CHEMICAL ENGINEERING AND ADVANCED MATERIALS
UNIVERSITY OF NEWCASTLE UPON TYNE

Wor' Department

ADVANCED PROCESS CONTROL

by: Mark J. Willis & Ming T. Tham

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SUMMARY

This report takes a non-technical look at the state-of-the-art in modern control engineering, focusing on techniques that are applicable to the process industries. As the rate of development in this field is phenomenal, the review is not exhaustive. What we have done is to draw upon the experiences of the Advanced Process Control Group at the Department of Chemical and Process Engineering, University of Newcastle upon Tyne. The group has been extensively involved in the fundamental development and application of modern control methods for nearly two decades.

It is also well known that any improvement in the performance of control strategies will result in more consistent production, facilitating process optimisation, hence less re-processing of products and less waste.

Process models underpin most modern control approaches. Depending on the model forms, different controllers can be synthesised. Even the prevalent Proportional+Integral+Derivative (PID) algorithm can be designed from a model based perspective. The performance capabilities of PID algorithms are limited though. More sophisticated strategies, such as adaptive algorithms and predictive controllers have been proposed for improved process control. Due to the emphasis on Quality, Statistical Process Control (SPC) techniques are also experiencing a revival. In particular, attempts are being made to integrate traditional SPC practice with engineering feedback control techniques. Each of these strategies possesses respective merits. Of special significance is the recent attention paid to developing practicable nonlinear controllers, in recognition of the fact that many real processes are nonlinear and that adaptive systems may not be able to cope with significant nonlinearities. There are two approaches. One attempts to design control strategies based on nonlinear black box models, e.g. nonlinear time-series or neural networks. The other relies on an analytical approach, making use of a physical-chemical model of the process. However, there are indications that the two approaches can be rationalised. Cheap powerful computers and advances in the field of Artificial Intelligence are also making their impact. Local controls are increasingly being supplemented with monitoring, supervision and optimisation schemes; roles that traditionally were undertaken by plant personnel. These reside at a higher level in the information management and process control hierarchy. Performing tasks

that relate directly to overall plant management objectives, they effectively link plant business objectives with local unit operations. The result is an environment that is conducive to more consistent production.

Modern process plants, designed for flexible production and to maximise recovery of energy and material, are becoming more complex. Process units are tightly coupled and the failure of one unit can seriously degrade overall productivity. This situation presents significant control problems. The literature on relevant control, monitoring, supervision and optimisation techniques is voluminous, each article exhorting a certain solution to a particular problem. However, it is generally acknowledged that there is currently not one technique that will solve all the control problems that can manifest in modern plants. Indeed, different plants have different requirements.

A systematic studied approach to choosing pertinent techniques and their integration into a co-operative management and control system will significantly enhance plant operation and profitability. ***This is the goal of advanced process control.***

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1. WHAT IS ADVANCED CONTROL?

Over the past 30 years, much have been written about advanced control; the underlying theory, implementation studies, statements about the benefits that its applications will bring and projections of future trends. During the 1960s, advanced control was taken to mean any algorithm or strategy that deviated from the classical three-term, Proportional-Integral-Derivative (PID), controller. The advent of process computers meant that algorithms that could not be realised using analog technology could now be applied. Feed forward control, multivariable control and optimal control philosophies became practicable alternatives. Indeed, the modern day proliferation of so called advanced control methodologies can only be attributed to the advances made in the electronics industry, especially in the development of low cost digital computational devices (circa 1970). Nowadays, advanced control is synonymous with the implementation of computer based technologies.

It has been recently reported that advanced control can improve product yield; reduce energy consumption; increase capacity; improve product quality and consistency; reduce product giveaway; increase responsiveness; improved process safety and reduce environmental emissions. By implementing advanced control, benefits ranging from 2% to 6% of operating costs have been quoted [Anderson, 1992]. These benefits are clearly enormous and are achieved by reducing process variability, hence allowing plants to be operated to their designed capacity.

What exactly is advanced control? Depending on an individual's background, advanced control may mean different things. It could be the implementation of feedforward or cascade control schemes; of time-delay compensators; of self-tuning or adaptive algorithms or of optimisation strategies. Here, the views of academics and practising engineers can differ significantly.

We prefer to regard advanced control as more than just the use of multi-processor computers or state-of-the-art software environments. Neither does it refer to the singular use of sophisticated control algorithms. It describes a practice which draws upon elements from many disciplines ranging from Control Engineering, Signal Processing, Statistics, Decision Theory, Artificial Intelligence to hardware and software engineering. Central to this philosophy is the requirement for an engineering appreciation of the problem, an understanding of process plant behaviour coupled with the judicious use of, not necessarily state-of-the art, control technologies.

This report restricts attention to control algorithms. Current approaches in this area rely heavily upon a study of system behaviour and the use of process models. Therefore this report will focus only on model based techniques. Although most of the methodologies to be described are applicable to a wide spectrum of systems, e.g. aerospace, robotics, radar tracking and vehicle guidance systems, only those pertinent to the process industries will be discussed.

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2. PROCESS MODELS

Any description of a system could be considered to be a model of that system. Although the ability to encapsulate dynamic information is important, some analysis and design techniques require only steady-state information. Models allow the effects of time and space to be scaled, extraction of properties and hence simplification, to retain only those details relevant to the problem. The use of models therefore reduces the need for real experimentation and facilitates the achievement of many different purposes at reduced cost, risk and time.

In terms of control requirements, the model must contain information that enable prediction of the consequences of changing process operating conditions. Within this context, a model could either be a mathematical or statistical description of specific aspects of the process. It can also be in the form of qualitative descriptions of process behaviour. A non-exhaustive categorisation of model forms is shown in Fig. 1. Depending on the task, different model types will be employed.

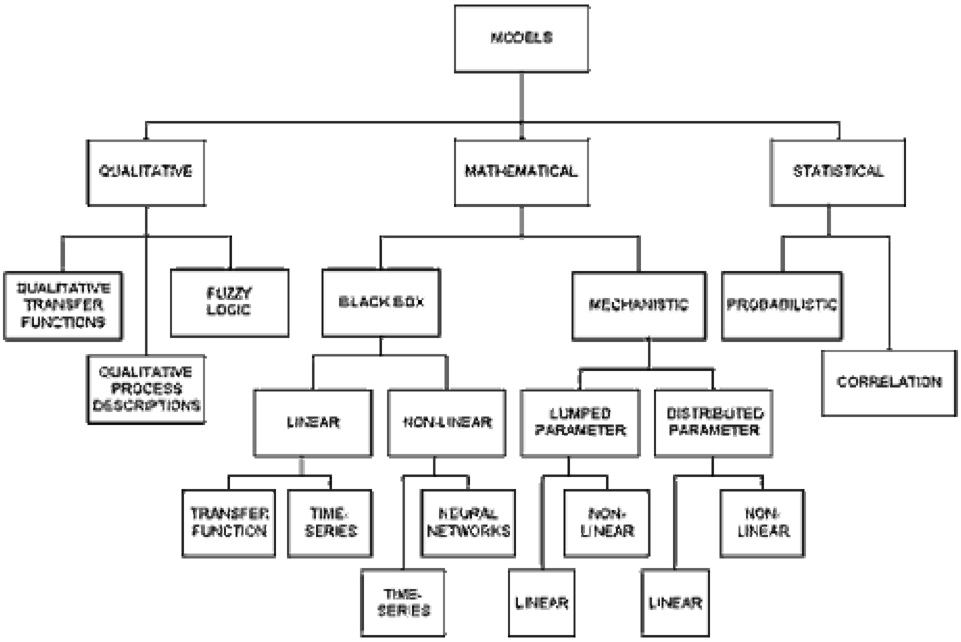

Figure 1. Classification of Model Types for Process Monitoring and Control

2.1. Mechanistic Models

If much is known about the process and its characteristics are well defined, then a set of differential equations can be used to describe its dynamic behaviour. This is known as 'mechanistic' model development. The mechanistic model is usually derived from the physics and chemistry governing the process. Depending on the system, the structure of the final model may either be a lumped parameter or a distributed parameter representation. Lumped parameter models are described by ordinary differential equations (ODEs) while distributed parameter systems representations require the use of partial differential equations (PDEs). ODEs are used to describe behaviour in one dimension, normally time, e.g. the level of liquid in a tank. PDE models arise due to dependence also on spatial locations, e.g. the temperature profile of liquid in a tank that is not well mixed.

Obviously, a distributed parameter model is more complex and hence harder to develop. More importantly, the solution of PDEs is also less straightforward. Nevertheless, a distributed model can be approximated by a series of ODEs given simplifying assumptions. Both lumped and distributed parameter models can be further classified into linear or nonlinear descriptions. Usually nonlinear, the differential equations are often linearised to enable tractable analysis.

In many cases, typically due to financial and time constraints, mechanistic model development may not be practically feasible. This is particularly true when knowledge about the process is initially vague or if the process is so complex that the resulting equations cannot be solved. Under such circumstances, empirical or 'black-box' models may be built using data collected from the plant.

2.2. Black Box Models

Black box models simply describe the functional relationships between system inputs and system outputs. They are, by implication, lumped parameter models. The parameters of these functions do not have any physical significance in terms of equivalence to process parameters such as heat or mass transfer coefficients, reaction kinetics, etc. This is the disadvantage of black box models compared to mechanistic models. However, if the aim is to merely represent faithfully some trends in process behaviour, then the black box modelling approach is just as effective. Moreover, the cost of modelling is orders of magnitude smaller than that associated with the development of mechanistic models.

As shown in Fig. 1, black box models can be further classified into linear and nonlinear forms. In the linear category, transfer function and time series models predominate. With sampled data systems, this delineation is, in a sense, arbitrary. The only distinguishing factor is that in time-series models, variables are treated as random variables. In the absence of random effects, the transfer function and time-series models are equivalent. Given the relevant data, a variety of techniques may be used to identify the parameters of linear black box models [Eykhoff, 1974]. The most common techniques used, though, are least-squares based algorithms.

Under the nonlinear category, time-series feature again together with neural network based models. In nonlinear time-series, the nonlinear behaviour of the process is modelled by combinations of weighted cross-products and powers of the variables used in the representation. The parameters of the functions are still linear and thus facilitates identification using least squares based techniques. Neural networks are not new paradigms to nonlinear systems modelling. However, the increase in cheap computing power and certain powerful theoretical results have led to a resurgence in the use of neural networks in model building [Cybenko, 1989; Lippmann, 1987, Rummelhart and McCelland, 1986].

2.3. Qualitative Models

There are instances where the nature of the process may preclude mathematical description, e.g. when the process is operated at distinct operating regions or when physical limits exist. This results in discontinuities that are not amenable to mathematical descriptions. In this case, qualitative models can be formulated. The simplest form of a qualitative model is the 'rule-based' model that makes use of 'IF-THEN-ELSE' constructs to describe process behaviour. These rules are elicited from human experts. Alternatively, Genetic Algorithms and Rule Induction techniques can be applied to process data to generate these describing rules [South et al, 1993]. More sophisticated approaches make use of Qualitative Physics theory [Bobrow, 1984; Weld and deKleer, 1990] and its variants. These latter methods aim to rectify the disadvantages of purely rule based models by invoking some form of algebra so that the preciseness of mathematical modelling approaches could be achieved.

Of these, Qualitative Transfer Functions (QTFs) [Feray Beaumont et al, 1992] appear to be the most suitable for process monitoring and control applications. QTFs retain many of the qualities of quantitative transfer functions that describe the relationship between an input and an output variable, particularly the ability to embody temporal aspects of process behaviour. The technique was conceived for applications in the process control domain. Cast within an object framework, a model is built up of smaller sub-systems and connected together as in a directed graph. Each node in the graph represents a variable while the arcs that connect the nodes describe the influence or relationship between the nodes. Overall system behaviour is derived by traversing the graph, from input sources to output sinks.

Models derived based on the use of Fuzzy Set theory can also be classified as qualitative models. Proposed by Zadeh [1965, 1971], fuzzy set theory contains an algebra and a set of linguistics that facilitates descriptions of complex and ill-defined systems. Magnitudes of changes are quantised as 'negative medium', 'positive large' and so on. The model combines elements of the rule based and probabilistic approaches and sets of symbols with interpretations such as, '*If the increment of the input is positive large, the possibility of the increment on the output being negative small is 0.8*'. Fuzzy models are being used in everyday life without our being aware of their presence, e.g. washing machines, auto focus cameras, etc.

2.4. Statistical Models

Describing processes in statistical terms is another modelling technique. Time-series analysis which has a heavy statistical bias may be considered to fall into this model category. Nevertheless, due to its widespread and interchangeable use in the development of deterministic as well as stochastic digital control algorithms, the earlier classification is more appropriate. The statistical approach is made necessary by the uncertainties surrounding some process systems. This technique has roots in statistical data analysis, information theory, games theory and the theory of decision systems.

Probabilistic models are characterised by the probability density functions of the variables. The most common is the normal distribution which provides information about the likelihood of a variable taking on certain values. Multivariate probability density functions can also be formulated but interpretation becomes difficult when more than two variables are considered. Correlation models arise by quantifying the degree of similarity between two variables by monitoring their variations. This is again quite a commonly used technique, and is implicit when associations between variables are analysed using regression techniques.

System dynamics are not captured by statistical models. However, in modern control practice, they play an important role particularly in assisting in higher level decision making, process monitoring, data analysis and obviously, in Statistical Process Control.

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3. MODEL BASED (MODERN) AUTOMATIC CONTROL

Given a representative model of a process, 'What-If' investigations can be made via simulation, to answer operational questions such as safety related issues and to provide for operator training. However, this approach is not suitable for real-time automatic control. Within the context of automatic control, the inverse problem is considered, i.e. given the current states of the process, what actions should be taken to achieve desired specifications. Depending on the form of the plant model, different control strategies can be developed. The attraction of adopting a model based approach to controller development is illustrated in the block diagram shown in Figure 2.

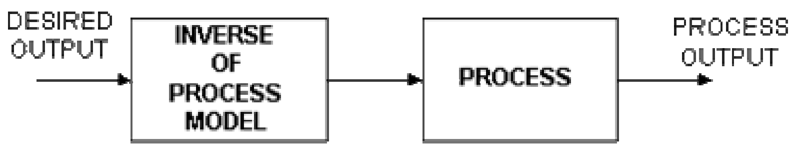

Figure 2. Ideal Model Based Control

By regarding the blocks to be mathematical operators, it can be seen that if an accurate model of the process is available, and if its inverse exists, then process dynamics can be cancelled by the inverse model. As a result, the output of the process will always be equal to the desired output. In other words, model based control design has the potential to provide perfect control. Hence, the first task in the implementation of modern control is to obtain a model of the process to be controlled. However, given that there are constraints on process operations; that all models will contain some degree of error and that all models may not be invertible, perfect control is very difficult to realise. These are the issues that modern control techniques aim to address, either directly or indirectly.

In the process industries, black box models are normally used for controller synthesis because the ill-defined nature of the processes makes mechanistic model development very costly. For process design purposes, precise characterisation is important. However, for the purposes of control strategy specification, controller design and control system analysis, models that can replicate the dynamic trends of the target processes are usually sufficient. Black box models have been found to be suitable in this respect and can be used to predict the results of taking certain actions.

Linear transfer functions and time-series descriptions are popular model forms used in control systems design. This is because of the wealth of knowledge that has been built up in linear systems theory. Increasingly, however, controllers are being designed using nonlinear time-series as well as neural network based models in recognition of the nonlinearities that pervade real world applications. The following sections briefly discuss the various algorithms that may arise from model based controller designs.

3.1. PID Control

The ubiquitous three-term Proportional+Integral+Derivative (PID) controller accounts for more than 80% of installed automatic feedback control devices in the process industries. In the past, these have been tuned using frequency response techniques or empirically derived rules-of-thumb. The modern approach is to determine the settings of the PID controller based upon a model of the process. The settings are chosen so that the controlled response adhere to user specifications. A typical criterion is that the controlled response should have a quarter decay ratio. Alternatively, it may be desired that the controlled response follow a defined trajectory or that the closed loop has certain stability properties [e.g. Warwick and Rees, 1988].

It can be easily shown that a Proportional+Integral controller is optimal for a first order linear process without time-delays. Similarly, the PID controller is optimal for a second order linear process without time-delays. In practice, process characteristics are nonlinear and can change with time. Thus the linear model used for initial controller design may not be applicable when process conditions change or when the process is operated at another region.

One solution is to have a series of stored controller settings, each pertinent to a specific operating zone. Once it is detected that the operating regime has changed, the appropriate settings are switched in. This strategy, called parameter- or gain-scheduled control, has found favour in applications to processes where the operating regions are changed according to a preset and constant pattern. In applications to continuous systems, however, the technique is not so effective.

A more elegant technique is to implement the controller within an adaptive framework. Here the parameters of a linear model are updated regularly to reflect current process characteristics [Warwick et al, 1987; Willis and Tham, 1989a]. These parameters are in turn used to calculate the settings of the controller as shown schematically in Fig. 3.

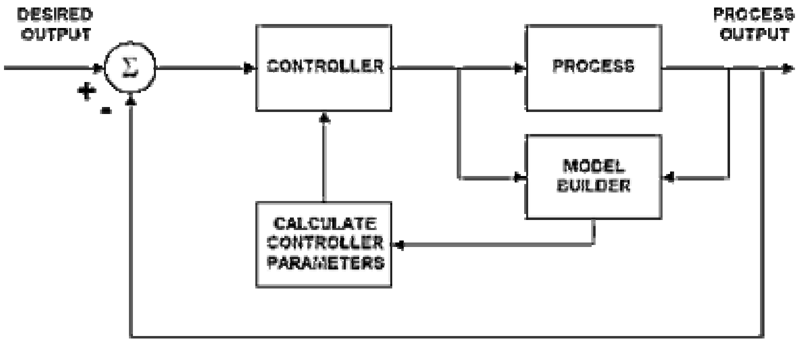

Figure 3. Simplified Schematic of the Structure of Adaptive Controllers

The settings of the controller can be updated continuously according to changes in process characteristics. Such devices are therefore called auto-tuning/adaptive/self-tuning controllers. In some formulations, the controller settings are directly identified. A faster algorithm results because the model building stage has been avoided. Currently, many commercial auto-tuning PID controllers available from major control and instrumentation manufacturers. The simplest forms are those based upon the use of linear time-series models Some PID controllers are also auto-tuned using pattern recognition methods [Bristol, 1977]. For example, the Foxboro EXACT controller changes its settings to maintain a user defined response pattern. A good review of auto-tuning PID controllers is given in Astrom and Hagglund [1988].

Theoretically, all model based controllers can be operated in an adaptive mode [e.g. Hang et al, 1993]. Nevertheless, there are instances when the adaptive mechanism may not be fast enough to capture changes in process characteristics due to system nonlinearities. Under such circumstances, the use of a nonlinear model may be more appropriate for PID controller design. Nonlinear time-series, and recently neural networks, have been used in this context. A nonlinear PID controller may also be automatically tuned using an appropriate strategy, by posing the problem as an optimisation problem. This may be necessary when the nonlinear dynamics of the plant are time-varying. Again, the strategy is to make use of controller settings most appropriate to the current characteristics of the controlled process. A self-tuning PID controller based on the use of a nonlinear neural net model has been reported by Montague and Willis (1993).

3.2. Predictive Constrained Control

PID type controllers do not perform well when applied to systems with significant time-delays. Perhaps the best known technique for controlling systems with large time-delays is the 'Smith predictor'. It overcomes the debilitating problems of delayed feedback by using predicted future states of the output for control. Currently, some commercial controllers have Smith predictors as programmable blocks. There are, however, many other model based control strategies have dead-time compensation properties. If there is no time-delay, these algorithms usually collapse to the PID form. Predictive controllers can also be embedded within an adaptive framework and a typical adaptive predictive control structure is shown in Fig. 4.

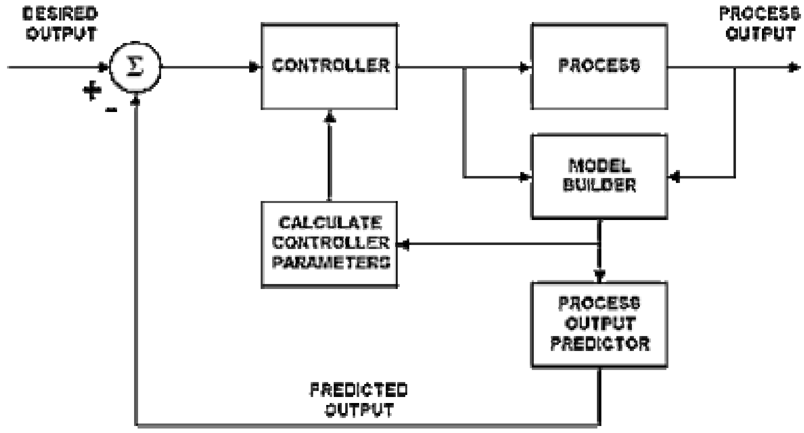

Figure 4. Simplified Schematic of Adaptive Predictive Controllers

The, by now, classical Generalised Minimum Variance (GMV) controller is an example of this philosophy [Clarke and Gawthrop, 1975]. GMV control minimises the squared weighted difference between the desired value and the predicted output while penalising excessive control effort. The prediction horizon is the time-delay of the system, and this is a fixed parameter. GMV control, however, cannot effectively cope with variable time-delays and process constraints. This led to the development of long-range predictive controllers, e.g. the Generalised Predictive Controller (GPC) and Dynamic Matrix Control (DMC) [Clarke et al, 1987; Cutler and Ramaker, 1979; Wilkinson et al, 1990, 1991a,b]. The control problem is formulated in a manner similar to that adopted in the GMV approach. The differences are that the model is used to provide predictions of the output over a range of time-horizons into the future. Usually the range is between the smallest and largest expected delays. This alleviates the problem of varying time-delays and hence enhances robustness. Calculation of the control signal is essentially an optimisation problem. Here, economic objectives as well as process constraints can be included in the problem formulation. Examples of process constraints are the limits to liquid flows in fixed sized piping, allowable temperatures and pressures in process units, emissions to atmosphere, etc. Nowadays, the phrase 'predictive control' refers to the application of long-range predictive controllers. Again, predictive controllers may be designed using linear or nonlinear models.

3.3. Multivariable Control

Thus far, we have only considered the case where the is one manipulated input and one controlled output; single-input single-output (SISO) systems. With most processes, there are many variables that have to be regulated. The chemical reactor is a typical example where level, temperature and pressure have to kept at design values, that is there are at least three control loops; a multi-loop system. If the actions of one controller affect other loops in the system, then control-loop interaction is said to exist. If each controller has been individually tuned to provide maximum performance, then depending on the severity of the interactions system instability may occur when all the loops are closed. SISO controllers, whether adaptive, linear or nonlinear strategies, may therefore not be applicable to such processes. Models used in the design of SISO controllers do not contain information about the effects of loop interactions. Thus, they cannot be expected to perform well. For a multiloop strategy to work, individual SISO controllers are usually detuned (made less sensitive), resulting in sluggish performances for some or all loops.

Ideally, multivariable controllers should be applied to systems where interactions occur. As opposed to multi-loop control, multivariable controllers take into account loop interactions and their de-stabilising effects. Fortunately, it is a relatively trivial task to modify model based controllers to accommodate multivariable systems. By regarding loop interactions as feed-forward disturbances, they can be easily included in the model description. This simple augmentation leads to multivariable linear decoupling controllers [Jones and Tham, 1987; Tham, 1985; Tham et al, 1991b; Vagi et al, 1991], as well as nonlinear neural network based multivariable control algorithms [Willis et al, 1991e]. Following SISO designs, multivariable controllers that can provide time-delay compensation and handle process constraints can also be developed with relative ease. By incorporating suitable numerical procedures to build the model on-line, adaptive multivariable control strategies result.

3.4. Robust Control and the Internal Model Principle

Using an on-line parameter estimation algorithm to identify the parameters of the model, the parameters of most linear model based controllers can be adjusted in line with changes in process characteristics. Although great strides have been made in resolving the implementation issues of adaptive systems, for one reason or other, many practitioners are still not confident about the long term integrity of the adaptive mechanism. This concern has led to another contemporary topic in modern control engineering; robust control.

Robust control involves, firstly, quantifying the uncertainties or errors in a 'nominal' process model, due to nonlinear or time-varying process behaviour for example. If this can be accomplished, we essentially have a description of the process under all possible operating conditions. The next stage involves the design of a controller that will maintain stability as well as achieve specified performance over this range of operating conditions. A controller with this property is said to be 'robust' [Morari and Zafiriou, 1989].

A sensitive controller is required to achieve performance objectives. Unfortunately, such a controller will also be sensitive to process uncertainties and hence suffer from stability problems. On the other hand, a controller that is insensitive to process uncertainties will have poorer performance characteristics in that controlled responses will be sluggish. The robust control problem is therefore formulated as a compromise between achieving performance and ensuring stability under assumed process uncertainties. Uncertainty descriptions are at best very conservative, whereupon performance objectives will have to be sacrificed. Moreover, the resulting optimisation problem is frequently not well posed. Thus, although robustness is a desirable property, and the theoretical developments and analysis tools are quite mature, application is hindered by the use of daunting mathematics and the lack of a suitable solution procedure.

Nevertheless, underpinning the design of robust controllers is the so called 'internal model' principle. It states that unless the control strategy contains, either explicitly or implicitly, a description of the controlled process, then either the performance or stability criterion, or both, will not be achieved. The corresponding 'internal model control' design procedure encapsulates this philosophy and provides for both perfect control and a mechanism to impart robust properties (see Fig. 5).

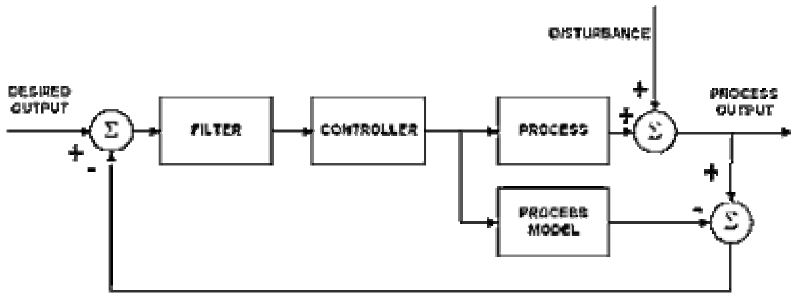

Figure 5. Schematic of Internal Model Control Strategy

If the process model is invertible, then the controller is simply the inverse of the model. If the model is accurate and there is no disturbance, then perfect control is achieved if the filter is not present. This also implies that if we know the behaviour of the process exactly, then feedback is not necessary! The primary role of the low-pass filter is to attenuate uncertainties in the feedback, generated by the difference between process and model outputs and serves to moderate excessive control effort. The strategy and the concept that it embraces are clearly very powerful. Indeed, the internal model principle is the essence of model based control and all model based controllers can be designed within its framework.

3.5. Globally Linearising Control

As mentioned previously, there are cases when adaptive linear control schemes would not perform well when faced with a highly nonlinear process. This is because the adaptive mechanism may not be fast enough to track changes in process characteristics. Appropriately designed nonlinear controllers would therefore be expected to perform better. The use of neural network model based controllers has already been mentioned. Another emerging field is that of nonlinear controller designed based on mechanisitc models via the use of differential geometric concepts [Brockett, 1976; Kravaris and Kantor, 1990]. The aim of the design is similar to the use of Taylor series expansion to linearise the nonlinear model prior to application of linear model based controller designs. However, instead of providing local linearisation, contemporary nonlinear control strategies aim to provide 'global' linearisation over the space spanned by the states of the process; Globally Linearising Control (GLC). Global linearisation is achieved by a pre-compensator, designed such that the relationship between the inputs to the pre-compensator and the process output is linear. Linear control techniques can then be applied to the pseudo linear plant. A schematic of this strategy is shown in Fig. 6.

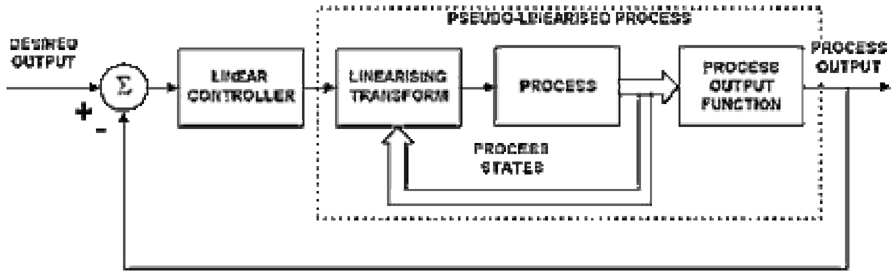

Figure 6. Schematic of Globally Linearising Control

Globally linearising control is a relatively new development and much research is being still being carried out to investigate the applicability of the technique [e.g. McColm et al, 1994]. McLellan et al [1990] provide a review of nonlinear controller designs based upon mechanistic models. An interesting development that avoids the requirement of mechanistic models, is to use neural networks models instead. Neural network models are transformed into an equivalent state-space representation, and the GLC is designed based upon this state-space model [Peel et al, 1994].

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4. STATISTICAL PROCESS CONTROL

Statistical Process Control (SPC) is widely applied in the parts manufacturing industries. Although the technique has been practised at various levels for more than 30 years, it warrants mention. In response to current total quality initiatives SPC has only just recently begun to be implemented in the process industries. SPC makes use of statistical models and procedures that to improve product quality and process productivity at reduced costs [Wetherill and Brown, 1991]. The objective is to bring and keep processes in a state where any remaining variations are those inherent to the process.

4.1. Conventional SPC

SPC has been traditionally achieved by successive plotting and comparing a statistical measure of the variable with some user defined 'control' limits. If the plotted statistic exceeds these limits, the process is considered to be out of statistical control. Corrective action is then applied in the form of identification, elimination or compensation for the 'assignable' causes of variation. The most common charts used are the Shewhart, Exponential Moving Average (EWMA), range and Cumulative Sum (CuSum) charts. (more)

4.2. Algorithmic SPC

Conventional SPC is basically an off-line technique. Whilst there are many reports of succesful cases in the parts manufacturing sector, this 'passive' control strategy does not suit continuous systems. Here, in addition to keeping products within specifications, there is a requirement to keep the process operating. Depending on the complexity of the process, the time taken to identify, eliminate and compensate for assignable causes of variation may not be acceptable. Nevertheless, the aim of both automatic process control and SPC is to increase plant profitability. Thus, it is reasonable to expect that the merger of these two apparently dichotomous methodologies could yield strategies that inherit the benefits associated with the parent approaches. This has been a subject of recent investigations [MacGregor, 1988; Tucker, 1989] where SPC is used to monitor the performances of automatic control loops. Such a strategy is sometimes called 'Algorithmic SPC' (ASPC), referring to the integrated use of algorithmic model based controllers and SPC techniques. Note, though, that the process is still being controlled by an automatic controller, that is the process is being controlled all the time.

4.3. Active SPC

Another way to integrate the two control approaches is to provide on-line SPC. Statistical models are used not only to define control limits, but also to develop control laws that suggest the degree of manipulation to maintain the process under statistical control. Thus, in applications to continuous processes, the need for an algorithmic automatic controller is avoided, leading to a direct or 'active' SPC strategy [Efthimiadu and Tham 1990, 1991; Efthimiadu et al, 1993]. Indeed, the technique is designed specifically for continuous systems. In contrast to ASPC, manipulations are made only when necessary, as indicated by detecting violation of control limits. As a result, compared to automatic control and ASPC, savings in the use of raw materials and utilities can be achieved using active SPC.

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5. DEALING WITH DATA PROBLEMS

In the field of modern control engineering, much effort has been expended into the development and analysis of novel control strategies. A common assumption in these studies is that the required data is available. Unfortunately, this is often not the case in practice. However, the problem is gaining attention and a variety of solutions have been proposed to deal with various aspects of the difficulties associated with data.

5.1. Inferential Estimation

A major problem is the lack of on-line instrumentation to measure quantities that define product quality, e.g. stickiness of adhesives, smoothness of sheet material, melt flow index of polymers, flash points of fuels, etc. These are often provided by laboratory analyses resulting in infrequent feedback and substantial measurement delays, rendering automatic process control impossible. Inferential estimation is one method that has been designed to overcome this problem. The technique has also been called 'sensor-data fusion' and 'soft-sensing'.

Apart from the main quality variable, there are usually other variables such as temperatures, pressures, flows, etc., that are associated with a process. Changes in some of these variables are indicative of changes in product quality. Thus, by monitoring suitable secondary variables, it is often possible to 'infer' the state of the quality variable. Process operators and engineers do this on a daily basis in running process plants. However, the process may be complex and there could be many factors that affect product quality. As a result, the relationship between process conditions and product quality may not be straight forward, leading to inaccuracies in human judgement. Inferential Estimation alleviates this problem. The technique uses easily obtainable measurements of variables that are known to influence product quality, together with those of product quality when available, to generate estimates of product quality.

As with feedback control strategies, in applications to non-linear systems, the relationship between secondary variables and the primary output can be 'learnt' automatically. Thus, parameters that define the relationship are adjusted to match changes in process characteristics [Guilandoust et al, 1987, 1988; Lant et al, 1993; Montague et al, 1990, 1992; Tham, 1989, 1991a]. Alternatively, the inferential estimators may also be designed based upon the use of a neural network model. As shown in Fig. 7, estimates of the quality which are generated at the measurement frequency of the secondary variables may then be used for process monitoring or control purposes. [**more**]

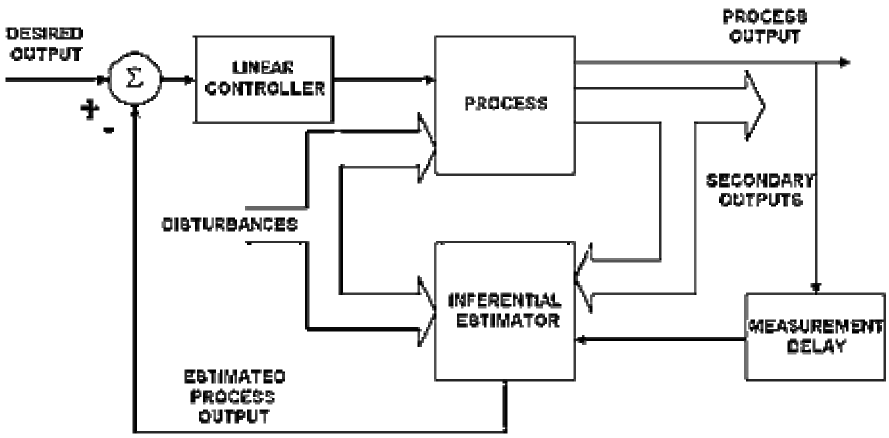

Figure 7. Schematic of Feedback Control using Inferential Estimator

5.2. Data Conditioning and Validation

Even if appropriate instruments exist, the data may not be of sufficient quality for desired goals to be achieved. Signals from plant are often corrupted by noise of varying magnitudes. All control methods are data driven. If appropriate measures are not taken to condition and validate the measured signals, then even the most sophisticated scheme will fail. In other words, the adage 'rubbish in, rubbish out' applies in the field of control.

In safety critical systems, such as the control and monitoring of nuclear reactors and power generators, steps are taken to ensure that the 'correct' signals are used for decision making. In these cases, it is common for both software and hardware redundancy schemes to be implemented. Redundancy is provided for by configuring software or hardware modules in duplicate or triplicate. Voting systems are then employed to validate output signals, retaining only those that are considered to be correct [Warwick and Tham, 1988, 1990].

In less critical applications, duplex or triplex redundancy configurations are not cost effective. Therefore, unless there is absolute need, the smoothing of noisy signals is accomplished via hardware or software filtering to attenuate noise in measured signals. However, a penalty is incurred if the signal is subject to spikes. To remove these spikes or rogue points, heavy filtering has to be applied whereupon significant time-lags may be introduced into the filtered signal. Time-lags in the filtered signal may however be reduced by employing 'logic' filters which combine conventional filter algorithms with SPC concepts to validate and condition process measurements. This integrated approach has been shown to be very effective [Parr and Tham, 1992; Tham and Parr, 1994]

5.3. Data Analysis

Even if 'clean' data is available, there may be many variables associated with a particular process unit. The specification of an appropriate control strategy and controller design become complicated. Which variable should be manipulated to control another? What is the effect of this choice of manipulated-input controlled-output pairings? These are some of the important questions that have to be answered before a candidate configuration can be applied. Indeed, the results dictate the kind of models to employ for controller design and hence final controller types, and the overall control strategy that should be implemented. Inappropriate choice of input-output pairs exacerbate the problem of loop interactions. If interactions are significant, then a multivariable control design is necessary. If the input-output relations indicate nonlinear behaviour, then nonlinear controllers may have to be applied.

Many techniques can be used to tackle these issues. They range from simple graphical techniques (scatter plots, Box-plots), statistical multivariate analysis (e.g. Principal Component Analysis, Correlation Analysis, Cluster Analysis) to control theoretic, relative gain and singular value analyses. The latter are used to investigate control loop interactions and robustness of control strategies. However, there is currently no all embracing procedure for a systematic analysis of data right through to determining the suitability of the final control scheme.

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6. HIGHER LEVEL OPERATIONS

6.1. Process Optimisation

The application of optimisation techniques is not restricted to the design of predictive constrained controllers. Process optimisation is a task in its own right. Unlike local controllers, which seek to maintain unit operating conditions at desired levels, the plant optimiser utilises a model of the plant to adjust operating conditions of the process so as to minimise raw material usage and maximise profits [Edgar and Himmelblau, 1989]. The outputs of the optimiser therefore set the targets for the local controllers, taking into consideration the operational limits of the plant. This effectively bridging the gap between the plant's true business objectives and its actual operations [Latour, 1979a, 1979b]. Figure 8 shows a generic configuration of a process optimisation scheme.

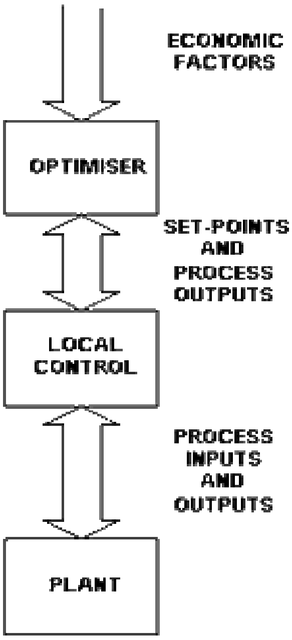

Figure 8. Structure of Optimisation Scheme

Due to the complexity and the scale of this type of optimisation problem, the model used is normally a steady-state description to enable a tractable solution. As with control algorithms, adaptive on-line optimisation is also feasible [e.g. Bamberger and Isermann, 1978; Kambhampati et al, 1992; Willis and Tham, 1989b, 1990].

6.2. Process Monitoring, Fault Detection, Location and Diagnosis

Fault diagnosis has become an area of primary importance in modern process automation. It provides the pre-requisites for fault tolerance, reliability or security, which constitute fundamental design features in complex engineering systems. The system under consideration is monitored and the data is passed to fault detection algorithms or procedures. The basic task of a fault detection scheme is to register an alarm when an abnormal condition develops in the monitored system. Once a fault is detected, procedures may also be subsequently used to identify or diagnose the cause of the abnormality.

Fault detection and diagnosis techniques are again based upon the use of process models. In addition to the mathematical models used in controller design, statistical as well as qualitative models are increasingly being employed [Isermann, 1984; Patton et al, 1989]. Mathematical models are normally used to develop state-estimators or state-observers. Data from the monitored plant is input to these algorithms and the outputs compared with the corresponding plant outputs. If there are discrepancies, then it is an indication that at least one fault has occurred. The next task is to determine the locations of these faults. Again a representative model, not necessarily the one used in fault detection, is employed. In some instances, the location of the fault may be deduced by the type of fault. Here genetic algorithms and rule induction systems can be used to classify the fault.

6.3. Process Supervision via Artificial Intelligence Techniques

Human beings are able to make judgements in the face of subtle nuances and ambiguities. These knowledge processing capabilities cannot be matched by number crunching data processing algorithms, such as those described above. Although, the human decision system may not be precise, the result is often of sufficient accuracy for quick and effective problem solving. It has been the goal of computer scientists for many decades to build systems that mimic the decision making powers of human beings, i.e. artificial intelligent (AI) systems. AI techniques are also model based. Some would regard neural network based techniques to fall into the AI category. However, we tend to consider neural networks as numerical function approximators. Although AI techniques can make use of mathematical and statistical models, including neural networks, much of their utility is based upon the use of qualitative models.

Perhaps the most well known AI process supervisory schemes is based upon the use of expert systems [Efstathiou, 1986]. Expert systems are made up of three components. The rule or knowledge base holds information and logical rules for performing inference between facts. Next, there is the inference engine which controls the operation of the system and carries out the logical inference by processing the information in the knowledge base. The user interface makes up the final component, enabling communication between the user and the computer. Thus, an expert system is a collection of computer programs which operate upon the knowledge of experts in a particular application domain. Its purpose is to enable a novice to solve a problem with the benefits of the expert's knowledge.

When the inference engine and the user-interface are packaged as a single entity, this is known as an expert system shell. Software for procedures that can be combined together to form such a shell are known as expert system tools. The increasing availability of expert system shells and tools is a major reason for the proliferation of expert systems, where all that remains to be done is the compilation of the knowledge base. The extraction of rules that govern the operation of a process is called knowledge elicitation. This is performed via question and answer sessions between the extractor of knowledge, the so called knowledge engineer, and the provider of knowledge, the domain expert. There are also systems that are able to generate rules for expert systems when presented with data collected from a process. These are either based on rule induction techniques or genetic algorithms. However, the knowledge base could comprise any of the other qualitative models described previously and in any combination, including mathematical and statistical models.

When the system is presented with a collection of facts or a process scenario, the inference engine moves through the knowledge base in a 'forward' manner to come up with 'expert' advice or suggestions. However, unlike the implementation of 'IF-THEN-ELSE' constructs in conventional programming languages, expert systems have the ability to traverse the knowledge base in a backward direction. Backward chaining is invoked when the expert system is presented with a final result, and it is asked to provide a line of reasoning as to the events that led to the given result. Thus, another distinguishing factor of expert systems is that they are also able to provide explanations as to why a particular piece of advice or suggestion has been made. Expert systems have therefore found use in providing operator advice and as a process simulator for operator training [Kaemmerer and Christopherson, 1985].

Expert systems can be operated in two ways. The most common is the consultative mode where the expert system asks the user a series of questions. Alternatively, the data required by the expert system is provided directly by interfacing to plant instruments. There is a growing number of expert system shells that can reason in real-time [Shaw, 1988]. Such Real-Time Knowledge Based Systems (RTKBS) have been used to tune controllers, supervise the performance of adaptive controllers, perform fault detection and diagnosis, perform alarm management and even provide direct on-line process control.

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7. ADVANCED CONTROL

The techniques described in the previous sections have been applied to a wide variety of systems. In the process industries, they have been applied to reactors, separation processes, power generation systems including boilers, HVAC and so on. Many of these are reported by academics, academics involved in industrial collaborative projects or by consultants. There are also many unreported cases of successful advanced control applications, primarily because of commercial confidentiality. An illustrative list of reported applications is given in Appendix A. Many of the applications reported in the literature describe the use of single techniques. However, our philosophy of advanced control is depicted in the following diagram.

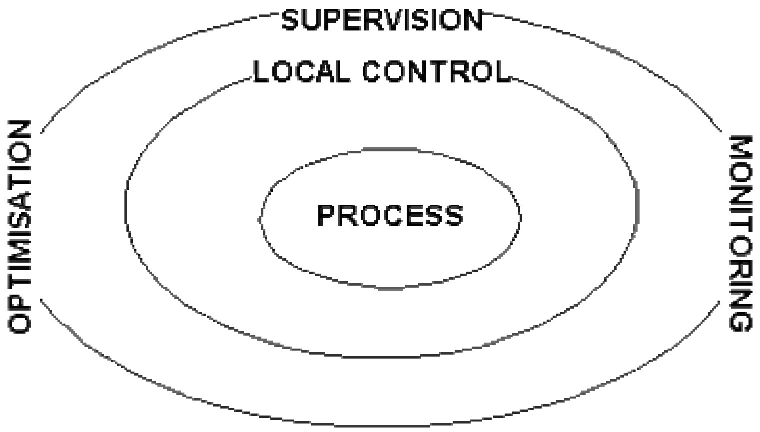

Figure 9. Hierarchical Layers in Integrated Modern Control

Local control is implemented, using appropriate controllers, to keep the process operating at desired conditions. Here, the type of local controllers employed depends on the task at hand. Although it is easier to tune and maintain simple controllers, some processes do require control by more sophisticated algorithms. However, unless such sophisticated controllers are installed and maintained by well trained trained personnel, they can be prone to failure. Until the last decade, the higher level tasks of monitoring, optimisation, and supervision were mainly carried out by human beings. Due to the advent of modern technology, and advances in the field of AI, these can now be automated. In particular, the installation, operation and integrity of modern controllers can be supervised by higher level systems.

Advanced control is the implementation of this hierarchical information and control structure. The flow of information is bi-directional, from management layer to process level and vice versa. The task here is to be able to integrate the various components in an efficient and manageable fashion. This can be facilitated by ensuring that each component is designed as a modular, yet integrable element.

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8. CURRENT RESEARCH AND FUTURE TRENDS

In the process industries, the biggest challenge facing process engineers will be the reduction of variable costs whilst maintaining product quality. Advanced process control is the most effective technology available to realise this objective, especially on established plants. As systems become more complex, another important aspect is the reliability of the implemented systems. Here, the reliability of hardware and software are issues which have to be addressed. Allied to this is the requirement for suitably designed man-machine interfaces to enable efficient and reliable information transfer and to facilitate systems management.

With regard to the primary modules making up an advanced control project, neural networks, nonlinear systems theory, robust control, knowledge based systems are areas which appear to have captured the attention of both researchers and practitioners in the field of control engineering. This trend will continue well into the next decade. Areas that will receive particular attention will be techniques that will translate raw data into useful information; improved measurement methods including inferential estimation; multivariable non-linear predictive control and formal techniques for analysing the integrity of neural network based methodologies.

All information is of value, and should not be discarded just because they do not conform to a particular model building procedure. Thus, new modelling methods are also required. These should provide a framework where *a priori* knowledge of the process could be combined with the various existing modelling techniques, leading to so called 'grey-box' models. The resulting models should also be amenable for utilisation by the different modern controller designs, thus rendering controller synthesis independent of model types.

The process industries have an enormous base of manufacturing facilities which are still being run by unsophisticated or primitive control schemes. Competitive pressures will not allow any company in these industries to ignore the significant efficiencies possible through adopting modern process control technologies. A major obstacle to realising the full potential of modern control techniques is the lack of exposure to advances in the field. This can be overcome by the development of portable computer based training packages. The current proliferation in multi-media computing systems is the ideal impetus for the development of such learning aids.

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CONTENTS

APPENDIX A: Examples of Reported Applications

Control

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Back to the Swot Shop

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