potential control difficulties. Thus, methods to analyse and measure the interaction are necessary.

Rijnsdorp (1965) suggested an interaction measure (κ) defined for 2×2 systems as

$$\kappa = \frac{g_{12}g_{21}}{g_{11}g_{22}} \tag{2.3}$$

This measure is often referred to as the Rijnsdorp interaction measure (RIM). Bristol (1966) suggested the relative gain array, **RGA**, which can be defined as

$$\mathbf{RGA} = \mathbf{G}. * (\mathbf{G^{-1}})^{\mathbf{T}} \tag{2.4}$$

where $.*$ denotes the Hadamard product. The RGA for 2×2 systems becomes

$$\mathbf{RGA} = \begin{pmatrix} \lambda_{11} & 1 - \lambda_{11} \\ 1 - \lambda_{11} & \lambda_{11} \end{pmatrix} \tag{2.5}$$

where

$$\lambda_{11} = \frac{1}{1 - \frac{g_{12}g_{21}}{g_{11}g_{22}}} \tag{2.6}$$

and the relationship between λ_{11} and κ for 2×2 systems becomes

$$\lambda_{11} = \frac{1}{1 - \kappa} \tag{2.7}$$

Although the relative gain array originally was proposed for steady-state analysis, and thus the model in equation 2.2 would represent a steady-state model, the RGA can also be used for frequency dependent analysis (Skogestad and Postlethwaite, 1996). A value of λ_{11} close to one, or κ close to zero, implies that there is little or no interaction in the process. As the magnitude of κ increases, so does the interaction.

In particular the relative gain array has gained wide acceptance as a method for interaction analysis (McAvoy, 1983; Shinskey, 1984). The RGA is, e.g. often used to choose control structures in distillation control (Shinskey, 1984).

2.2 Analysing Directionality

Interaction in multivariable processes can be of different types. Some processes showing strong interaction can be easier to control than others (McAvoy, 1983). Thus, it is important to be able to classify not only the level of interaction but also the type of interaction.

The term ill-conditioned is in matrix algebra used to refer to how close a matrix is to being singular (Golub and Van Loan, 1996) and in control the term directionality refers to the degree of ill-conditionedness of a process (or actually process model). In matrix algebra as well as in control analysis the singular value decomposition (SVD) is used to analyse the level of ill-conditionedness. The SVD decomposes a matrix (such as a frequency-dependent process model in equation 2.1) according to

$$\mathbf{G} = \mathbf{U}\mathbf{\Sigma}\mathbf{V}^{\mathbf{T}} \tag{2.8}$$

where $\mathbf{U}$ is an orthogonal matrix containing the left singular vectors (the output directions), $\mathbf{V}$ an orthogonal matrix containing the right singular vectors (the input directions) and $\mathbf{\Sigma}$ a real diagonal matrix containing the singular values σ, such that $\sigma_1 \geq \sigma_2 \geq \cdots \geq \sigma_n \geq 0$. The singular values are interpreted as bounds on the possible gain of $\mathbf{G}$. σ_1 is referred to as the largest singular value (the largest possible gain, commonly denoted $\bar{\sigma}$) and σ_n as the smallest singular value (the smallest possible gain, denoted $\underline{\sigma}$). The high and low gain directions for the inputs and the outputs are given by the singular vectors. The condition number is the ratio between the largest and smallest singular values, $\gamma = \bar{\sigma}/\underline{\sigma}$. An ill-conditioned matrix is a matrix with a large condition number.

Assume that changes in the inputs of a linear 2×2 system are performed so that they describe a circle, compare figure 2.1. The corresponding changes in the outputs will then form an ellipse. The gain at a certain input direction of the process is defined as the length of the output vector divided by the length of the input vector. When applying the SVD in process control, one has to take into account not only the (frequency-dependent) matrix relating the inputs and the outputs but also the fact that the inputs and outputs need to be scaled in some way as they are related to appropriate physical variables. Thus, the scaling dependency of the method of analysis used is of importance. Whereas the RGA and the RIM are scaling independent the SVD and also the condition number are scaling-dependent measures.

Consider the following example taken from McAvoy (1983). We have two steady-state gain matrices, given by

$$\begin{pmatrix} y_1 \\ y_2 \end{pmatrix} = \begin{pmatrix} -1 & -0.5 \\ -1 & 0.5 \end{pmatrix} \begin{pmatrix} u_1 \\ u_2 \end{pmatrix} \tag{2.9}$$

$$\begin{pmatrix} y_1 \\ y_2 \end{pmatrix} = \begin{pmatrix} -1 & -0.01 \\ -1 & 0.01 \end{pmatrix} \begin{pmatrix} z_1 \\ z_2 \end{pmatrix} \tag{2.10}$$

These gain matrices are, as noted in McAvoy (1983), the same if one does not put limitations on the possible scaling. Assuming we have the freedom to choose units for the process description as we wish, it is easily seen that by substituting u_1 for z_1 and u_2 for $0.02z_2$ in equation 2.10, the descriptions are the same. This can also be seen as the (1,1)-element of the RGA for both systems is 0.5 (the RGA is scaling independent). Figures 2.1 and 2.2 show the input and output directions for the two matrices in equation 2.9 and 2.10, respectively. Figures 2.1 and 2.2 indicate a significant difference between the models. By the use of scaling, however, the models become the same.

Generally, scaling can be formulated as

$$\mathbf{G^S} = \mathbf{S_1 G S_2} \tag{2.11}$$

where $\mathbf{S_1}$ and $\mathbf{S_2}$ are diagonal scaling matrices. It is obvious that scaling matrices can be chosen such that the system descriptions in equations 2.9 and 2.10 are given by (for example)

$$\mathbf{G^S} = \begin{pmatrix} -1 & -1 \\ -1 & 1 \end{pmatrix} \tag{2.12}$$

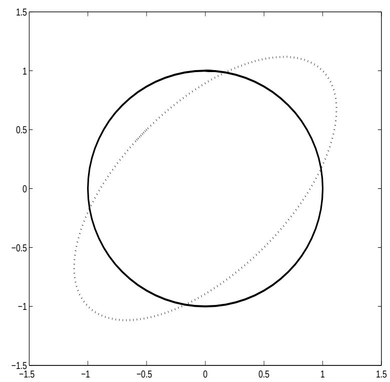

Figure 2.1: Input (solid line) and output (dotted line) directions of the gain matrix in equation 2.9. The x-axis represents the change in the first input and the first output and the y-axis represents the change in the second input and the second output.

In such a case, the input and output spaces both represent circles, and thus there does not seem to be any directionality at such a scaling.

If the scalings do represent physical limitations on the system, such that the scaling of the variables are chosen to be, say, between 0% and 100%, then the models in equations 2.9 and 2.10 differ significantly. From a performance point-of-view it seems reasonable to scale the variables to be between 0% (e.g. a fully closed actuator, the minimum of a controlled variable, etc.) and 100% (e.g. a fully open actuator, the maximum of a controlled variable, etc.) as was suggested in, e.g. Moore (1986). The model in equation 2.10 (referred to as ill-conditioned in McAvoy (1983)) is if the model is based on such a scaling, designed such that a desired change of, e.g. 3% in the first process output while keeping the second output constant is physically impossible. This is the case since the second process input has almost no effect on either one of the process outputs. Thus we are, in effect, in a situation where we have two desired outputs, but only one input. This will, indeed, lead to control problems.

As Paper **I** of this thesis shows, such a process is not necessarily ill-conditioned from the point-of-view of stability. It is merely a weighting (or design) problem. Thus ill-conditionedness due to inability to affect the outputs is a design error, similar to (again assuming scaling between 0% and

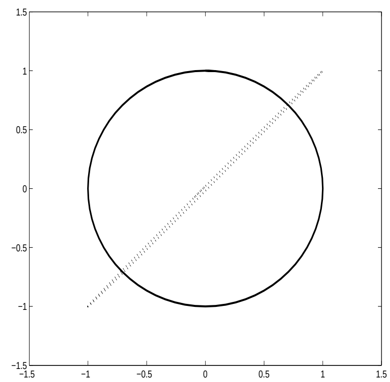

Figure 2.2: Input (solid line) and output (dotted line) directions of the gain matrix in equation 2.10. The x-axis represents the change in the first input and the first output and the y-axis represents the change in the second input and the second output.

100%) the control of

$$\begin{pmatrix} y_1 \\ y_2 \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ 0 & 0.01 \end{pmatrix} \begin{pmatrix} u_1 \\ u_2 \end{pmatrix} \tag{2.13}$$

This represents two independent control loops, each with one input and one output. Obviously there is no interaction and thus this is not really a multivariable process, but still there is "ill-conditionedness" as the condition number is 100. Also, there will surely be control problems in the second loop, as a 100% (full range) change in the manipulator results in a 1% percent change of the defined range in the controlled output. Thus, this is not a process where we actually can make sufficient changes in the manipulators to drive the outputs over the entire range of interest. The same applies for the process in equation 2.10.

All models discussed above are actually well-conditioned as long as we have the freedom to choose the scaling. However, there is another kind of ill-conditioned plants, which are ill-conditioned regardless of scaling. Such cases are close to singular in the sense that although both inputs have a strong impact on the outputs, the way either of these inputs affects both the outputs is almost identical. Thus it will be difficult to separate them.

Assume a gain matrix according to

$$\begin{pmatrix} y_1 \\ y_2 \end{pmatrix} = \begin{pmatrix} -1 & 0.95 \\ -0.95 & 1 \end{pmatrix} \begin{pmatrix} u_1 \\ u_2 \end{pmatrix} \tag{2.14}$$

For such a matrix, the input and output directions represent a graph according to figure 2.3. This matrix is optimally scaled, i.e. it cannot be rescaled in

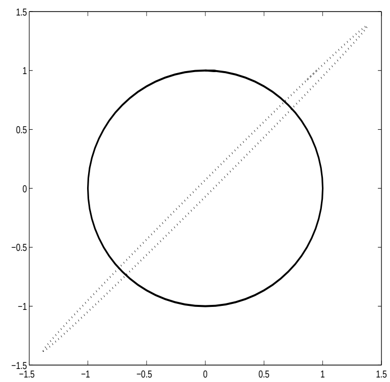

Figure 2.3: Input (solid line) and output (dotted line) directions of the gain matrix in equation 2.14. The x-axis represents the change in the first input and the first output and the y-axis represents the change in the second input and the second output.

any way so that the output vector would be closer to a circle. The possible effect of the scaling on the degree of directionality is not clear merely by looking at the graphs. Thus, it is important to use the full range of measures available.

Scaling is thus a key component in directionality analysis. One way to keep the focus on control engineering and not design issues is to assume that we have defined the operating ranges of our manipulators and our outputs in such a way that one manipulator can drive one output anywhere within the desired operating range, as long as the other loops are on manual, etc. In such a case, the difficulties in the control which might rise are due to the multivariable nature, and thus to the interaction and/or the directionality, of the plant, not to the design issues.

An optimal scaling is the scaling that minimises the condition number. Two optimally scaled matrices, with the same amount of interaction in the sense that the magnitude of the Rijnsdorp interaction measure is the same, are given by

$$\mathbf{K_1} = \begin{pmatrix} 1 & k_{12} \\ -k_{12} & 1 \end{pmatrix} \tag{2.15}$$

$$\mathbf{K_2} = \begin{pmatrix} 1 & k_{12} \\ k_{12} & 1 \end{pmatrix} \tag{2.16}$$

As k_{12} goes from 0 towards 1 for K_1, the determinant goes from 1 to 2. This is the well-conditioned case, which is the case for 2×2 systems, if the matrix elements have an odd number of negative signs. The well-conditioned case does not bring the matrix closer to singularity although the interaction increases. This is also seen as the well-conditioned case has a mimimised condition number = 1. For K_2, which is the ill-conditioned case, the determinant goes from 1 towards 0 as k_{12} goes from 0 towards 1, and thus the matrix comes closer to singularity. This is the case for 2×2 systems if the matrix elements have an even number of negative signs.

Again, as more thoroughly discussed in Paper **I** of this thesis and also in Waller, Sågfors and Waller (1994a) and Waller, Sågfors and Waller (1994b), scaling when analysing stability issues is irrelevant, and a scaling independent measure should be used (e.g. RGA or the minimised condition number, $\gamma_{\min}$). However, when it comes to analysing potential performance issues (e.g. compare weights), scaling can be used to emphasise the differences in the variables.

As seen, the scaling dependency can cause some confusion even for the linear case when analysing processes with potentially high directionality. Moore (1986), Andersen and Kümmel (1991) and Andersen and Kümmel (1992) recommend a scaling dependent on the relative importance of variables or on the physical limitations. Many authors, such as Lau, Alvarez and Jensen (1985), Andersen, Laroche and Morari (1991) and Papastathopoulou and Luyben (1991) seem to prefer physical scaling. Other papers, such as Grosdidier, Morari and Holt (1985)and Skogestad and Morari (1987) seem to take the view that the scaling that minimises the condition number is the correct one. Often, the process model used is merely assumed to be properly scaled (Brambilla and D'Elia, 1992; Freudenberg, 1989; Freudenberg, 1993). This is further discussed in Paper **I** of this thesis, and in the references Waller et al. (1994a) and Waller et al. (1994b).

2.3 Controlling ill-conditioned plants

As ill-conditioned plants are a subgroup of multivariable plants in general, multivariable control in general is applied to controlling ill-conditioned plants. In this thesis we briefly discuss two approaches to multivariable control. First, we shall look at control structures including decoupling (see also Paper **II** of this thesis and the references Waller and Waller (1991a), Waller and Waller (1991b) and Waller and Waller (1992)).

In process control, the use of decoupling is well established (Luyben, 1970; Waller, 1974). Furthermore, it is well known (McAvoy, 1983) that ill-conditioned processes are difficult to control by the use of decoupling. According to McAvoy (1983), this is due to the increased sensitivity of the ill-conditioned plant to disturbances.

To illustrate the sensitivity of the decoupling approaches, we can look at the matrices in equation 2.15 and 2.16. Assume the formulation that either $\mathbf{K_1}$ or $\mathbf{K_2}$ represent the actual plant to be decoupled and that the matrix used for calculating the decoupling is referred to as $\hat{\mathbf{K}}_\mathbf{1}$ and $\hat{\mathbf{K}}_\mathbf{2}$, respectively. The decoupling matrix is thus (for example) $\mathbf{D_1} = (\hat{\mathbf{K}}_\mathbf{1})^{-\mathbf{1}}$ and $\mathbf{D_2} = (\hat{\mathbf{K}}_\mathbf{2})^{-\mathbf{1}}$. If $\hat{\mathbf{K}}_\mathbf{1}$ and $\hat{\mathbf{K}}_\mathbf{2}$ include errors as compared to $\mathbf{K_1}$ and $\mathbf{K_2}$ of no more than +/-2% in each element, we can calculate the error of the decoupling strategy for example as

$$\mathbf{E_i} = \max ||(\mathbf{I} - \mathbf{D_i K_i})||_\mathbf{2} \tag{2.17}$$

The errors are visualised for the two matrices in figure 2.4 as functions of the off-diagonal element k_{12}.

Another approach to controlling ill-conditioned plants is a computation-based approach, which is presented in the sequel and in Paper **V** of this thesis.

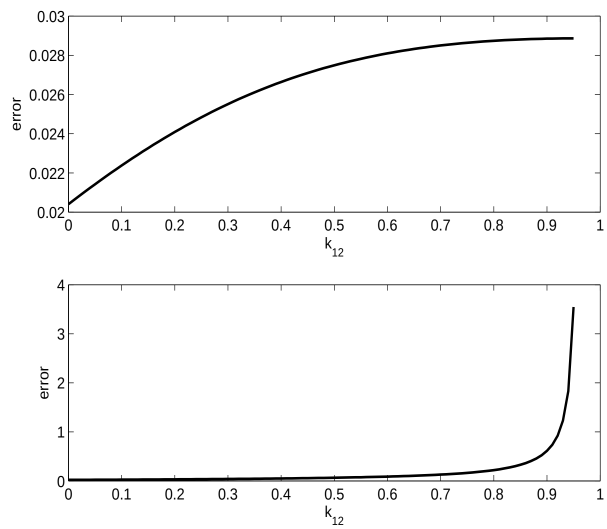

Figure 2.4: The errors of the decoupling scheme as functions of the off-diagonal element for optimally scaled matrices. Upper graph shows the well-conditioned case and lower graph shows the ill-conditioned case.

Chapter 3

Nonlinearity

Analysing the multivariable nature of a plant, such as interaction and directionality, as done above, is not enough to assure a thorough understanding of the plant studied and, thus, to achieve potential for good control. Many processes of industrial importance, such as the distillation process, often show both high directionality and interaction and also strong nonlinearity. Thus, modelling techniques for nonlinear ill-conditioned plants are of importance.

For the sake of illustration, we can look at the directionality of a nonlinear system, given by

$$\begin{aligned} y_1 &= u_1 + u_2^2 \\ y_2 &= u_1^2 + u_2 \end{aligned} \tag{3.1}$$

For such a process, the input and output spaces represent a graph according to figure 3.1. Also for such a system, the scaling-dependency must naturally be accounted for.

3.1 Nonlinear modelling

Generally, many approaches to nonlinear modelling and control are being studied. The construction of a process model is normally based on several different sources of knowledge (Denn, 1986; Stephanopoulos and Han, 1994). A very important topic in nonlinear modelling is the development of hybrid modelling approaches that allow fundamental and empirical process knowl-

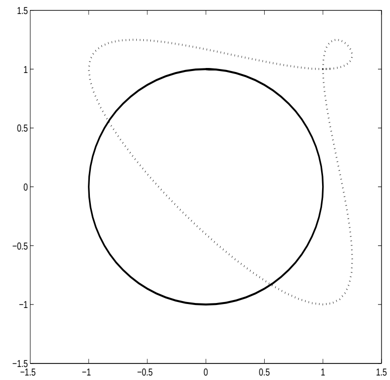

Figure 3.1: Input (solid line) and output (dotted line) directions of the gain matrix in equation 3.1. The x-axis represents the change in the first input and the first output and the y-axis represents the change in the second input and the second output.

edge to be integrated (Henson, 1998). Denn (1986) points out three methodologies to obtain a process model; fundamental theories, analogy to other known relationships and empirical data. In turn, Stephanopoulos and Han (1994) note that a likely future scenario for the use of intelligent systems is the integration of multiple knowledge representations, so that all relevant knowledge is captured and utilised.

Increased computational power and more and more complex control problems in combination with higher demands on control quality have led to an increased demand for control methods focusing on nonlinear control. Practically all control methods are, in way or other, model-based. There are a wealth of nonlinear modelling methods, see, e.g. the section on nonlinear MPC below. One option for modelling nonlinear processes is by use of so-called quasi-ARMAX modelling schemes. Quasi-ARMAX modelling approaches have been studied in among others Johansen and Foss (1993), Hu, Kumamaru, Inoue and Hirasawa (1998), Hu, Kumamaru and Hirasawa (2001) and Young, McKenna and Bruun (2001). See also the references therein. The principle of these modelling approaches is similar. The idea is to use well established models of input-output type in the ARMAX formulation, and add nonlinear features to the models by, e.g. the use of fuzzy logic or neural network approximations. Here the following formulation is considered as an example of a nonlinear quasi-ARMAX modelling approach. For a more thorough presentation, please see Papers **III** and **IV** of this thesis and the references therein.

We assume that our plant can be represented by an input/output representation of the type

$$\begin{aligned} y(k) &= g(\varphi(k)) + v(k) \\ \varphi(k) &= [y(k-1), \ldots, y(k-n), \\ &\quad u(k-d), \ldots, u(k-m-d+1)]^T \end{aligned} \tag{3.2}$$

where $y(k)$ is the output at discrete time-intervals, $u(k)$ the input, $v(k)$ a disturbance, d the time delay, $\varphi(k)$ the regression vector and g a nonlinear function. The system can, after some manipulation, be expressed as

$$y(k) = \varphi^T(k)(\theta + \Delta\theta) + v(k) \tag{3.3}$$

Let the parameters θ represent parameters of a global linear model, and $\Delta\theta$ represent the deviations from this linear model. These deviations can be referred to as local, linear models activated by corresponding fuzzy membership functions

$$\Delta\theta_i = f_i(\varphi(k)), \quad i = 1, \ldots, n+m \tag{3.4}$$

with

$$f_i(\varphi(k)) = \sum_{j=1}^{M} \omega_{ij} N_f(p_j, \varphi(k)) \tag{3.5}$$

where $N_f(p_j, \varphi(k))$ are fuzzy basis functions and ω_{ij} and p_j are parameter vectors. The number of local models used is denoted M.

Such a model has the benefit of following a familiar modelling approach in its ARMAX-like structure. Thus, this familiarity can be seen as a strength when interpreting the model and also as a strength when choosing initial values for the modelling or identification. However, it is by no means claimed that this modelling approach would be the best. It is merely used as an example of a modelling approach aiming at combining traditional modelling methods such as ARX or ARMAX-like input/output models on one hand and methods based on computational intelligence (such as neuro-fuzzy methods) on the other.

3.2 Nonlinear control and the NMPC formulation

According to Takatsu et al. (1998), in a survey on industrially implemented advanced control methodologies, and Qin and Badgwell (1998), model predictive control (in the sequel denoted MPC) and fuzzy control techniques are increasingly employed especially in the refinery and petrochemical industries. In this thesis the nonlinear model predictive control formulation is used as an example of a successful method of implementing nonlinear control. MPC is here used to describe a family of control methods, all having the same characteristic features. These controllers are also referred to as receding or moving horizon controllers.

The strong position MPC has reached in certain industrial fields is probably due to the straightforward design procedure, a clear open-loop optimisation approach and the ease with which the method handles the process model (Camacho and Bordons, 1999). In addition, a main motivation behind the use of MPC is that MPC can easily incorporate constraints on the variables already at the design stage of the controller. It is worth noting that although many processes under MPC control are nonlinear by nature, the vast majority of MPC applications are based on a linear model (referred to as linear MPC). These linear models are commonly derived simply from step or impulse identification experiments (Qin and Badgwell, 1998; Camacho and Bordons, 1999).

The idea of the MPC formulation is to perform a (possibly time-consuming) minimisation of a loss function with respect to a number of future control moves (a control horizon) at every sampling instant. The loss function is a function of these control moves and predicted process outputs. For the prediction, in turn, a process model is used. The controller implements a receding strategy so that at each instant the horizon is displaced towards the future, which involves the application of the first control signal of the sequence calculated at each step.

MPC can be described as an open-loop optimal control technique where feedback is incorporated via the receding horizon formulation (Henson, 1998). This open-loop optimality corresponds to a sub-optimal feedback control strategy (Yang and Polak, 1993). This fact is excellently illustrated in Rawlings, Meadows and Muske (1994), where, for a certain control problem with stochastic disturbances, the MPC only achieves 36% of the possible cost reduction achievable by feedback control.

Mathematically, the MPC formulation can be stated as

$$\min_{\mathbf{u}(k),\mathbf{u}(k+1),\ldots\mathbf{u}(k+N_u)} J \tag{3.6}$$

where

$$\begin{aligned} J \;=\; & \sum_{j=N_1}^{N_y} (\mathbf{y_r}(k+j) - \hat{\mathbf{y}}(k+j|k))^T \boldsymbol{\Gamma}(j) (\mathbf{y_r}(k+j) - \hat{\mathbf{y}}(k+j|k)) \\ & + \sum_{j=1}^{N_u} \boldsymbol{\Delta}\mathbf{u}(k+j-1)^T \boldsymbol{\Lambda}(j) \boldsymbol{\Delta}\mathbf{u}(k+j-1) \end{aligned} \tag{3.7}$$

with $\boldsymbol{\Gamma}$ and $\boldsymbol{\Lambda}$ as diagonal weighting matrices. The vector of predicted process outputs is denoted $\hat{\mathbf{y}}$ and the reference values are denoted $\mathbf{y_r}$. The vector of process inputs is denoted $\mathbf{u}$, and $\boldsymbol{\Delta}\mathbf{u}(j) = \mathbf{u}(j) - \mathbf{u}(j-1)$. An MPC controller needs explicitly to be designed to provide integral action (or offset-free control). This is, basically, done in two ways (Muske and Badgwell, 2002). The first way is to modify the objective of the controller to include integration of the tracking error, as is done in, e.g. the PI- or PID-controller algorithms. The second approach is to augment the process model to include a constant step disturbance, and the effect of the disturbance on the controlled variables is removed by shifting the steady-state target of the controller. Our approach, presented in Paper **III**, as our modelling is input-output based, simply includes a correcting term to remove the steady-state error in the process output prediction. Thus, it provides integral action without the drawback of an augmented state vector which would add to the dimensions of the state vector and thus make the optimisation problem more difficult, which is the case in the method mentioned in Muske and Badgwell (2002).

In MPC, as in other model-based controllers, the importance of having an accurate process model is crucial. In particular when it comes to nonlinear modelling techniques (where there still is a large degree of work to be done), the nonlinear model used for NMPC should be given extra attention. The steps in a nonlinear identification problem are (as in linear identification) listed by Henson (1998) as structure selection, input sequence design, noise modelling, parameter estimation and model validation. Each of these poses more challenging theoretical questions than their linear counterparts.

The types of discrete-time nonlinear models utilised for NMPC in the recent literature include

- Hammerstein and Wiener models (for example in Fruzzetti, Palazoglu and MacDonald (1997), Bloemen, Chu, van den Boom, Verdult, Verhagen and Backx (2001) and Pomerleau, Pomerleau, Hodouin and Poulin (2003))
- Volterra models (Maner, Doyle, Ogunnaike and Pearson, 1996; Maner and Doyle, 1997)
- Polynomial ARMAX (Banerjee and Arkun, 1998)
- Artificial neural networks (Arahal, Berenguel and Camacho, 1998; Rohani, Haeri and Wood, 1999a; Rohani, Haeri and Wood, 1999b; Piché, Sayyar-Rodsari, Johnson and Gerules, 2000)
- Fuzzy logic models (Sousa, Babuska and Verbruggen, 1997; Fisher, Nelles and Isermann, 1998)

MPC is well covered in the literature, see, e.g. Camacho and Bordons (1999) and Rawlings (2000). Excellent surveys and tutorials on NMPC can be found in for example Rawlings et al. (1994) and Henson (1998). An overview of industrial applications of advanced control methods in general can be found in Takatsu et al. (1998) and of NMPC in particular in Qin and Badgwell (1998). Texts focusing on the optimisations required for NMPC are, for example, Mayne (1995), Biegler (1998) and Gopal and Biegler (1998). See also Hussain (1999) for a survey of process control applications using MPC with neural networks. A short introduction to some of the applications in nonlinear MPC recently presented follows.

- Sousa et al. (1997) present NMPC based on a Takagi-Sugeno fuzzy model used for the prediction. The controller proposed is a combination of a model predictive controller and an inverse based controller (IMC). If no constraints are violated, an inverse based control algorithm is used. When constraints are violated, the required optimisation used is a branch-and-bound algorithm. Sousa et al. (1997) illustrate their controller by applying it to a laboratory scale air-conditioning system.

- Fruzzetti et al. (1997) use simulation studies of a pH-process and a binary distillation column to illustrate their proposed controller. The model used is a Hammerstein model with the motivation that many chemical processes can be modelled as such, i.e. as a static nonlinearity followed by a linear dynamical model. The optimisation algorithm used is an ellipsoidal cutting-plane algorithm.

- Banerjee and Arkun (1998) present nonlinear MPC for control of plants that operate in several distinct operating regions, and for the control during the transition between these regions. The method used is to identify several linear models and interpolate the nonlinear model between the linear ones. The nonlinear model structure used is a polynomial ARX-model. The resulting nonlinear MPC controller is applied to a CSTR example.

- Arahal et al. (1998) apply neural predictors to generalized predictive control (one version of MPC) for nonlinear control. They apply their controller to a solar power plant. The control scheme is implemented in such a way that the response of the plant is divided into a free and a forced term (Camacho and Bordons, 1999). A linear model is then used for the forced part (thus making calculations of the optimal control sequence straightforward) and a nonlinear model for the free part (taking into account the effect of perturbations).

- Rohani et al. (1999b) look at model predictive control and Rohani et al. (1999a) discuss appropriate models (linear and nonlinear) for the purpose. The process studied is (simulations of) a crystallisation process under NMPC control with a model based on a feedforward neural network. The process is multivariable with significant interaction.

Chapter 4

Approximating control strategies

As the NMPC formulation above can be extremely time consuming, due to the nonlinear optimisation problem to be solved at every sampling instant (compare equation 3.6), there might be a need to relax the computational burden. This is especially important for control problems with a short sampling time. Different possibilities to perform such relaxation exist. These include use of a linear model (and thus a linear MPC formulation) even for control of nonlinear processes or use of short prediction and control horizons. Another way to approach this problem is to use nonlinear function approximators, designed to approximate, e.g. the behaviour of the nonlinear MPC controller. Such approximations are discussed in Papers **VI** and **VII** of this thesis, and in, e.g. Parisini and Zoppoli (1995), Gómez Ortega and Camacho (1996), Parisini and Zoppoli (1998) and Cavagnari, Magni and Scattolini (1999).

As one formulates the issue of approximating optimal or near-optimal control actions, the problem can be formulated in at least two different ways. On the one hand, given a certain state, an approximator can approximate the designated control action. The controller then takes this action and the procedure is repeated from the resulting state. We shall refer to this as approximation of the control policy. On the other hand, it is possible to approximate the smallest future cost taking a certain action in a certain state will give rise to. If such an approximator is capable of approximating the whole state-action space, then it is possible to choose the best action to take from such an approximation of the value function, or cost-to-go function. This will be referred to as an approximation of the value function.

4.1 Neurodynamic programming

The idea of approximating the value function corresponding to a state-action set is similar to neurodynamic programming (Bertsekas and Tsitsiklis, 1996; Haykin, 1999) and reinforcement learning (Sutton and Barto, 1998) and thus also to Q-learning (Sutton and Barto, 1998; Hagen, 2001). The value function can, in reinforcement learning terms, be said to represent the future sum of expected reinforcements associated with a given state,

$$\min_{\mathbf{u}(k)} V(\mathbf{S}(k), \mathbf{u}(k)) \tag{4.1}$$

The notation $V(k)$ is used to denote the value function $V(\mathbf{S}(k), \mathbf{u}(k))$ in the sequel, for the sake of simplicity. A common formulation of the value function is to calculate $V(k)$ as a quadratic loss function according to

$$\begin{aligned} V(k) &= \sum_{j=k}^{\infty} (\mathbf{u}(j) - \mathbf{u}(j-1))^T \mathbf{\Lambda} (\mathbf{u}(j) - \mathbf{u}(j-1)) \\ &\quad + \sum_{j=k+1}^{\infty} (\mathbf{y_{sp}}(j) - \mathbf{y}(j))^T \mathbf{\Gamma} (\mathbf{y_{sp}}(j) - \mathbf{y}(j)) \end{aligned} \tag{4.2}$$

The value (or loss) function thus represents a weighted sum of the loss in future control moves and future errors between the reference values (i.e. the set-points) and the actual process outputs. In practice, ∞ is replaced by a sufficiently long horizon. The loss function can be replaced by an immediate loss function and a future cost-to-go according to the dynamic programming formulation

$$
\begin{aligned}
V(k) &= R(k) + \tilde{V}(k+1) \qquad (4.3)\\
V(k) &= (\mathbf{u}(k) - \mathbf{u}(k-1))^T \mathbf{\Lambda}(\mathbf{u}(k) - \mathbf{u}(k-1)) \\
&\quad + (\mathbf{y_{sp}}(k+1) - \mathbf{y}(k+1))^T \mathbf{\Gamma}(\mathbf{y_{sp}}(k+1) - \mathbf{y}(k+1)) \\
&\quad + \min_{\mathbf{u}(k+1),\ldots} \left\{ \sum_{j=k+1}^{\infty} (\mathbf{u}(j) - \mathbf{u}(j-1))^T \mathbf{\Lambda}(\mathbf{u}(j) - \mathbf{u}(j-1)) \right. \\
&\quad \left. + \sum_{j=k+2}^{\infty} (\mathbf{y_{sp}}(j) - \mathbf{y}(j))^T \mathbf{\Gamma}(\mathbf{y_{sp}}(j) - \mathbf{y}(j)) \right\}
\end{aligned}
$$

where thus

$$
\begin{aligned}
R(k) &= (\mathbf{u}(k) - \mathbf{u}(k-1))^T \mathbf{\Lambda}(\mathbf{u}(k) - \mathbf{u}(k-1)) \\
&\quad + (\mathbf{y_{sp}}(k+1) - \mathbf{y}(k+1))^T \mathbf{\Gamma}(\mathbf{y_{sp}}(k+1) - \mathbf{y}(k+1)) \qquad (4.4)
\end{aligned}
$$

and $\tilde{V}(k+1)$ (the future cost-to-go function) is given by

$$
\begin{aligned}
\tilde{V}(k+1) &= \min_{\mathbf{u}(k+1),\ldots} \left\{ \sum_{j=k+1}^{\infty} (\mathbf{u}(j) - \mathbf{u}(j-1))^T \mathbf{\Lambda}(\mathbf{u}(j) - \mathbf{u}(j-1)) \right. \\
&\quad \left. + \sum_{j=k+2}^{\infty} (\mathbf{y_{sp}}(j) - \mathbf{y}(j))^T \mathbf{\Gamma}(\mathbf{y_{sp}}(j) - \mathbf{y}(j)) \right\} \qquad (4.5)
\end{aligned}
$$

The process of how to evaluate the future reinforcement (or cost-to-go function), given a current state and action pair is the critical issue in this approach. Q-learning is a model-free approach, where the loss is approximated by visiting states. The approach used in this thesis is based on calculating the cost-to-go from a given state and action pair based on simulations using an MPC controller. Thus, by offline calculations the cost-to-go function for a large set of state-action pairs can be calculated and then approximated. Such an approximation is discussed in Paper **VI** of this thesis.

However, it is worth noting that the approximation of the value function can be quite difficult (Anderson, 2000), and therefore an alternative approach of approximating the control policy might be computationally and practically more feasible. Approximation of the policy function is discussed in Papers **VI** and **VII** of this thesis.

Chapter 5

Outline of the papers

5.1 Paper I

Defining Directionality: Use of Directionality Measures with Respect to Scaling

In the first article of the thesis, the definitions of the concepts of directionality and ill-conditionedness are studied and an investigation of the use of these terms in the process control literature is carried out. The paper illustrates that the commonly used definition of directionality is insufficient, due to the wide range of different applications connected to directionality studied in the field of process control. The paper points out that, due to this, the concept of directionality is occasionally used in a somewhat confusing manner.

Directionality is closely related to the singular value decomposition, which in turn is a method used in matrix algebra to measure, among other things, how close a matrix is to being singular. One of the measures used in the literature to measure directionality is the condition number, i.e. the largest singular value divided by the smallest singular value.

In practical cases, however, the matrices studied actually represent process models. These process model matrices are strongly influenced by the units used to model the system. This fact is recognised by the singular value decomposition (SVD) in the sense that the SVD is scaling dependent. Thus, an analysis of directionality, or ill-conditionedness, must first treat the scaling question and choose a scaling in accordance with the analysis at hand. If this is not done and scaling is performed based on, e.g. physical units, it would imply that the control difficulties related to directionality would change depending on whether it is, for instance, a British or a French engineer that examines the process. Other measures also used in directionality analysis such as the relative gain array or the minimised condition number are scaling independent.

By examining the use of the concept of directionality, a refinement of the definition of directionality is proposed so as to give a more meaningful measure. The refinement divides the concept of directionality into two parts, which are connected to stability and performance aspects, respectively. The refinement of the definition clarifies the connection between control difficulties and directionality and it also contributes to clarifying the scaling choice when modelling a process with respect to directionality analysis.

5.2 Paper II

Decoupling Revisited

Approaches to controlling multivariable processes by the use of simple, intuitive means have commonly been popular in process control. Such approaches include "common-sense" methods, such as decoupling. Decoupling, in turn, can be seen as a special implementation of a control structure. Decoupling has been particularly well-used and successful in distillation control. Thus, the field of distillation has seen several methods of designing decoupling controllers, such as steady-state decoupling, ideal decoupling or simplified decoupling.

However, these common methods in distillation control have not gained recognition in all fields of control. To illustrate this, an example from the literature is picked for further study, where decoupling schemes originally designed for distillation control are applied to control of a solid-fuel boiler. A dynamic decoupling approach performs well as compared to the original static decoupler proposed in the literature, as expected.

In addition, a reformulation of the design procedure when designing dynamic decouplers is presented. This reformulation makes it easier always to find a realisable dynamic decoupler for the process at hand by adding the necessary dynamics to the primary control loops.

5.3 Paper III

Nonlinear Model Predictive Control Utilizing a Neuro-Fuzzy Predictor

Nonlinearity is another of the main challenges facing the field of process control. Thus, in the third paper, the focus is temporarily shifted away from ill-conditioned plants, and instead concentrates on the nonlinearity often associated with process control problems.

The third paper thus investigates nonlinear modelling techniques for use with the MPC controller in a process control environment. A modelling technique of quasi-ARMAX type which recently has been presented in the literature is discussed as regards process control applications and formulated to be used in the MPC framework.

In association with the nonlinear modelling technique, the (nonlinear) MPC controller formulation is investigated. This is done by looking at simple examples of control problems emphasising the challenge of processes with a dynamic behaviour that changes with the operating region, as is often the case in process control.

The nonlinear modelling scheme studied here has the benefit of being similar to the commonly used input/output models of ARMAX-type. Thus, it is well motivated for a straightforward controller approach such as the MPC formulation and it retains the intuitive appeal of the MPC formulation.

5.4 Paper IV

A Neuro-Fuzzy Model Predictive Controller Applied to a pH-neutralization Process

The fourth paper in the thesis continues where the third paper left off. The paper investigates how the quasi-ARMAX modelling scheme works for modelling a highly nonlinear pH-neutralization process. The nonlinearities of the pH-process strongly depend on the operating region, and thus the quasi-ARMAX model, consisting of a global model and of local models active in different regions, is well suited to model such nonlinearities. This pH-process has been used in several case-studies as an illustration of means to control nonlinear plants. Please see the references in the paper.

The pH-process is then controlled to handle both set-point changes and unmodelled disturbances by the use of the nonlinear model predictive control formulation. Integral action is incorporated in the controller by correcting the predicted output based on measurements of the last available output. The controller works well as compared to other controllers for this process, which have been studied in the literature.

5.5 Paper V

Multivariable Nonlinear MPC of an Ill-conditioned Distillation Column

The fifth paper in this thesis consists of an investigation of control of a nonlinear and ill-conditioned distillation column. This paper thus works as a conclusion of the part concerning quasi-ARMAX nonlinear model predictive control.

First, the plant is investigated and the nonlinear ill-conditionedness of the distillation column is characterised. The quasi-ARMAX model is reformulated so as to model multivariable systems. The nonlinear MPC formulation, including the integral action, is then used as a controller for control of two compositions at the distillation column. Successful control of the nonlinear ill-conditioned process both in the face of set-point changes and for eliminating the effect of unmodelled disturbances is illustrated.

5.6 Paper VI

Value Function and Policy Approximation for Nonlinear Control of a pH-neutralization Process

One of the main disadvantages of the MPC formulation is that it is often computationally demanding. Thus, different approaches to relieve this computational burden are of interest.

The formulation of control problems as optimisation problems of dynamic programming-type has received a large interest in fields such as reinforcement learning and neurodynamic programming. In such a formulation, the optimal cost-to-go function is divided into an immediate cost and a future cost-to-go, given a certain state. Thus, by estimating this future cost-to-go function by some kind of function approximator, one can formulate the control problem as a value function approximation.

In the sixth paper in this thesis, a value function approximating scheme is investigated, first on a simple linear process and then on the pH-process used in Paper **IV**. The future cost-to-go function is then approximated by the use of a feedforward neural network. For training of the neural network used for the function approximation, the future control moves are calculated by use of a nonlinear MPC formulation.

As the approximation of the value function demands much data, an alternative strategy is a formulation where the optimal control policy is approximated instead. In the paper this is also shown to work well for control of the pH-process.

5.7 Paper VII

Neural Network Approximation of a Nonlinear Model Predictive Controller Applied to a pH Neutralization Process

The concept of approximating the optimal control policy introduced in Paper **VI** is taken further in this paper.

In this paper, the pH-process is modelled by a set of linearised models obtained by velocity-based linearisation. The velocity-based linearisation uses the latest measurement of the pH-value as the scheduling variable. In theory, the nonlinear plant could be described exactly by a set of linearised models, although in practice errors are unavoidable.

A neural network function approximator is then used to approximate the velocity-based linearised model predictive control strategy. The network used is a feedforward neural network. Furthermore, the controller includes integral action.

The accuracy of the neural network controller approximation which is required to ensure stability and performance is shown to be related to the fragility of the original model predictive controller, and it can be characterised in terms of an l_2-induced norm defined for the closed-loop system.

Chapter 6

Conclusions

This thesis addresses some relevant problems in the field of process control. First, an analysis of the multivariable nature of process models is made. The terminology, such as directionality, interaction and scaling, is clarified. Inconsistencies in the common use of this terminology are pointed out. Further, a consistent use of this terminology makes it possible to relate it to robustness and performance aspects, respectively.

This indicates how an improved understanding of the concepts of interaction, directionality and scaling can improve the analysis and thus also the quality of control results in multivariable process control.

Second, "conventional intelligence" in the form of control structures is applied as a means to deal with the problem of controlling multivariable, possibly nonlinear, plants. Decoupling, which is a control structure commonly used in process control, is discussed and studied as an example of how basic process understanding or, if one wishes, basic engineering wisdom, can be used to solve seemingly difficult control problems in an intuitively appealing and efficient manner.

The interaction between different control loops is, as mentioned, considered to be one of the main challenges in process control. Another significant challenge in process control is handling the nonlinear features of the process under control. As a means to tackle this challenge this thesis investigates how an input/output based nonlinear modelling technique manages to capture the nonlinearities.

Also, as computational capabilities increase, the emphasis in controller implementation can shift towards more computation-demanding applications. As such, this thesis has studied the model predictive control formulation for use for control of some relevant processes. In particular, the model predictive control formulation in conjunction with a quasi-ARMAX modelling technique is studied. These studies are performed on case studies representing important process control problems. A highly nonlinear pH-neutralization process in a single-input single-output formulation is studied. Also, a binary distillation column is studied as it is highly challenging in the sense that it exhibits both significant nonlinearity and ill-conditionedness. The technique discussed here shows good results on both processes, as compared to other results presented in the literature.

Furthermore, as the nonlinear MPC formulation might lead to extremely time-consuming computations, techniques for approximating the behaviour of the MPC controller by means of both value function and policy approximating methods are studied. These approximation techniques manage to reduce the computational burden significantly, without a significant reduction in control quality.

Although the potential of computation-intensive control methods, such as computational intelligence and online optimisations, is large and positive results have been presented (Takatsu et al., 1998; Hussain, 1999), there have been sometimes constructive but often destructive discussions concerning traditional control versus (mainly) fuzzy control (Åström and McAvoy, 1992; Kosko, 1993; Abramovitch, 1994; Bezdek, 1994; Zadeh, 1994; Zadeh, 1996; Abramovitch and Bushnell, 1999; Abramovitch, 1999; Ho, 1999). These discussions could be seen as an indicative reference frame to the mentality within the field of process control. As we see it, one of the main challenges in process control is the ability to combine the established methods, including *ad hoc* methods, rule-of-thumb and engineering wisdom with the computation-based cognitive methods based on computational intelligence and computational power, such as fuzzy logic, neural networks and MPC calculations. The potential gain of a more constructive cooperation is enormous.

This thesis has tried to discuss two of the large challenges in process control, namely directionality and nonlinearity, from two different approaches. First directionality is studied from the conventional wisdom approach, and second, nonlinearity is studied from a computational approach. Furthermore, on an introductory level this thesis discusses the meeting place of these two approaches with the control of a nonlinear, ill-conditioned distillation column. Here, the challenge does not lie in one of the two discussed problems, but in both. Also, controllers able to combine the appeal of conventional methods, such as input/output modelling, with methods based on computational intelligence, such as neuro-fuzzy modelling, in an environment allowing for computation-intensive methods have been discussed. These controllers aim at pointing toward the benefit of combining methods from different disciplines, in order to perform truly intelligent control in the future.

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